ePMPS – ePilot Manufacturing Plant Simulation

A CLOUD-BASED SIMULATION FRAMEWORK TO SUPPORT PULL-TYPE DECISION-MAKING PROCESSES FOR DAIRY MANUFACTURING

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This thesis is submitted in accordance with the requirements of
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Declaration

I hereby certify that this material, which I now submit for assessment on the programme of study leading to the award of Doctor of Philosophy is entirely my own work, and that I have exercised reasonable care to ensure that the work is original and does not to the best of my knowledge breach any law of copyright, and has not been take from the work of others save and to the extent that such work has been cited and acknowledged within the text of my work.

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Cristiani Eccher

Date: 24/01/2022

"Já que se há de escrever, que pelo menos não se esmaguem com palavras as entrelinhas. O melhor ainda não foi escrito. O melhor está nas entrelinhas." (Clarice Lispector)

DEDICATION

When I was a child, during reading and writing my first words, I unsuccessfully described the symptoms of a terrible sore throat to my granny: “Granny, I have a cough that ends with **Rs**”. I explained. She didn’t understand. She couldn’t. I discovered at that moment that my grandmother was illiterate.

I remember reading and teaching her numbers using coins. Later, despite her financial situation, she helped me during my first month when I started in college. This entire thesis is for you, for being such a strong woman and your ability to withstand heavy loads without failure cannot be explained through Engineering Equations.

To my entire family who supports me every day. I love you so much.

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Go raibh maith agaibh!

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literature," in 1st Conference of the EURO Working Group on Sustainable Supply Chains, 2016. 293

L.2 C. Eccher and J. Geraghty, "MODELLING & SIMULATION AS A STRATEGIC TOOL FOR DECISION-MAKING PROCESS IN THE DAIRY INDUSTRY," in International Conference on Decision Making in Manufacturing and Services (DMMS 2017), 2017, pp. 97–107.C. 294

L.3 C. Eccher and J. Geraghty, "INDUSTRY 4 . 0 AND THE FUTURE FOR DAIRY SUPPLY CHAINS," Int. J. Mech. Prod. Eng., vol. 8, no. 2, pp. 7–13, 2020..... 295

L.4 C. Eccher and J. Geraghty, "Incorporating sustainable criteria in a dynamic multi-objective recommendation planning tool for a continuous manufacturing process : A dairy case study," J. Manuf. Syst., vol. 55, no. April, pp. 159–170, 2020. https://doi.org/10.1016/j.jmsy.2020.02.008. Impact Factor: 5.105. 296

L.5 C. Eccher and J. Geraghty, "Modelling & Simulation as a Strategic Tool for Decision-Making Process: A Dairy Case Study," Int. J. Decis. Mak. Manuf. Serv., vol. 14, no. 1, 2020. https://doi.org/10.7494/dmms.2020.14.1.2785..... 297

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List of Abbreviations

API: Application Programming Interface, 84

BOD: Biological Oxygen Demand, 24

BSCS: Base Stock Control Strategy, 44

CIP: Cleaning In Place, XXI, 4

CMSD: Core Manufacturing Simulation Data, 32

COD: Chemical Oxygen Demand, 24

CONWIP: CONstant Work In Process, XXI; CONstant Work-in-Process.

DB: Database, 85

DBMS: Database Management System, 83

DF: Desirability Function, 7

DOE: Design of Experiments, 127

DPTC: Dairy Processing Technology Centre, 3

DREAM: Decision support in Real-time for Efficient Agile Manufacturing, 32

DSC: Dairy Supply Chains, 14

EMA: European Medicines Agency, 4

EOQ: Economic Order Quantity, 4

ePMPS: e-Pilot Manufacturing Plant Simulation, XXI

ER: Entity Relationship, 88

EU: European Union, 18

F&B: Food And Beverage, 1

FDA: Food and Drug Administration, XXI, 4; Food and Drug Adminstration, XXI

GMP: Good Manufacturing Practices, XXI, 4

HLA: High Level Architecture.

IoT: Internet of Things, 36

JIT: Just In Time, 1

KCS: Kanban Control Strategy, XXI, 9

KPI: Key Performance Metric, 6

LCA: Life Cycle Assessment, 35

M&S: Modelling and Simulation, 2, 29MDP: Markov Decision Process, XXI; Markov Decision Process, 8

MES: Manufacturing Execution Systems, 32

MIP: Mixed Integer Programming, 35

MPC: Milk Protein Concentrates, 15

MTBF: Mean Time Between Failure, 117

MTF: Make-To-Forecast, 42

MTO: Make-To-Order, 42

MTS: Make-To-Stock, 42

MTTR: Mean Time to Repair, 117

OECD: Economic Cooperation and Development, 16

PBC: Psychrotrophic Bacterial Count, 4

PCS: Production Control Strategies, XXI, 8; Production Control Strategy, 1

PLC: Programmable Logic Controller, 21

POC: Proof of Concept, 6

RSM: Response Surface Methodology, 2

SaaS: Software as a Service, XXI, 2

SCC: Supply Chain Council, 13

SCM: Supply Chain Management, 1

SCOR: Supply Chain Operations Reference, 12

SIPOC: Suppliers Input Process Output Customers, 39

SLA: Service Level Agreement, XXI

SME: Subject Matter Expert, 5

SMP: Skimmed Milk Powder, 18

SQL: Structured Query Languages, 87

TBC: Total Bacteria Count, 4

TPS: Toyota Production System, 1

UI: User Interface, 83

VSM: Value Stream Mapping, 40

WIP: Wok In Process, XXI

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ABSTRACT

Cristiani Eccher

ePMPS – ePilot Manufacturing Plant Simulation

A CLOUD-BASED SIMULATION FRAMEWORK TO SUPPORT PULL-TYPE DECISION-MAKING PROCESSES FOR DAIRY MANUFACTURING

Several challenges have been identified in the dairy bulk powder commodity sector due to the nature of this particular manufacturing environment. Internal and external factors compromise the efficiency of the production process and must be mutually addressed. The impact of seasonality and the frequency of deliveries performed by milk suppliers are evident in dairy manufacturing since they restrict the raw material availability and cause bottlenecks at the initial manufacturing stages due to the variability of the raw material supplied. A short raw material lifespan restricts the time for intermediate storage. In discrete manufacturing processes, for example, parts can be stored for extended periods while in dairy manufacturing, the raw material has a limited time to be processed due to a high level of perishability. Therefore, a fast rate in processing Work-in-Process (WIP) is required owing to the limited storage capacity. Constant interruptions caused by Cleaning in-Place (CIP) cycles are critical since they compromise the system processing capacity and also must comply with regulatory authorities such as Food and Drug Administration (FDA) and Good Manufacturing Practices (GMP) to reduce contamination risks. Therefore, operations must be adapted to increase the response during such unforeseen events. The complexity is potentially increased when available resources are poorly managed due to the lack of visibility, and inefficient support decision tools intensify this scenario as observed by the increase of WIP levels at distinct manufacturing stages without adding value to the final product processing.

This research conducts an investigation incorporating the internal and external factors in the sector investigated on a framework designed to simulate this environment entitled ePMPS (e-Pilot Manufacturing Plant Simulation). The innovation of the architecture proposed is the ability to simulate several scenarios through Software-as-a-Service (SaaS) where inputs are received in a structured file and the output is presented on a multi-device dashboard. The dairy manufacturing environment is generalised into a three-stage production flow where the main Production Control Strategies (PCSs) traditionally implemented in discrete manufacturing are investigated and replicated in this environment. The main pull-type systems were mathematically modelled in a Markov Decision Process (MDP) considering the impacts of CIP cycle times and supply variability. In addition, the requirements for implementing production policies such as CONstant Work-in-Process (CONWIP), Kanban Control Strategy (KCS), and Hybrid CONWIP/KCS are explored and compared to two distinct seasons.

By examining the trade-off between conflicting objectives: maximising Service Level Agreement (SLA) and minimising WIP levels, it is possible to observe that this sector requires specific WIP levels at each manufacturing stage. The results presented by KCS demonstrated an efficient strategy in absorbing the variability caused by supply deliveries during peak season since a systematic volume authorisation controls the excess of material within the system. During off-seasons or specific periods of the year under extra production capacity, an optimised production plan according to the volume supplied is more appropriate. Distinct strategies are required for distinct seasons and the results demonstrated have provided a fundamental basis to support decision-makers in addressing the challenges faced by this sector.

CHAPTER 1
INTRODUCTION

Digital technologies have allowed new possibilities for Supply Chain Management (SCM) to increase productivity and achieve customer satisfaction in a complex interconnected environment. In addition, benefits such as risk mitigation are also achievable by incorporating digital innovation into the SCM decision-making process through simulated what-if analysis and real-time information.

For any sector, balancing supply-demand, reducing the impact of variability and lowering inventory costs are managed at different decision levels and require distinct levels of information. Data analytics dashboards and innovative solutions to increase SCM visibility are examples of efficient resources to reach smart results and generate new value for customers. Several supply-pipeline problems were unable to be addressed without the application of information technology as stated by Schonberger [1].

In this digital scenario, the development of simulation models to enhance the decision-making process has been widely applied to the manufacturing environment and further extended to Supply Chain networks. Efficient models representing real-world activities are continuously providing significant insights for decision-makers.

Simulation models incorporating Just-in-Time (JIT) and pull-type Production Control Strategies (PCS) have proved to be efficient methods to manage the impact of extra inventory within the system and enhance desired key performance metrics. However, the majority of the models are mainly focused on mass production, namely due to its origin in the Toyota Production Systems (TPS).

The advantage of simulating manufacturing processes in order to evaluate the impact of decision-making on the current process is also observed in the chemical sector through physical pilot plants used for the development of new products and processes, as described by Houston in [2] : "*After rigorous test and validation, the desired changes are then further approved for production scale-up*". Nevertheless, as observed in the literature, the consequences of a deviation from the pilot plant to the manufacturing environment will be more significant owing to the larger production volume. Additionally, a substantial investment is required, and simplified changes regarding processing flow and capacities would benefit from data-driven simulation models.

In continuous processes such as the dairy sector, namely the dairy bulk powder commodity investigated in this research, limited studies exploring simulation were found, despite the applications to similar industries such as pharmaceutical and Food and Beverage (F&B) as explored in this research. Studies focused on pull-type PCS are non-existent.

Similar to other sectors, dairy manufacturing is affected by internal and external factors and efficient strategies and technologies are required to deal with particular challenges. However, even in the big data era where data is easily collected from sensors and Industry 4.0 promises an innovative revolution in the manufacturing system, the dairy sector demonstrates inefficient processes impacting subsequent stages in the Dairy Supply Chain.

Milk is the primary raw material used in the dairy bulk powder commodities production, which refers to the initial stages in the Dairy Supply Chain. New opportunities have emerged for the Irish sector since 2015 owing to the milk production quotas removal motivating companies to innovate and improve their current process.

Dairy is one of the most significant sectors for the Irish economy. It is currently experiencing the most significant growth in the Irish food industry, as published by Bord Bia Performance & Prospects Report in 2019 [3] and in 2020/2021 [4]. The value of dairy exports in 2020 was €5.2bn — a 3% increase in 2019. Dairy exports have been worth more than €5bn in two consecutive years, despite the significant challenge faced by the global pandemic and the decline of -2% on global exports of food and drink.

1.1. Research Motivation

There is a strong industrial motivation for the development of this research since the new positioning of the Irish market is encouraging companies to increase their competitiveness to fulfil future demand. Significant improvements could be obtained by adapting mature methods such as pull-type Production Control Strategies (PCSs), lean principles combined with breakthrough technologies to the dairy sector.

The development of simulation models for manufacturing environments to address specific problems in SCM has been constantly studied in the academic field. However, much of the literature on the dairy sector is focused on optimising the makespan and production plan of finished products for end consumers.

The academic motivation of this research is grounded on solid foundations as described as follows. Fundamental gaps in the literature relative to the research field were investigated including, but not limited to, the Dairy Supply Chain, lean principles focused on pull-type Production Control Strategies PCS, trends in cloud-based Modelling and Simulation (M&S) and optimisation methods such as Multi-Objective Algorithms and Response Surface Methodology (RSM). In addition, by combining real case studies, this research contributes to filling the gap in implementing an innovative and effective pull-type PCS for the dairy manufacturing environment obtained from the three main areas, i.e., pull-type lean principles, simulation-based for decision-support and optimisation methods focused on dairy manufacturing.

Due to the importance of the sector to the Irish Economy, the Dairy Processing Technology Centre (DPTC) funded by Enterprise Ireland and Dairy Industry Partners was created as part of an industry–academic collaborative research centre, hosted by the University of Limerick, with a research agenda driven by the long-term growth opportunities for the dairy sector.

DPTC was established as a centre of excellence for dairy processing research and innovation. The centre supports the Irish dairy sector by performing research focused on cost-efficient processing, facilitating a step-change in environmental sustainability and creating, validating and commercializing a pipeline of science and technology-based manufacturing platforms for dairy ingredients. The foundation of the DPTC is a strong, long-term industry–academic collaborative partnership that will develop, build and translate the knowledge and capabilities in dairy processing that are needed today and for the long-term growth development of the sector [5]. Figure 1.1 illustrates all the DPTC Dairy Industry Partners and the Research Performing Partners.

Figure 1.1 – DPTC - Dairy Industry Partners and the Research Performing Partners [5]

1.2. Challenges and Research Problem

During this research, several challenges have been identified in the Irish dairy sector and are fundamental to contextualising the extent and significance of this research to the field. These challenges can be easily generalised into other dairy bulk powder manufacturers due to the nature of this environment, outlined as follows.

In a standard discrete manufacturing process, parts can be stored for extended periods. In contrast, the main raw material must be steadily and rapidly processed due to the risk of perishability in dairy manufacturing [6]. The short lifespan of the raw material requires a lower level of intermediate Work-In-Progress (WIP) storage at different stages in the manufacturing process. In addition, the physical storage is limited by the silo capacity, which might restrict the entire production flow.

By storing WIP for an extended time, the growth of microorganisms becomes a critical factor in determining the quality of the milk and therefore, it must be considered in dairy optimisation solutions. Microbial tests such as the Total Bacteria Count (TBC) and Psychrotrophic Bacterial Count (PBC) are used to characterize raw milk quality and have been demonstrated to be affected by storage time and also by temperature.

Secondly, regarding inventory levels, a fast rate for processing the WIP is required due to the raw material perishability. Constant interruptions caused by Cleaning In-Place (CIP) cycles compromise the system's processing capacity. In addition, the cleaning process must comply with regulatory authorities such as the Food and Drug Administration (FDA) for the USA [7], the European Medicines Agency (EMA) for the EU and Good Manufacturing Practices (GMP) [8] to prevent contamination risks.

In addition, the impact of seasonality and the supply frequency on the manufacturers' operations is evident owing to the volume provided by suppliers. Seasonality plays a fundamental role in defining strategies for production since the volume diverges throughout the year and little research combining the impact of seasonality and other internal factors was observed in the case studies and also as explored in the literature review. The supply frequencies increase the variability in the system, despite the presence of storage or buffer silos. Traditional replenishment policies, such as Economic Order Quantity (EOQ) [9] for example, are insufficient to guarantee the principal raw material availability in the dairy bulk powder manufacturing environment.

Ultimately, regarding production strategies, the push system type is the type of production naturally adopted to increase the processing flow by pushing the material volume to further production stages. However, this lack of control observed among the dairies contributes to an undesirable level of inventory and increases the risk of discharging potentially commercialisable raw material into waste streams. Therefore, as observed, relevant exploration regarding the most suitable production control for the dairy sector remain unexplored by previous research.

1.3. Research Objectives, Significance and Generalisation

The primary objective of this research is to contribute to the understanding of the pull-type PCS performance under the dairy bulk powder environment. This manufacturing process is heavily impacted by particularities challenges identified in this sector such as: limited storage capacity between manufacturing stages, constant interruptions caused by CIP processes, perishability due to the short life span of raw material and seasonality, which dictates the volumes available to be processed and internal and external stochastic events commonly found in the dairy sector.

The research objectives are achieved in two phases (Chapters 3 and 4): (I) Through the development of an innovative cloud-based simulation framework model based on the particularities found in this sector, to be used by dairies manufacturers and potentially be easily scaled to other dairies according to the structured files. Allowing the accessibility for dairies manufacturers through a cloud-based structure with a user-friendly interface for the subject-matter expert (SMEs). The production plant, such as production flow and capacities, are built according to spreadsheet input files in order to improve management decisions when comparing the current state and the impact of simulated future state strategies. The simulated scenarios are then demonstrated on a dashboard available for multi-devices.

(II) Through the identification of optimised volumes (factors) to be authorised for each manufacturing stage and evaluate the impact on the key performance metrics in this environment. In optimisation problems based on the pull-type PCS researched, reducing the overall WIP average in the system is one of the criteria traditionally sought. However, it was observed that for dairy bulk powder manufacturing the perishability pattern increases significantly after passing through the separation process [10], therefore individual levels of inventory according to specific stages are required. In addition, the average as a KPI might hide potential bottlenecks when the limited capacity is reached. Therefore, to fill the current gap on optimising specific metrics for this sector, the WIP levels must be measured individually for each stage and maximum WIP levels are more appropriate to be considered conversely to the overall average WIP conventionally adopted.

The innovative framework is specified in detail within the methodology chapter including all assumptions and limitations of the sector investigated. The initial manufacturing stages are characterised by a three-stage production line considering the raw material supply and storage. Hence, generalisations of the method, inferences, findings and contributions can be easily extended to similar production processes.

1.4. Research Structure

The research structure explains the methodology developed to achieve the objectives previously defined for this research. The thesis structure outlines and presents each chapter as follows.

1.4.1. Research Methodology

The research methodology is divided into two parts: Chapters 3 and 4, respectively. This division was important due to the complexity of the environment design and the multi-disciplinary subjects involved in this research. In Chapter 3, three DPTC industrial partners presented in Figure 1.1 are investigated as case studies for this research. These processes are explored where an individual simulation model was developed for each case study, as described in section **3.2 - DPTC Dairy Industrial Partners – Case** Studies. In case study 1, an investigation of the manufacturing system during peak seasons was conducted when the internal production capacity is insufficient to process the volume of the raw material supplied. Potential solutions to minimise the excess of intermediate WIP are proposed. Case Study 2 was not entirely explored; however, it provided valuable insights regarding internal and external factors for the dairy sector. The impact of external factors such as supply variability and different volumes received throughout the day and how it affects the internal production system. The impact of internal variability such as breakdowns and capacity limitation when the WIP is produced internally and received from external dairies are observed for this environment. Finally, for case study 3, the impact of short-term decisions such as selecting the best set of equipment and optimising the production flow according to the raw material available are investigated. All three case studies contributed to a generalised model designed in section **3.3 Initial stages in Dairy Manufacturing - Generalisation**, where the source of variability of each stage is investigated individually.

In addition, the development of the framework for bulk powder manufacturing environment entitled ePMPS, which stands for e-Pilot Manufacturing Plant Simulation, is described in section **3.4 - ePilot Manufacturing Plant Simulation Framework for Dairy Industry**. Technical description regarding the framework such as architecture, language, integration between front-end and back-end platforms, flow and structure of the information processed, interface, security, simulation package and database storage are described in this section. Finally, one of the case studies is replicated under the ePMPS framework in order to demonstrate the simulated results and the behaviour of the manufacturing system at a specific hour/day as a Proof of Concept (POC). This environment was deployed not only for the case studies explored in this research, but to all DPTC dairies manufacturers demonstrated in Figure 1.1 with similar manufacturing processes.

In Chapter 4, the framework developed can be used to replicate the production and test the optimum condition for this environment since a generalised manufacturing process environment is available and can be designed according to the structured files. Therefore, primary experiments under the current production system were simulated. Initially, some Key Performance Metrics (KPIs) to analyse the performance of the overall system were defined as described in section **4.2 Performance metrics.** A systematic increase in the volume is proposed according to 5-day periods selected from the case studies during distinct seasons as defined in sections **4.3 - Research Space Assumptions** and **4.4 - Simulating and Analysing the Current Production System**. A control group composed of distinct 5-day periods was selected to analyse the impact of the supply variability within the environment designed and also to replicate the experiments under current and optimum conditions. The current push system was observed in the case studies investigated as described in section **3.2 - DPTC Dairy Industrial Partners – Case** Studies**.** A comparison of the current push system identified in the dairy environment and a simplified pull-type is exemplified in section **4.5 - Exploring push and pull systems in dairy manufacturing**. This section is crucial to understand the pull-type production system and how the application of a simplified authorisation of raw material observed in the literature might negatively impact the current production flow, namely when two basic conditions in the dairy bulk powder manufacturing environment are ignored: WIP levels and CIP processes.

In section **4.6 - Modelling pull-type PCS for Dairy Manufacturing** all three types of PCS are modelled and adapted according to dairy manufacturing environment. In section **4.7 - Optimisation Methods** the approach to identify the optimum responses is described. The Pareto Frontier algorithm was developed and applied to visualise the optimised area for conflicting responses according to the simulations responses. Response Surface Methodology (RSM) and Desirability Function (DF) are used to identify the best factors or best volumes at each stage in the manufacturing process that would optimise the response evaluated. The optimisation models and the defined space are then described in sections **4.8 - Defining all Factors for the Optimised Responses for each PCS** modelled in the previous section, and **4.9 - Responses Optimisation Methods.** Finally, an adaptive optimisation model based on KCS is proposed in section **4.10 - Adaptive Pull-Type Approach.** As observed, for peak seasons, the volume of WIP must be internally controlled, whereas during medium or off seasons the internal capacity must be optimised due to the raw material restrictions.

All experiments are performed on the framework developed and described in Chapter 3, allowing manufacturers to extract the maximum efficiency of their processes according to the seasonality.

The summary of each step is outlined in the following sequence: 1) The first step consists of analysing the initial manufacturing stages in the dairy sector according to the data provided by the case studies and further identifying the value stream according to lean principles and the particularities of the current flow; 2) Exploring gaps identified in the reviewed literature; 3) Identifying potential sources of stochastic events for each stage is essential for the third phase which is dedicated to design a simulation model capable of emulating the flow of the current process in dairy manufacturing and make it available on a structured cloud-based environment; 4) Investigating of the most applied lean pull-type PCS successfully adopted by mature manufacturing sectors; 5) Modelling the pull-type PCS mathematically considering the dairy restrictions and particularities in order to optimise the current flow according to the internal and external factors. Figure 1.2 illustrates the structured methodology.

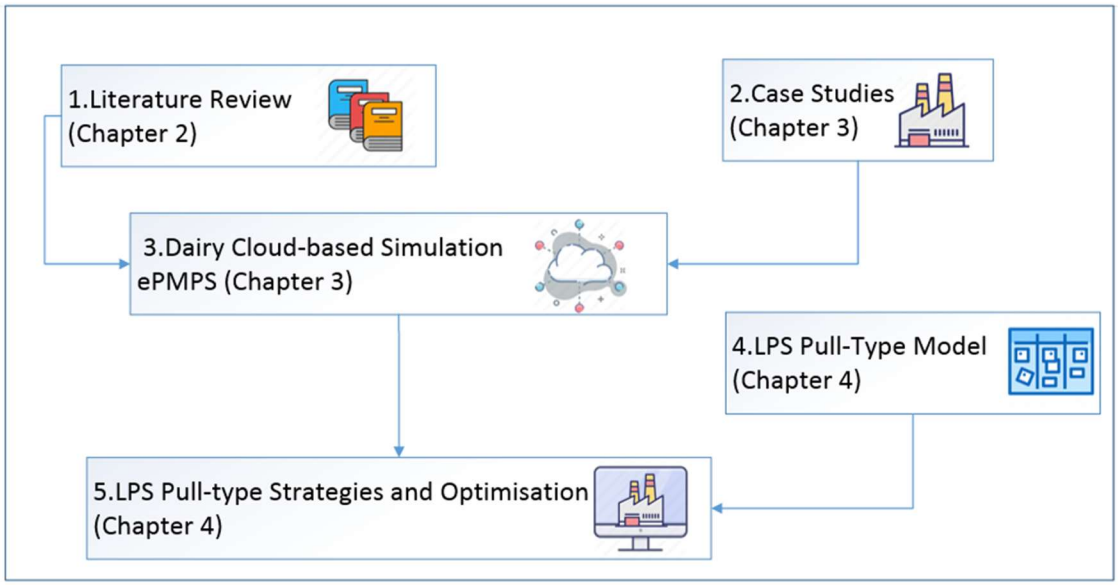

Figure 1.2 –Structure of the Research Methodology

1.4.2. Thesis Overview

This thesis is organised into seven chapters and described as follows:

- Chapter 2 presents concepts of Supply Chain Management (SCM) and Dairy Supply Chains according to different decision levels. This chapter is dedicated to providing the background of this research. The main inbound activities and equipment required for a traditional Dairy Manufacturer including requirements for Cleaning-In-Place (CIP) to reduce the risk of contamination. The volatility of dairy market prices and the importance of Irish Drink and Food Export products are also examined. The main issues addressed by previous research and the methods used to solve specific problems focused on the Dairy Sector were fully explored. Trends for cloud-based Modelling and

Simulation (M&S) are also presented providing directions for the defined research objectives. A review of lean principles, application to dairy and pull-type Production Control Strategy (PCS) applied in mature manufacturing environments are explored.

- Real challenges faced by dairy manufacturers are presented in Chapter 3 through three Irish case studies. The contributions of these three Industrial Partners were essential to identify fundamental processes and define significant similarities in each manufacturing stage to be further incorporated into the framework proposed by this research project. This chapter also explores each stage in the production flow and evaluates the main causes of variability. The cloud-based simulation model structure and interface are designed and further presented in this chapter.
- In Chapter 4, a mathematical Markov Decision Process (MDP) is modelled considering the actions at each stage in a manufacturing system according to the pull-type PCS. Also, all requirements for implementing production policies such as CONstant Work-in-Process (CONWIP), Kanban Control Strategy (KCS), and Hybrid CONWIP/KCS are modelled considering the particularities of the dairy sector. Optimisation methods such as Response Surface Methodology are explored in this section.
- In Chapter 5, experiments for each pull-type PCS investigated are then replicated into two levels of raw material seasonality: Medium and High seasons and further replicated into three 5-day periods of raw material supplied. The periods were selected according to the supply real data in order to demonstrate the impact of the variability observed on each pull-type PCS strategy explored. Ultimately, an adaptive model specially designed for this environment is proposed where similar results are compared to the pull-type PCS investigated.
- In Chapter 6, the findings, discussion and limitations of this research are presented, followed by the conclusion and directions for future work in Chapter 7.

CHAPTER 2
LITERATURE REVIEW

2.1. Introduction

The aim of this chapter is to present the review of the current theory studied including relevant multi-disciplinary fields explored to support this research.

Initially, the required background knowledge to elucidate the Dairy Supply Chain, all characteristics identified in this sector and the inbound manufacturing process are described. The supply chain activities are compared to similar manufacturing sectors in order to establish the peculiarities observed in the dairy industry. In addition, the concepts of modern mass production are also examined since it has evolved with respect to technology, research investment and continuous process improvement.

Cutting edge simulation methods and tools addressed by previous research such as Modelling and Simulation (M&S) and cloud-based simulation applied to the manufacturing environment are also investigated. Furthermore, current simulation-based studies concentrated on the dairy environment are explored in order to present the gaps identified in this sector.

Ultimately, concepts of lean principles focused on pull-type Production Control Strategy (PCS) are explored. The main pull-type mechanisms are studied with the objective of evaluating the benefits of incorporating this mature approach in the dairy bulk-powder manufacturing environment.

2.2. Supply Chain Management Overview

Supply Chain Management (SCM) is the integration of supply and demand within and across companies, including planning and management involved in sourcing and procurement, transformation and logistics activities. In this concept, coordination and collaboration with channel partners, such as suppliers, intermediaries and third-party services are also considered according to the Council of Supply Chain Management Professionals [11].

Several contributions also defined SCM as an aggregate set of value chains linked by inter-organizational relationships, both upstream and downstream in order to deal with each involved flow (cash, material, information and time), from the first supplier's supplier to the last customer of the end customer, as well as the reverse flow of products and returnable and disposable products [9], [12]–[18].

Beyond integrating activities, goods are produced and delivered in the right quantities and at the right time in order to satisfy customers' demands, as stated in lean principles by Kerber and Dreckshage [19]. This concept has already been tested efficiently by nature. The delivery of the right quantity at the right time was essential to the human body's evolution. Making an analogy with Supply Chain activities, the right quantity

of nutrients, the flow of oxygen delivered by the blood to the brain, as water and food are essential to guarantee an improved system performance [20].

SCM is defined as a network of multiple businesses and relationships [13]. As shown in Figure 2.1 the vertical dimension represents the numbers of suppliers and the horizontal dimension represents the tiers across the supply chain. These two dimensions define the size and structure of supply chains.

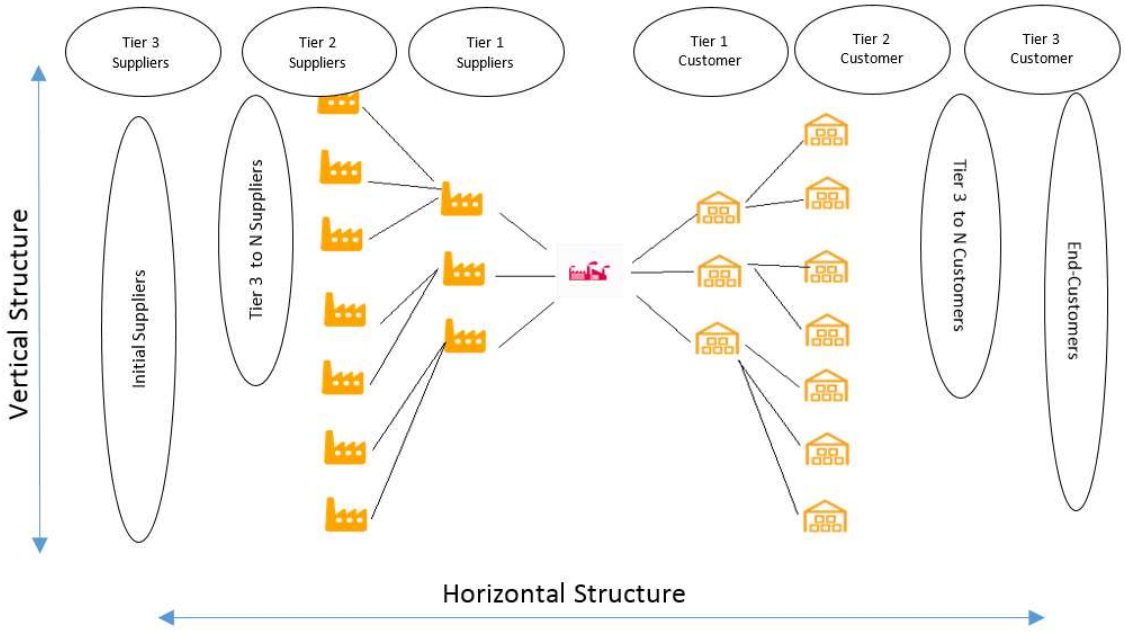

Figure 2.1 - Supply Chain network - Adapted [13]

A recent representation of a multitier Supply Chain dependency is shown in Figure 2.2. According to Gartner [21], multinational companies scan the entire world to locate the most cost-efficient and high-quality components, the most efficient to manufacture cost-effectively, and how to best distribute finished products to markets which justifies the increase in complexity.

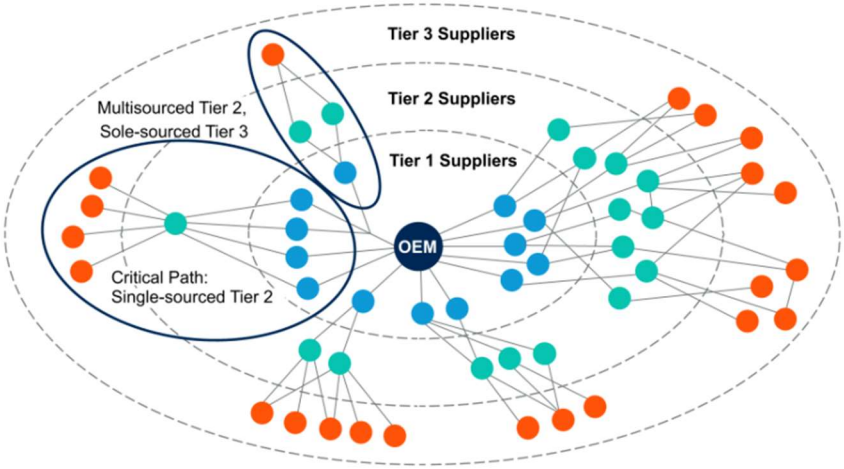

Figure 2.2 - Supply Chain Multitier Supply Chain Dependencies – Gartner [21]

In addition, sustainability or Green Supply Chain (GrSCM) has been widely explored by the literature due to the importance of the subject and also due to the multidisciplinary characteristics beyond the reverse logistics activities. Activities such as environmental risk assessment, waste management, product quality and safety, pollution prevention and cost reduction, for example, are not limited to transportation and storage tasks [22].

The current Reverse Logistics relationship network supported by the "Recovery Facility" is covered in [23] exploring the concept of Closed-Loop Supply Chains (CLSC) where the treatment is conducted by each activity in the Supply Chain in order to achieve significant cost savings. Figure 2.3 presents an example of reverse logistics. A basic system feedback structure had already been referred to as a closed-loop where the inputs generate actions impacting the final results in a continuous circulating process [14].

Regarding Supply Chain flow, financial elements are incorporated as found in [24], [25] and time as found in [26]. However, the successful integration of the entire supply chain depends on the availability of information from distinct sectors and dimensions to be shared by each activity. An indicator of flexibility to adjust and rebuild plans in real-time and to rapidly respond to unforeseen circumstances is measured by Agile Supply Chains as described in [17].

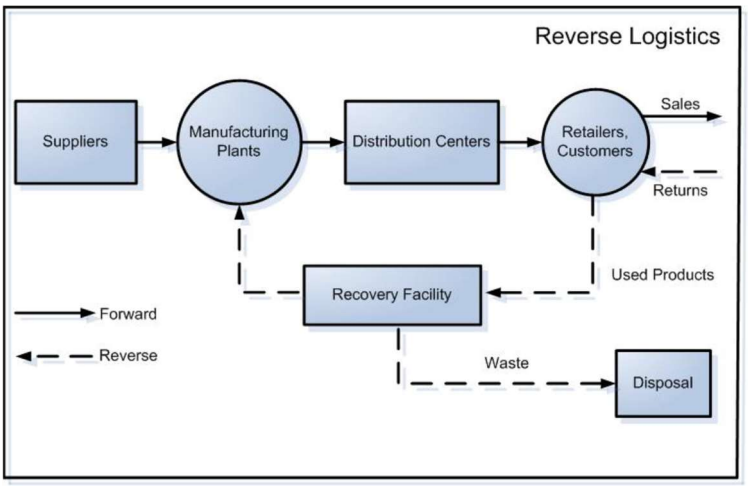

Figure 2.3 - Generic Representation of Closed Loop Supply Chain [23]

In order to address, improve, and communicate supply chain activities simplifying and increasing the understanding regarding SCM, a standardised framework was developed by Supply Chain Operations Reference (SCOR) [27] and it is described as follows.

2.2.1. Supply Chain Operations Reference Model

The Supply Chain Operations Reference (SCOR) model was introduced in 1996 and it has been endorsed by the Supply Chain Council (SCC), a global SCM organisation. This model is being globally adopted by many business companies in order to standardise supply chain processes. SCOR is composed of five general processes: Plan, Source, Make, Deliver and Return. The SCOR approach, as shown in Figure 2.4, relies on the assumption that any supply chain can be represented by these five basic processes [27]:

- Plan: for balancing the demand and supply to best meet the sourcing, production, and delivery requirements.
- Source: for purchasing goods and services to meet planned or actual demand.
- Process: for including goods transformation to meet planned or actual demand.
- Deliver: for providing finished goods and services to meet planned or actual demand, typically including order, transportation and distribution management.
- Return: for returning products to customers or receiving returned products from suppliers.

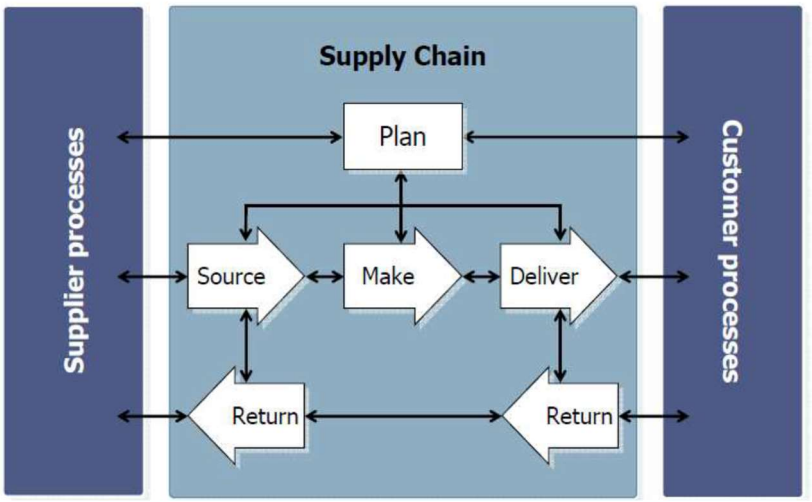

Figure 2.4 - SCOR management processes [27]

2.2.2. Decision Levels in Supply Chain Management

The level of decisions classified as Strategic, Tactical and Operational, refers to their dependency on time horizon and impact on the investment required in supply chains as explored by [17], [18], [23], [24], [28], [29]. Key Performance Indicators (KPIs) are created to manage the activities according to individual level of decision:

- At the strategic level, long-term decisions are defined according to the business plan strategies such as location, strategic partnership, new products and lifecycle products, make-buy decisions, investment capacity in new pieces of equipment, new plant capacity, international partnership and organisational goals are also defined at this level.

- At the tactical level, medium-term decisions are performed. The time horizon covers 1 to 6 months approximately. The main objective is to support the strategic level previously defined and assure that the operational level will follow the business plan directions. Decisions regarding inventory policies, safety stock levels, transportation route and order sequences are defined at this level.
- At the operational level, short-term decisions are defined, and time horizons are often covered daily, weekly and monthly. Operations previously planned at the Tactical level must be executed and deviations are properly recorded to be managed for future directions. Activities such as equipment scheduling, inventory levels and order entry fulfilment, which refers to managing internal resources to provide improved service levels are performed at this level.

Improvements in the Supply Chain activities should consider the time horizon required to reach the expected results. Changes by sequencing products, for example, are performed at the operational level and require low capital investment. Conversely, at the strategic level, bottleneck capacity improvement and commodity exportation among countries require the involvement of multidisciplinary departments where the decision-making process is not locally defined, especially when capital investment is required.

Supply Chain activities differ among sectors according to the nature of the finished goods. For finished goods that require temperature control, for example, special transportation is needed, while agricultural bulk logistics is concerned with high volumes of storage and transportation. Identical issues are observed in the dairy supply chain, the main raw material requires temperature control while bulk-powder yield requires a high volume of storage capacity. The main issues related to the dairy supply chain are explored in the following section.

2.3. The Dairy Supply Chain

In Dairy Supply Chains (DSC) multiple entities are connected in a coordinated network, including but not limited to primary and secondary manufacturers, suppliers, warehouses, distributors, customers and final consumers. The DSC is composed of farms, equipment suppliers, processors, retailers and distribution channels.

A generic flow based on the SCOR model previously described in section 2.2.1 and the literature explored in this section was specially designed during this research and presented in Figure 2.5 in order to demonstrate the DSC inbound and outbound activities. Dairy processors also receive concentrated products and by-products in the liquid form as raw material to be further transformed from other dairies. This collaborative system is observed among dairy manufacturers given the shortage capacity and specialised equipment to process the concentrated form into the final product, highlighting the importance of the DSC network.

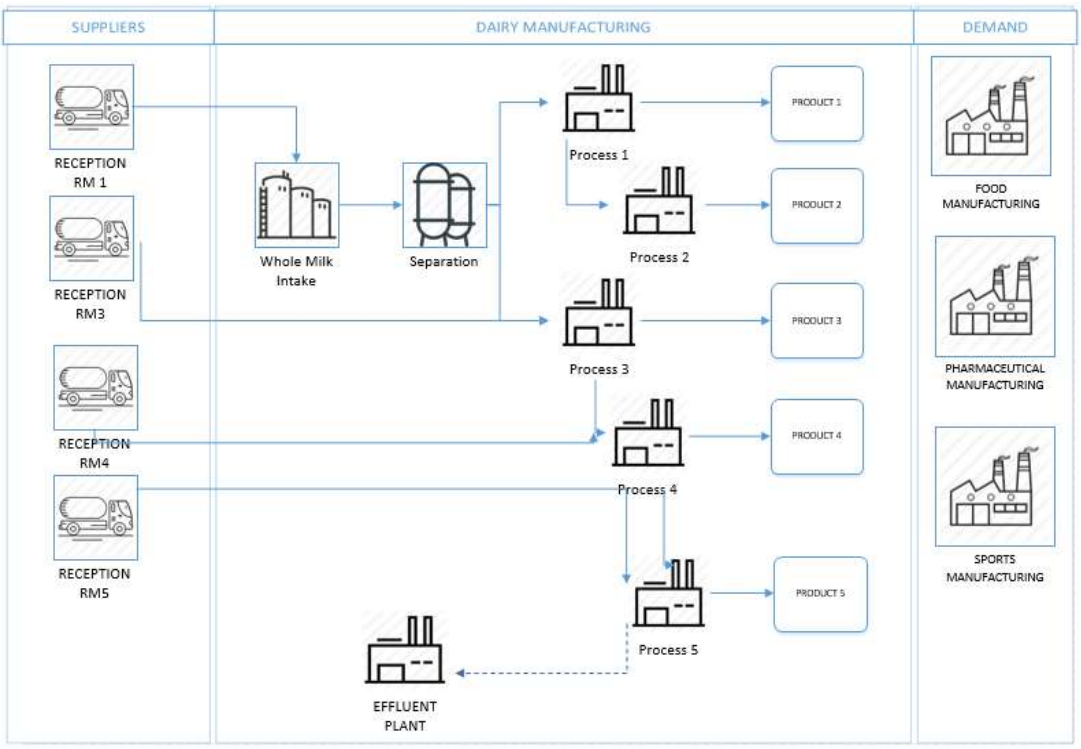

Figure 2.5 – Example of Dairy Supply Chains

On the supply side, the illustrated raw materials RM1, RM3, RM4 and RM5 are previously planned according to SCOR plan section. The supplier's area refers to the raw material received and sent to the production plant according to the SCOR source section. The manufacturing area refers to the raw material processed according to the SCOR make section, and fulfil the demand represents the SCOR deliver process. On the demand side, all five products supply distinct sectors. Lactose, for example, is widely used as a filler or filler-binder in the manufacture of pharmaceutical tablets. The physical properties of the lactose heavily impact the tablet compressibility, flowability and compactibility [30].

Milk proteins, on the other hand, are free of lactose. High milk protein powders are also known as milk protein concentrates (MPC) [31] . The protein structure responds to environmental factors such as temperature, pH and pressure.

Casein and Serum or Whey are examples of proteins widely applied to the Food and Beverage (F&B) sector. Manufactured whey could also be transformed into several end-products. See **Appendix A.1 - Whey Potential Division** for some branches in whey production. See **Appendix A.2 - Gross Composition and Milk Properties** for contents and heat treatment according to each dairy manufactured product.

In the dairy sector, a significant number of end-products are produced from a single raw material and common production processes. This environment is referred to as joint products or multiple end-products and requires different strategies to determine the production mix [32]. See **Appendix A.3 - Dairy Products Manufactured,** for fresh cow milk decomposition into primary and secondary final products. This decomposition is relevant to this research in order to demonstrate how the dairy sector differs from other

manufacturing sectors such as assembly lines. In the dairy sector one primary raw material is decomposed and transformed into multiple finished products.

In addition, the Organisation for Economic Cooperation and Development (OECD) and Food and Agriculture Organisation (FAO) [33] constantly disclose a list of predicted commodities production for a ten-year forward period see **Appendix B.1 - Exports of Dairy products by Region.** The most updated list for 2018-2027 is available in **Appendix B.2 - OECD-FAO – Dairy Agricultural Outlook 2018-2027 – Production.** The projected list demonstrates the expected increase in dairy commodities and potential insights for future investment in this sector.

2.3.1. Milk Seasonality

The milk supply fluctuates according to the milk seasonality. Milk availability is explained by the lactation curve as described in [34], where the lactation reaches a maximum of 1 to 2 months after calving and after this period, the volume steadily falls every month. Lactation curves are valuable tools for dairy manufacturers to enhance decision-making. Specific research simulating the lactation curve was found in an attempt to predict lactation through a mathematical model [35]. Seasonality also affects milk composition and influences the final production quality as described in [36].

The Irish milk intake production for 2018-2019 is illustrated in Figure 2.6 and for 2019-2020 in Figure 2.7 where it is possible to observe the peak season throughout two years.

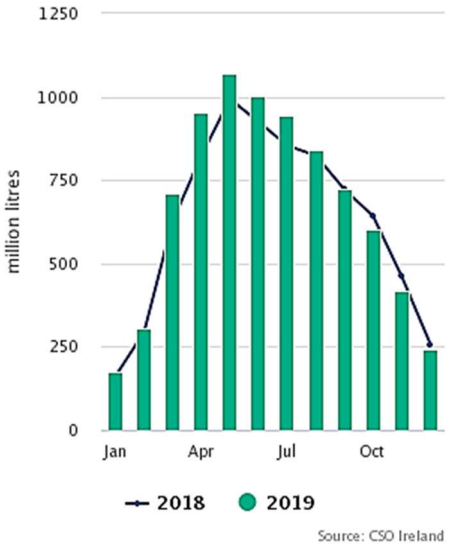

Figure 2.6 – Irish Milk Intake 2018 and 2019 [37]

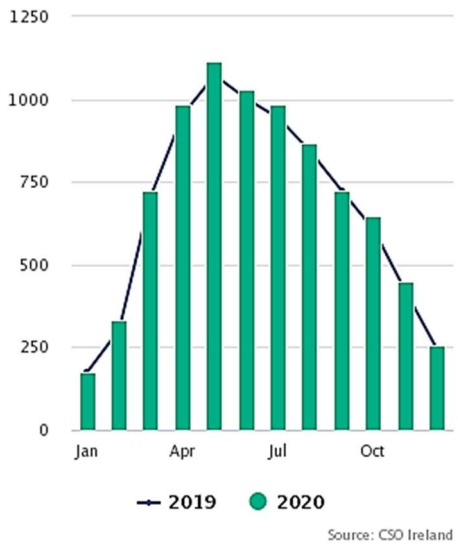

Figure 2.7 – Irish Milk Intake 2019 and 2020 [38]

Not only is seasonality observed in the DSC, but as a common phenomenon in several areas of study. A systematic review conducted by [39], for example, explored the effect of season on food intake consumed

by adults. It is observed that according to each season, the behaviour of consumption demand is heavily changed.

Some studies are observed for managing the impact caused by demand seasonality on supply chain activities [40]–[42]. Supply seasonality is also characterised by a cyclical pattern and is observed in sectors as follows:

I. In perishable raw material and short shelf-life, as observed in Food Supply Chains [43]–[46].
II. Impact of weather on electricity supply [47]
III. In natural resources extraction, such as Pulp and Paper and Natural Rubber industries as observed in Forest-based Supply Chains [48].

Supply chains are directly impacted by supply and demand fluctuations. Regarding the dairy sector, managing seasonal supply chains is essential to identify strategies to mitigate the impact on the internal processes.

2.3.2. Dairy Market Prices

Dairy commodities are driven by market prices and the EU provides product information through a section called "*Milk market observatory*" available in [49]. Such reports aim to guarantee transparency circulating market data and short-term analysis for decision-makers in the dairy sector.

Research regarding the impacts of milk prices on dairy commodities is increasing due to the importance of farmers in properly responding to changes caused by market prices. The postponement of investments adopted by farmers during the financial crisis [50] and the exploration of the impact of laws and regulations on dairy cooperatives that reduce milk price volatility [51] are examples of approaches that have been researched. In addition, the element of changing prices in free markets is also explored owing to the emergence of exceptional price volatility potentially increasing the complexity for processors, farmers and indirect entities within supply chains [52].

To overcome the effect of fluctuating market prices on the Dairy Sector, Market Based Price Risk Management Instruments are used by processors and farmers to reduce the price volatility based on protective contracts [52]:

- Over the Counter (OTC) Contracts: The prices are derived from the value of an underlying asset, reference rate or index. These contracts are individually customised to an end-user's risk preference and are highly flexible.
- Forward Contract: It is an agreement to sell a stated quantity of a good or service, at a stated period into the future, at a stated price. This type of contract is privately negotiated and not standardised.
- Future Contract: Conversely to the forward contract, futures contracts are standardised and traded on commodity exchanges. These contracts allow market participants to hedge their position in the

market and reduce the risk of unfavourable price movements between the time the hedge is placed and when the delivery of the commodity is made.

The Skimmed Milk Powder (SMP) and the butter prices are shown in Figure 2.8 and Figure 2.9, respectively. Skimmed had the market price increased for years 2019 and 2020 in comparison to 2018, while the butter price had decreased. In the graphs, the values are demonstrated from 2018 to Feb-2021 [49]. Protective contracts are fundamental for mitigating the impact caused by price volatility on the dairy supply chain activities.

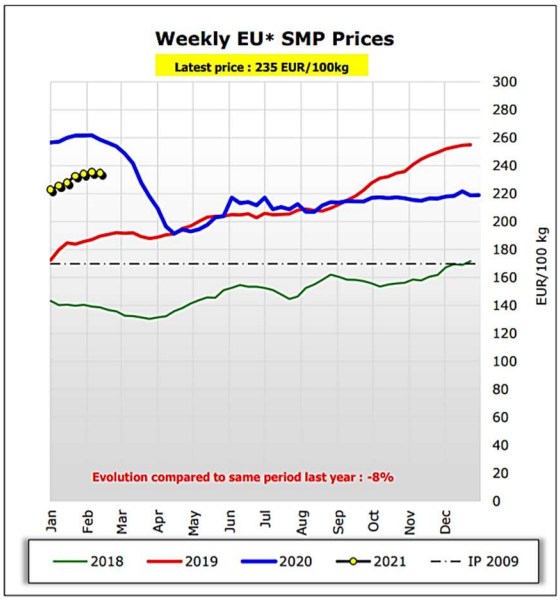

Figure 2.8 – SMP Market Price [49]

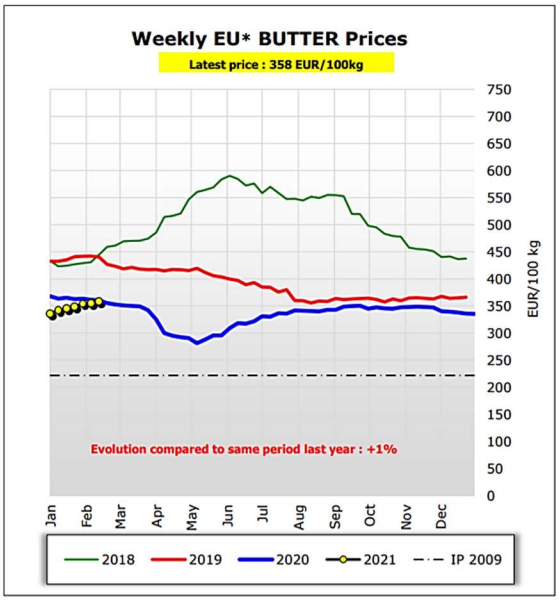

Figure 2.9 – Butter Market Price [49]

2.3.3. The Irish Dairy Market

Since the European Union (EU) milk quotas were abolished in 2015, Irish milk production has increased the production level. According to Bord Bia Export Performance Prospects Report 2020/2021 [4], the value of dairy exports in 2020 was EUR 5.2 billion which represents a 3% increase on the value in 2019. This is the second year that dairy exports have been worth more than EUR 5 billion. This growth was achieved despite commodity price reductions for key elements of the export mix including butter as previously presented in Figure 2.9.

Dairy Sector was responsible for 33% of the total exports of Irish Drink and Food Export products according to Bord Bia Export Performance Prospects Report 2019/2020 [3]. Irish Drink and Food Export products were estimated at EUR 12.1 billion in 2018. Butter exports exceeded EUR 1 billion, a 22% increase in 2017's value. In 2018, the estimated domestic milk intake in litres by creameries and pasteurisers in Ireland was 7.5 million litres, an increase of over 4% in 2017 [37].

Despite the disruptions posed by Covid-19, the Irish dairy industry has proved its resilience, particularly given the uncertainties in relation to Brexit and logistical challenges. According to [4], Irish dairy production growth continued in 2020 and is expected to exceed eight billion litres, which is an increase of 3% on 2019 production. Even though the butter market price experienced a decline in 2020, the export volume increased by 12% in comparison to 2019.

2.4. Dairy Manufacturing

Milk processing is essential for Dairy Supply Chains, especially for bulk-powder commodities owing to the necessity for specialised equipment to transform raw material into a required finished product. Several aspects must be considered when designing a dairy production line since it must be aligned to the product requirements. The most relevant processes in a dairy manufacturer are described as follows due to their importance for the aim of this research.

2.4.1. Milk Reception and Storage

In the reception area, the load is recorded by a platform balance where the milk is firstly tested and then authorised to be further processed [53]. The raw material supplied must be supplied according to the volumes established between farmers and manufacturers. Raw milk requires refrigerated transportation and therefore, the location between farms and processors reduces overall costs of transportation [36].

The raw milk quality is essential and must be verified before entering in the manufacturing process. The milk received must be stored at 4^{o} C to extend the storage lifespan [54]. Keeping quality is defined as the storage time during which the milk remains suitable for processing. The count of microorganisms after 24h should not exceed 1.0×10^{6} ml^{-1} to guarantee the quality of the raw material [55].

Total Bacteria Count (TBC) and Psychrotrophic Bacterial Count (PBC) are microbial tests used to characterize raw milk quality. Experiments conducted by [56] suggest that the TBC in bulk tank milk was affected by storage time ($P < 0.001$), temperature ($P < 0.001$), and the interaction between storage time and temperature ($P < 0.001$). In this study fresh milk was supplied two times during the day.

2.4.2. Pasteurisation

Raw milk must be pasteurised to ensure it has been adequately heated in order to avoid bacterial growth. The trade-off between time and temperature is an important issue within industries owing to the fact that a higher temperature reduces process time and also damages the structure of the milk. The desired combination for time and temperature is: Heating for 30 min at 68°C. However, the heat treatment of 1 sec at 145°C degrees is also observed in several manufacturing environments as stated by [53]. Therefore, by

decreasing the time required for pasteurisation the manufacturing cycle time is also decreased which reduces the makespan of the final manufactured product.

According to [56], two bacterial groups that are capable of surviving pasteurization and that can cause illness when ingested in large numbers are *Bacillus cereus* (aerobic spore-formers) and sulphite-reducing Clostridia (SRC; anaerobic spore-formers). The numbers of *B. cereus* and SRC present in milk are closely monitored during the manufacture of infant milk formula due to the possibility of toxin production and the vulnerability of its consumers.

2.4.3. Separation

Separation by centrifugal force is essential to efficiently separate solids from the liquid form. The milk enters into separated channels at the external edge of the disk and flows through the channels toward the axis of rotation leaving the vessel at the top [57]. The solids are separated and sent back along the undersides of the discs to the boundary of the bowl. The equipment is illustrated in Figure 2.10.

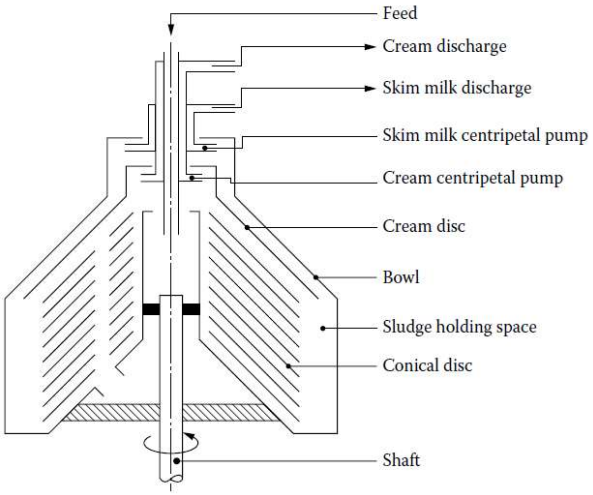

Figure 2.10 – Separator [53]

For skimmed milk efficiency, the amount of fat that can be separated from milk depends on the design of the separator, the rate at which the milk flows through it, and the size distribution of the fat globules. The main difference between a centrifugal clarifier, which is used to recover fines from the whey process for example, and a separator is the design of the disk stack and the number of outlets.

There are two types of modern separators: semi-open and hermetic. The differences in outlet performance of hermetic and paring-disc separators is that the first one is able to create high pressure, which increases the fat content to around 72% of globular fat [36].

The separation efficiency is critical for skimmed milk powder quality [53]. After the separation of fat and proteins through a centrifugal separator, the standardisation process is required to correct the level of fat in

the milk processed, by adding cream or skimmed milk in order to reach a given fat content [57]. This process is shown in Figure 2.11. Programmable Logic Controller (PLC) manufacturers control the valves to correct the fat content to the required level.

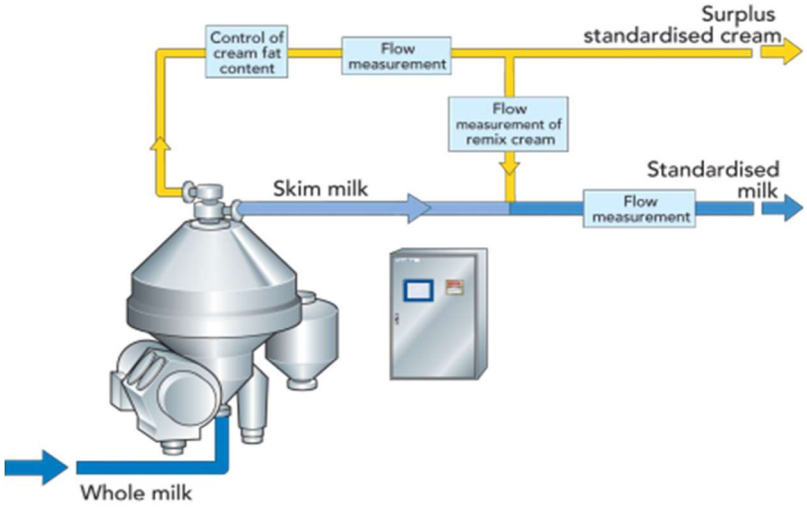

Figure 2.11 - Standardization process [36]

The milk spoilage pattern changes significantly after passing through the separation process decreasing the milk lifespan. In [10] several studies reported by various countries that the average shelf life of skim milk stored was less than those of the corresponding whole milk are highlighted. The results strongly suggest that a higher level of production of protease in skim milk is a key factor in producing the difference in stored pasteurised skim and whole milk.

Decanters are another type of centrifuge mainly applied to the casein process, crystallized lactose and milk extracted from soybeans, for example, due to their solid content. Additionally, it continuously operates to suspend solids from liquids through centrifugal force where the solid phase is discharged by gravity (3), the liquid phase discharge (2), followed by feed suspension (1). Disc and paring chamber (4), bowl (5) and screw conveyor (6) are internal components as shown in Figure 2.12.

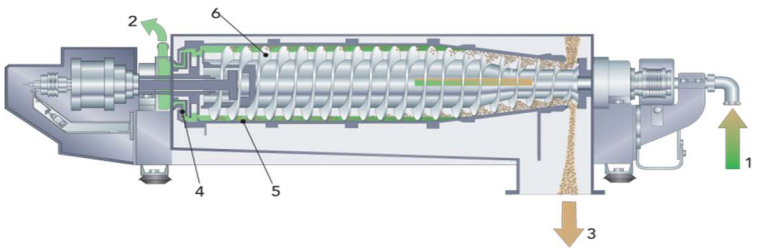

Figure 2.12 - Suspension of solids from liquids by decanting process [36]

In dairy manufacturing, milk separation is of utmost importance for maximum performance of the process to produce different types of products. In specific cases, the separation at the molecular and ionic levels has

to be achieved. This particular case of separation is known as membrane technology and it relies on the particle size and molecular weight [6] as follows:

- Reverse Osmosis (RO): the concentration is obtained through water removal, generally applied to dehydration of milk, such as whey.
- Nanofiltration (NF): also known as partial demineralization, the concentration is obtained through the removal of chlorine and sodium.
- Ultra-Filtration (UF): the concentration of large molecules, such as proteins, widely applied to the yoghurt and cheese separation process
- Microfiltration (MF): removal of bacteria, widely applied to skimmed milk.

The capacity of separation is impacted by the membrane resistance when a formation of layers increases the resistance of the flow. The fouling effect is a common consequence of a gradual accumulation of components over the surface reducing the output and it is described in section **2.4.6 Cleaning-In-Place CIP.**

2.4.4. Evaporation

The concentration of components, Total Solids (TS) or Dry Matter (DM), is a key factor for the evaporation process efficiency [53]. In addition, the energy consumption required to remove water from a solution is high and to minimize this effect, evaporators are designed to operate with multiple effects which can reduce the consumption of vapour in this process [58].

There are several types of evaporators for different methods. The tubular evaporators are the most commonly used in the dairy process. Vertical tubes are usually found where the product flows downward on the inner surface, and the heating steam condenses on the outer surface of the tubes.

Multiple-effect evaporators are widely used to increase the efficiency of the evaporation process. A second effect evaporator is able to operate at a higher vacuum condition and at a lower temperature. The total volume in the evaporator system increases due to the number of effects connected to the series [58]. Figure 2.13 depicts a simplified diagram where the principle of a multiple-effect evaporator is given; the temperature in A2 is lower than that in A1 [53].

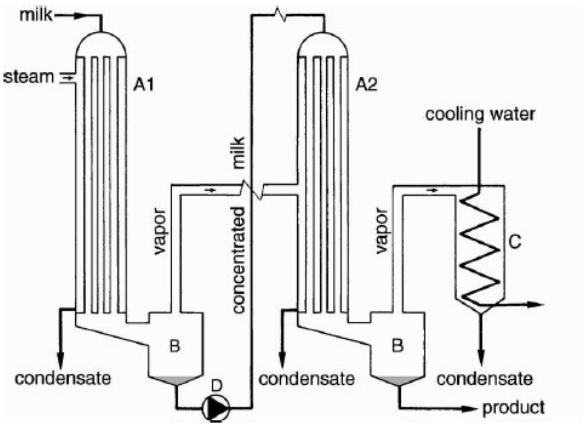

Figure 2.13 – Multi-effect evaporator diagram [53]

2.4.5. Drying

The drying process is required to extend the product shelf-life, improve the handling, reduce the volume, and after reconstitution with water, the products' properties are very similar to the original material [53]. Since water removal is a substantial activity regarding time and energy consumption, the drying process is usually recognized as a bottleneck among dairy processes.

Figure 2.14 illustrates the most common method of drying process known as spray dryer. The air is heated at 200°C and leaves at 200°C. This effect produces small droplets, which are dried immediately. The cyclones are usually used to separate the air from the powder produced.

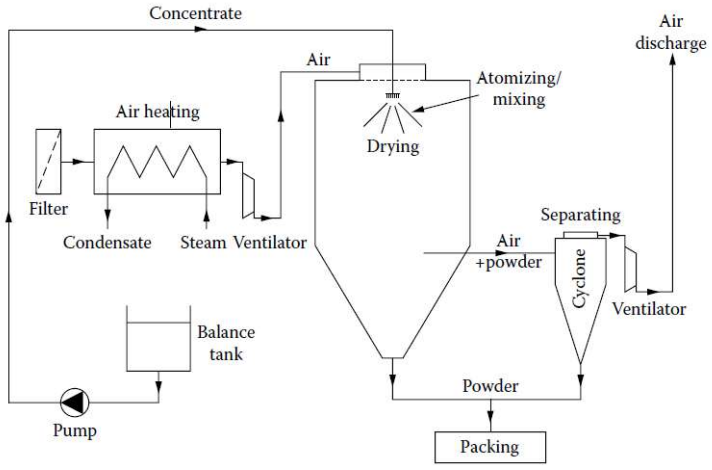

Figure 2.14 – Spray Dryer Diagram [53]

In the drying process, air temperature is a critical issue to be addressed in dairy powder bulk production, mainly because of its effect on the dried product. The presence of moisture might cause inaccuracy in volumetric measurement, fouling and consequently efficiency reduction [36].

2.4.6. Cleaning-In-Place CIP

The fouling effect is a critical challenge for dairy equipment requiring constant cleaning cycles. According to [59] the deposition of proteins and minerals on the equipment walls is caused by the constant heating during the production flow and the cleaning depends on the solid constituents deposited on the surface of the equipment. In addition, a long processing cycle is a critical factor of importance since an extended production time results in increasing the fouling effect. Cleaning cycles are an essential process for dairy equipment to remove such deposition.

This process was time demanding in the past because every machine had to be manually disassembled and cleaned daily [57]. Cleaning-In-Place (CIP) was introduced around 1950 and dramatically reduced the time spent cleaning since detergent solutions were replaced by disassembling machine parts [36]. However, the time required to complete the CIP process varies according to the equipment and must be considered in the overall efficiency for planning and performance assessment.

Most CIP systems consist of three processes: a pre-rinse step to remove any loose raw material or product remains, a hot caustic wash to clean equipment surfaces, and a final rinse to remove any remaining traces of caustic from the previous process [60].

2.4.7. Wastewater

Dairy manufacturing produces significant volumes of wastewater. The composition of the wastewater generated from dairy processors relies mainly on organic material called Aggregate Organic Constituents [61]. Organic compounds are usually composed of proteins. In general, the waste resulted contains high concentrations of organic material such as proteins, carbohydrates, and lipids, high concentrations of suspended solids, high Biological Oxygen Demand (BOD) and Chemical Oxygen Demand (COD), high nitrogen concentrations, high suspended oil and grease contents, and large variations in pH, which all require specific treatment to prevent environmental risks [60].

The process of separating proteins from skimmed milk or whey produces large volumes of by-products to be further processed. However, decision-making regarding by-products processing is a critical issue among manufacturers regarding not only wastewater treatment but also capital and operation costs involved in this process [53].

2.5. Comparing Dairy Supply Activities Across Similar Sectors

In this section, an exploration of types of production systems is highlighted to shed light on the DSC activities. According to [9] SCM is responsible for coordinating the movement of goods from suppliers to the final

customers and the manufacturing process is an essential piece in transforming raw material into finished goods for several sectors.

According to [62] there are three types of Production Systems: (i) Job Production: where the production must achieve specific orders; (ii) Batch Production: which is limited by an economic or capacity restriction to produce a number of identical products, (iii) Continuous Production: the machinery and equipment is dedicated in producing large volumes output with high demand. Within Continuous Production, two other processes are identified: (i) Mass Production: usually assembly lines and (ii) Flow Production where there is a continuous movement of products and the manufacturing plant is designed for producing a specific product such as observed in dairy bulk-powder commodities.

Given the dairy bulk-powder manufacturing environment is a continuous production flow, Supply Chain activities for both production types, mass and flow production, are explored. Mass production environment is used as a reference due to the level of maturity and best-in-class lean principles as described by Womack and Jones in [63]. In addition, F&B and Pharmaceutical Manufacturing driven by high-volume and constant production processes [64] are also examined and presented in Table 2.1.

Table 2.1 - Comparison between Mass Production and Flow Production

Supply Chain Activities	Bulk-Powder Dairy Manufacturing	Mass Production Discrete Manufacturing	Flow Production Beverage Manufacturing	Flow Production Pharmaceutical Manufacturing
Raw material Scheduling	Farms are the main suppliers of fresh milk which is daily received by manufacturers. The milk composition is impacted by the Dry Matters (DM) index and the production mix might be redefined according to seasonality [36].	Parts are produced or supplied from several suppliers according to the Master Production Schedule (MPS) and MRP [65]. Raw material scheduling is also combined with Just-in-Time (JIT) policies [66], [67].	Soft drinks processors are largely dependent on water and High Fructose Corn Syrup (HFCS) producers [68]. For brewing, grains are used as the raw material such as barley. Water is an indispensable ingredient and it must have excellent quality treatment [69].	Pharmaceutical raw materials are classified into active pharmaceutical ingredients (APIs), intermediaries, and additives. For overseas raw material replenishment such as API, the lead-time to the manufacturing plant must be considered [70].
Raw material Distribution and Storage	Milk must be stored at 4ºC to extend its lifespan. The growth of microorganisms must be less than 1.0 x 10^6 ml to guarantee the milk quality [55]. Raw milk requires refrigerated transportation Regulation (EEC) No 852/2004 [71] which states that storage and transportation should preserve proper conditions to avoid contamination. Therefore, the proximity between farms and manufacturers reduces transportation costs [36].	Parts are stored according to the company's strategy [66]. Imported parts require appropriate replenishment policies such as Economic Order Quantity (EOQ) [9] are defined to reduce storage, distribution costs and risk of shortage. [72].	Massive quantities of raw materials are required such as bags and barrels, wooden and plastic pallets; primary packaging such as bottles and cans. According to [69], heavy investments in inventory control are required due to the variety of finished products. Same regulation for Dairy No 852/2004 [71]. According [73], cross-contamination is of paramount concern in the F&B Industry.	Storage conditions must follow appropriate tolerances. Thermal stability is tested, and moisture sensitiveness is one of the major concerns in storage conditions ICH-Q01A [74]. According to ICH-Q07[8], for intercontinental API shipments appropriate control is required for packaging and supply chain integrity.
Demand Strategy and market prices	Production is impacted by raw-milk seasonality. The need for cost efficiency is increased to guarantee competitive prices [75] Several types of contracts are adopted to mitigate risk and support the demand process.	To reduce the impact of variability, production strategy combines inventory policies to fulfil the demand curve as explored in [76]	For final products a similar strategy used in discrete manufacturing combining inventory policies to fulfil demand as stated by [76] and [77] are observed. However, the final price is impacted by severe tax policies for soft drinks and the brewing industry. [78]	After regulatory approval of product and process, new drugs are launched under patent protection into the market [70]. As the patent expires the profit margins are reduced forcing companies to reduce operational costs [79].
Traceability	Even though a traceable system can be implemented from farms to the milk reception [6], traceability is a complex task when a variety of small farms compose the dairy supply chain [80].	Parts can be traced according to their part numbers [81]. In the error detection process, traceability is essential [82]. Global Trade Item Number (GTIN) is the code used among manufacturers to trace their trade items. [83].	Stock movement recording procedure is required and must comply with the commercial uses, good hygiene practices and food and feed safety regulations of European and national traceability rules. Beverages are produced under strict sanitary guidelines which comprise the category of food. [73]	Agents, brokers, traders, distributors, or relabellers must maintain complete traceability of APIs and intermediates distributed GMP-Q7.[8], [79]

Table 2.2- Comparison between Mass Production and Flow Production (continued)

Supply Chain Activities	Flow Production Dairy Manufacturing	Mass Production Discrete Manufacturing	Flow Production Beverage Manufacturing	Flow Production Pharmaceutical Manufacturing
Rework Scraps	In the Dairy process rework requires additional capacity since the product is reprocessed. Specific results of off-spec batches can be reworked and sold to a secondary market or discharged [80].	Scraps and rework require additional capacity and inventory to the entire system. In some sectors, defective parts can be replaced to avoid compromising the final product. In addition, scraps are processed by a secondary market [76].	In the beverage industry, the most common cause of rework results from high speed over filling which increases product losses [77]	Rework must be subjected to appropriate evaluation when it is related to the production, stability testing, and documentation to prove equivalent quality between reworked products when compared to the original produced [8].
Production capacity	The bottleneck dictates the production flow. However, the variability of indirect production branches also causes disruptions due to the limited storage capacity [36].	The total production is restricted by the bottleneck capacity and unbalanced production lines cause an excess of inventory [84].	The bottling process is the most critical due to the high level of automation. According [77] filling and labelling benefit from sensors when the presence of bottles in the entrance of the previous belt is detected. The speed is adjusted according to the number of bottles in the machine.	In a batch process, pharmaceutical plants process low production volumes in shared multipurpose pieces of equipment [85]. In a continuous environment, similar challenges found in the dairy process are observed due to the limited storage capacity [64].
Work-in-Process (WIP)	WIP heavily impacts the production process owing to the limited capacity of Silos/Equipment followed by short product shelf-life [53]	Disruptions cause undesired queues which increase the WIP levels according to Little's law [76] [86].	Similar to dairy, WIP volumes impact the production process due to the limited silos/tanks capacity and large volumes of liquid during the intermediate process. For soft drinks, due to their pH level, high sugar level decreases the product lifespan [87]	Regarding WIP, an important trade-off between batch size and changeover frequency is observed [88] since large batches are desirable to avoid frequent changeovers [89] causing an impact on WIP levels.

2.5.1. Supply Chain Activities - Summary and Positioning of this Research

Supply Chain activities and the main steps in dairy manufacturing were described and further compared to the key activities of distinct sectors in this section. This comparison is essential for positioning this research in order to highlight the limitations, similarities and differences exclusively identified in the dairy environment. From raw material activities such as supply, storage, transportation and traceability, dairy faces specific challenges due to the fragmented volume supplied.

Firstly, as opposed to the sectors investigated and presented in Table 2.1, in the dairy manufacturing flow the high level of raw material perishability requires a restricted period of time for storage followed by a strict temperature control system when compared to other manufacturing environments. In addition, the frequency of raw material supplied is also particular to this sector when compared to the beverage sector for example, despite the similarities presented in the manufacturing environment for both sectors dairy and beverage, the variability of the raw material supplied causes particular impact on dairy manufacturing process not observable in the beverage environment.

Similar stages in the manufacturing of dairy bulk-powder and pharmaceutical bulk-powder for APIs, for example. Traditionally, the pharmaceutical industry has relied on batch production processes. However, continuous processing is being focused as a means of extending production time and ensuring consistent quality [90]. Regarding production capacity, the system flow is dictated according to the bottleneck capacity for both environments.

The dryer stage in the dairy process is comparable to the pharmaceutical environment since the use of the spray drying process is observed in sectors: dairy and pharmaceutical. In dairy bulk powder under rework conditions such as skimmed milk powder drying process, for example, the reworked product must guarantee the same quality of the original product, otherwise it is sent to a secondary market or even discarded.

In pharmaceutical solid dosage forms, subsequent stages such as tableting or capsule filling require a fully automated downstream process, as found in the beverage sector, due to high speed and the variety of finished products produced. This condition diverges from dairy bulk-powder production investigated since the volumes produced are commercialised in tonnes.

Regarding WIP management, in infinite storage capacity environments, queues are determined according to Little's law, increasing the waiting time of the product in the system. According to Little's law WIP is the result of the Throughput and the Cycle time (WIP = TH x CT) [86]. WIP refers to “number of units in the system” whereas Cycle Time refers to the “arrival to the system”. Thus, this relationship refers to the mean number and mean wait in a queue. Little’s law is explored in diverse fields of research such as computer architecture, multi-processing servers, customer queueing at the supermarket, and a variety of applications of arrival and waiting problems. In restricted storage capacity systems, as identified in the beverage and dairy powder bulk manufacturing, individual process flow stages must be interrupted.

With respect to external factors, such as marketing and demand patterns, since dairy bulk-powder is an upstream commodity of the DSC, as opposed to downstream manufacturing such as finished products for final customers, the demand pattern is dependent on exports and diverges from pharmaceutical dosage solids and F&B, for example. In addition, the market price previously explored in section 2.3.2 presents a specific behaviour which differs from the other sectors analysed.

The sectors examined have evolved their supply chain activities through advanced investment in technology and implementation of efficient continuous process improvement in order to create new value for customers. In section **2.6 Simulation-based Models for Dairy Supply Chains and Cloud-based Simulation**, the application of simulation models for discrete manufacturing as means for achieving efficient processes is widely researched as follows.

2.6. Simulation-based Models for Dairy Supply Chains and Cloud-based Simulation

Current trends in Modelling and Simulation (M&S) in real case studies are increasing especially due to the advent of applications based on innovative technologies provided by smart manufacturing [91], creating new opportunities to improve the decision-making process.

In conventional discrete-event simulation approaches, the construction and use of a model is a complex, multi-stage, iterative process as thoroughly described by [92]. Due to the advantages of traditional M&S observed in several sectors, this section explores fundamental studies relevant to the aim of this research. In addition, the state-of-the-art in cloud-based modelling is also fully explored in order to provide the required background for the development of the cloud-based simulation framework for dairies.

2.6.1. Simulation-based over the Web

According to [93] web service "refers to message-based design frequently found on the Web" and it is responsible for transferring data from one domain to another and also between applications. The security is provided by document authentication through Extensible Mark-up Language (XML) Encryption and XML Signature.

A significant number of papers approaching concepts of simulation over the web is observed since 1998, such as proposed by [94] where a user invokes a simulation residing on a remote computer – a basic application of client-server model of computing and as proposed by [95] where an exploration of types of web services structure are described.

In addition, during the exploration of the literature, efforts of applying web-based simulation were studied in [96] where a configuration of manufacturing systems through the Internet was proposed. However, examples of practical results are limited.

In a systematic review, Byrne et al. [97] presented the advantages and disadvantages of web service structures. However, over time, the concept of web-simulation has changed from the original structure presented and some middleware that are now arguably obsolete. New technologies emerged, including all options provided by suppliers such as Google and Amazon in a concept of Software as a Service (SaaS) or Cloud Computing.

2.6.2. Cloud Computing Background and Trends

In [98] Cloud Computing is defined as: "… is a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources that can be rapidly provisioned and released with minimal management of the effort of service provider interaction". This guideline specifies three different types of service:

- Infrastructure as a Service (IaaS) provides access to raw computing hardware over the Net, such as servers or storage.
- Software as a Service (SaaS) where the application runs.
- Platform as a Service (PaaS) developed applications using Web-based tools run on software and hardware provided by another company.

An extra service is referred to in [99] as:

- Database as a Service (DBaaS) where the database runs on the service provider's physical infrastructure.

Cloud computing is beneficial since it offers scalable and adaptable computing and storage services [100]. The advancement in cloud storage contributes to a reduction in storage costs due to the centralised strategy supported by cloud supporting management functions such as replications and backups [99].

SaaS cloud performance evaluation is growing in attention due to variability in the computational workload demand [101] namely due to the increase in cloud applications. Data analytics, data mining, scientific, engineering and financial applications, gaming and social networking which require data-intensive activities benefit from cloud computing. Existing cloud applications could be divided into three groups: (i) processing pipelines, (ii) batch processing systems; and (iii) web applications.

From cloud computing, other approaches emerged, such as fog computing and jungle computing. Fog computing or fogging is a distributed computing infrastructure in which application services are handled on a smart device and in a remote data centre – on the cloud. The main objective is to efficiently improve computing and reduce the data transferred from the cloud to storage, processing and analysis. This distributed approach is increasing in popularity due to the Internet of Things (IoT) and the massive amount of data provided by sensors [99].

The European Grid Initiative (EGI) is responsible for providing advanced computing services to support scientists, industries, multinational projects and research infrastructures [102]. Grid or grids are compared

to web-services in [103]. Grids are also referred to as grid middleware [104]. Due to the necessity of specific simulation models to run a large number of experiments, the process of simulating industry experiments would benefit from this architecture.

2.6.3. Cloud Computing and Cybersecurity

Due to the growth of business processes dependent on technology, companies need to navigate safely in the digital environment known as cyberspace. According to the International Organization for Standardization ISO/IEC 27032 (2012), "cyberspace is defined as the complex environment resulting from the interaction of people, software and services on the Internet by means of technology and networks connected to it, which does not exist in any physical form" [105]. The ISO/IEC 27000 family contains a Security Management guideline providing requirements for a consistent Information Security Management System (ISMS). Using them enables organizations of any kind to manage the security of assets such as financial information, intellectual property, employee details and information entrusted by third parties.

The increase in investment to protect sensitive information is also critical in the digital world since it requires new methods and technologies to guarantee the security of the data. Cybersecurity is vital since it is designed to protect the networked systems and applications against potential threats, whether those threats originate from inside or outside of the organization. A strong cybersecurity strategy has layers of protection, including a distinct strategy to defend the system against particular threats, including but not limited to attacks that attempt to access, change, or destroy data [105].

For any cloud-based environment, trustworthy confidential computing that encrypts cloud data stored, in motion - from and within the cloud - and during processing to support customer privacy, business requirements and regulatory compliance standards are required. In addition, considering that the risks are also still expanding, with thousands of new vulnerabilities emerging, opportunities for human error are also a considerable challenging, due to negligent employees or contractors who unintentionally cause a data breach. Therefore, building security awareness across the organization to strengthen endpoint security is fundamental. From the application perspective, the encryption in transit protects the data by using authentication, integrity, and encryption to guarantee the data security. All of these measures usually performed by companies are less expensive since they are performed by cloud providers [106]. Therefore, significantly costs of maintenance regarding data security are reduced by SaaS as a system platform.

The cloud computing providers offer data security not only related to accessing the application but also the infrastructure and how the data is transferred within the cloud. SaaS solutions are more reliable because the investment in security is provided by those suppliers. According to Security, Privacy, and Cloud Compliance supplier by Google [106], six-layer of protection is provided for their physical datacentres : (i) boundaries, access to the physical gate, (ii) smart fencing, monitoring and systems to control the people movement, (iii) building access and biometric systems to control access, (iv) security operation centre (v) on

the data centre floor, only technicians have access to maintenance; the data is encrypted and (vi) disks are destroyed and replaced by new.

2.6.4. Integration and Interoperability between Models

Concerns regarding integration and interoperability between simulations have been previously studied. As shown in [97] models addressed by High-Level Architecture (HLA) standards were explored. The objective of the HLA is to provide a structure for supporting the reuse of different simulation models [107], thus, reducing the cost and time required to create new solutions [108].

In order to facilitate interoperability between simulation systems, namely for the manufacturing environment, a common standard file which stands for a Core Manufacturing Simulation Data (CMSD) was designed by Simulation Interoperability Standards Organization (SISO) for discrete manufacturing simulation models. It is an open standard data structure to enable an efficient exchange of manufacturing data in the simulation environment [109].

CMSD are structured files used to address interoperability issues between simulation and manufacturing applications. As found in [110] a DES system based on a CMSD to optimise an assembly line process was modelled and the model changes according to the file structure. A similar application of CMSD for manufacturing flow was also observed in [111] and [112]. The application of CMSD in several manufacturing sectors and the integration between MES and DES by means of CMSD files was recently presented by [113] and [114].

A simulation-based decision support project entitled Decision Support in Real-time for Efficient Agile Manufacturing (DREAM) focused on the advancement of discrete event simulation technology to promote the embedding of simulation-based decision support across the array of multi-level decisions faced by European Manufacturing Enterprises [115] was previously developed based on such files. In this research, a variety of simulation models developed were tested under ManPy libraries and compared to a Plant Simulation designed for a specific manufacturer.

The main advantage of using this format is the dynamic definition of technical and organisational data according to the model desired. These characteristics are relevant for data-driven model generation approaches. CMSD capabilities were explored by [109] with a practical application of the CMSD standard. However, the drawback is the necessity of internal algorithms to generate those files. In addition, appropriate interfaces for accessing XML files and the simulated results restrict the utilisation to technical resources.

Data interchange standards (e.g. XML) were previously applied in [116] and [117] to facilitate the interaction between simulation models. Even though this is still the reality for many data interchange models, a fully automated industrialised process is also a future communication trend between Machine-to-Machine (M2M) reducing time to transferring data from pieces of equipment. In addition, embedded systems have

been improved in collecting real-time information from several sources, intelligent sensors, actuators and distributed control structures which replace the centralized computer as stated by [118].

The main benefit of integrating M&S and Manufacturing Execution Systems (MES) is the accuracy in data collections due to the reduction of errors in data manually collected. The idea of integrating raw and automated data in a simulation model for manufacturing is observed in [119] since it was shown that the effort required to collect raw data and further process it into appropriate inputs for simulation is a time-consuming task.

2.6.5. Elasticity and Scalability of Cloud Computing

The application of cloud-based simulation contributes to the use of traditional simulation tools for modelling development and cloud interface to connect distinct models [120]. The main characteristics of cloud computing are: on-demand self-service, broad network access, resource pooling, rapid elasticity, scalability, and measure service.

In cloud computing, the terms Elasticity and Scalability are used interchangeably and are related to handling the system's workload and resources. However, despite being essential elements in this environment, there are differences between these two concepts.

Elasticity is described by [99] as the main advantage of cloud computing since it is the ability to grow the current resources dynamically as required by the users. Similar to a manufacturing system when the capacity needs to be increased to reach the demand considering the current structure plant, whereas Scalability is related to the hardware, which was totally relied on the company's infrastructure in the past. As stated by [121] scalability can be defined as the ability of a system to fit a problem as the scope increases. The ability to scale up a system may depend on its design, data structure, algorithms and communication mechanisms. It refers to the ability to increase the current capacity and long-term decisions. Scalability and Elasticity metrics, such as volume processed, bottlenecks and time of response, are essential to measuring the features of the system to identify patterns and guarantee a reliable structure [122].

2.6.6. Cloud-based M&S - Summary

By analysing previous research regarding cloud-based simulation described in this section, a summary of the main concerns are presented in Table 2.2 as follows:

Table 2.2 – Modelling and Simulation – Summary

Licence	The necessity of acquiring licences from commercial software for companies to run academic experiments can be a restriction. According to [123] the adoption of Open Source (OS) software proved to be appealing to organizations with limited financial resources.
Usability	The importance of models reuse was presented by [124] with criticism about the capability of a specific model developed for a production line being used by different processes.
Portability	It is also defined as a cross-platform capability, portability and interoperability were one of the most critical concerns in the past regarding WBS benefits [125] and it is of paramount concern for simulation developers with respect to interoperability and reuse of simulation models regardless of the platform.
Loss in Speed	Performance is one of the essential characteristics for all SaaS applications [101].
Interface and User Experience (UX)	The interface has an enormous impact on how the model is perceived by the end-user. From the end-user perspective, a user-friendly interface such as wizard sequences or mandatory fields, for example, are strategies to guarantee that all steps will be correctly followed.
Security and Controlled Access	It is of paramount importance to provide data confidentiality. Regarding Service Oriented Architecture (SOA), commercial providers are publicly traded companies and flaws in the security system can experience negative global repercussions. As explored by [126], security issues are essential especially to the data vulnerability such as Denial of Service (DoS) attacks, for example.
Distributed Computing Resources	One of the challenges of extensive simulations is the amount of time required on sequential computers [91], especially due where vast volumes of information are being collected from a variety of devices [119].

Developing cloud-based solutions for simulating industry is a complex task since it requires appropriate expertise towards the processes and the technology involved. In the next section, areas researched focused on M&S applied to dairy supply chains are studied as follows.

2.6.7. Simulation to Support Dairy Supply Chain Activities

In this section, an exploration of the literature review concentrated on simulation models addressing current challenges in the dairy sector is structured in Table 2.3. The relevance of the presented literature in this table for this project is to demonstrate the summary of the contribution of previous research to the investigated field and the evolution through time, suggesting how simulation are growing in popularity for this sector. The analysis of the extension of each literature and the gaps identified is then presented as follows.

Table 2.3 - Research concentrated on Simulation applied to the Dairy Supply Chain

Ref.	Year	Application	Approach
[127]	2018	Decision support tool combing MLP and simulation for Casein/Caseinate production planning	Production Planning
[128]	2017	A pasture-based dairy farm in robotic the Irish milking environment.	Supply
[129]	2016	Analysis of seasonal costs in the Irish milk production processing and how to achieve improved results by smoothing the milk supply.	Milk Seasonality
[130]	2016	A small-scale payment system to compensate farmers for delivering quality dairy goods are proposed where a spreadsheet decision support tool was designed to calculate the profit based on suppliers' milk quality.	Supply Farmers Assessment
[131]	2015	A Mixed-Integer programming (MIP) model was proposed for optimising the shift work in finished goods warehouses considering the packaging and the interaction of several tiers in the dairy supply chain.	Production Scheduling
[132]	2015	A model to explore the effects of an appropriate pricing strategy for wealth generation and health improvement at the Base of Pyramid (BoP) in Bangladesh.	Price Policies
[133]	2014	An assessment of conventional and organic dairy production in Austria based on farms and product biodiversity.	Life Cycle Assessment (LCA)
[134]	2014	The application of Modelling and Simulation to evaluate Specific Energy Consumption (SEC) and Greenhouse Gas (GGH) mission was used in the fluid milk process combining capital cost assessment of different types of heat treatment.	Pasteurisation Energy Consumption
[135]	2013	The model evaluated GHG emissions per kg of packaged milk and the global warming potential related to USA milk processing.	Life Cycle Assessment (LCA)
[136]	2013	Combining Mixed-Integer Linear Programming (MILP) and simulation in a hybrid model to improve the yogurt production planning in Turkey	Production planning
[137]	2012	An analysis regarding milk transport costs and carbon emissions the Irish dairy sector	Transportation
[138]	2014	Explores the specific trade structures of the German milk supply chain, highlighting the impact of a hypothetical risk of contamination	Contamination risk assessment
[41]	2012	A multi-objective integrated production and distribution plan for perishable products.	Perishability scheduling plan
[139]	2011	An economic approach was studied describing the effects of contracts arranged several months in anticipation, especially the price-demand curve in the New Zealand Dairy sector.	Market Price and supply uncertainty
[140]	2011	Agricultural policy modelling under imperfect competition applied to the Italian dairy sector.	Price Policies
[141]	2011	A hybrid proposed for the top-ten Iranian dairy industry supply chains to address its ability as a robust, straightforward, and well-posed tool to measure the efficiency of agility in Supply Chains.	Supply Agility
[142]	2010	Quality-control and moral hazard to consider the quality approach of the milk's depots and the processors in the Chinese dairy sector.	Dairy Storage
[143]	2009	The effects of a constrained supply in the food supply chains and the impact on many firms constrained by raw material supply.	Supply Restriction
[144]	2009	A decision support approach specific to irrigation scheme for dairy farmers was designed in Morocco.	Supply Assessment
[145]	2008	A simulation and optimisation-based decision support tool was developed between two factories and the integration of a large quantity of milk suppliers and the uncertainty in demand were explored.	Balancing Supply and Demand
[146]	2008	An analysis of the effects of each activity on dairy processes from mixing raw material to the final product packaging	Production Environment
[147]	2007	Optimising the production scheduling of fresh yoghurt was conducted minimizing the cost of production in different lines of production.	Production Scheduling
[148]	2006	A centralized management optimisation proposes a simulation method comparing strategic decisions about centralization and decentralization and its impact on the Chinese Supply Chain Network.	Supply Network
[149]	2003	The model proposed a reduction of cost over time through improvements in quality and quantity metrics.	Lean / Cost Production
[150]	2001	The incorporation of sustainable aspects of SCM through LCA.	Life Cycle Assessment (LCA)

Solutions for specific processes and fragmented activities applying M&S within the Dairy Supply Chain have been widely researched in several countries as observed and discussed in this section.

On the supply side, namely the agriculture side, the recent incorporation of new technologies is observed in [128] through the adoption of farming techniques exploring the Internet of Things (IoT), fog computing and data analytics in the Irish milking environment which highlights the adoption of innovative solutions for current issues.

Agriculture issues impacted by imperfect competition of market prices are explored in [140]. In a situation of imperfect competition, the law of supply and demand is insufficient in determining prices. In this study, the simulation model created several scenarios for several dairy products and compared them to a desired perfect competition environment. However, even though the presented results provided insights for future work, this study is limited to the Italian retail dairy sector.

A sustainable supply approach is observed in [144] and [133]. The relationship between agricultural raw material and water savings, [144]. Four scenarios that simulate the impacts of crops and irrigation techniques on farm income and water consumption are investigated in Tadla region to support dairy farmers. Farming practices and a method for assessing farmers' milk supply in the Austrian dairy sector is studied by [133]. The objective is to evaluate the quality of organic farms and its impact on biodiversity.

A trade-off between supply and demand pricing strategy is explored in [132]. The research proposed insights to find the best price and decisions regarding distributions of fresh dairy products in Bangladesh. Fundamental elements in the dairy sector, such as maximal production capacity and potential new customers, are studied. However, it focuses on one specific fresh dairy product as opposed to the dairy powder bulk environment.

Research focused on quality and risk assessment is also observed. The risk of contamination in the German dairy sector is studied by [138] where possible variations in the trade links among milk producers, manufacturers and consumers are investigated. Agility and efficiency metrics for the Iranian dairy supply farms are proposed by [141]. This research is concentrated on low shelf-life goods. An analogous approach focused on quality-control is observed in [142] for the Chinese dairy sector.

The impact of milk quality from farms on final products was the aim of the study conducted by [130] where a small-scale framework to support planning decisions regarding the production mix was developed through an automated spreadsheet. Limitations regarding the number of suppliers and the number of end products restrict the scalability of the proposed solution to other dairies.

Additionally, a scheduling support tool for balancing milk supply and demand is proposed by [145]. In this approach, a simulation model was designed to calculate the best route of suppliers in order to achieve the current demand. Limitations regarding milk processing and internal capacities are unexplored. In addition, implications regarding bulk powder production are limited, as observed in this study. The approach

researched and adopted by [130] and [145] highlights the importance of practical data-driven solutions and an evident gap faced by this sector.

Seasonality and its impact on bulk powder production are found in [129], where the seasonal cost advantage in milk production for the Irish dairy sector is evaluated through several scenarios. In the scenarios proposed it was studied the potential benefits by elevating the average utilisation rates of existing plants by smoothing the production. However, the presented results suggest that seasonality will remain a dominant factor for the Irish dairy sector.

Seasonality focused on fresh dairy transportation products in the Irish dairy sector is studied by [137]. In this research, the trade-off between milk availability and the number of suppliers is analysed. In addition, milk transportation costs and carbon dioxide emissions are also analysed. Despite the supply variability investigation, the impact on production and milk processing which is fundamental in determining the optimum volume to be processed among dairies was not explored.

On the manufacturing side, studies such as [149] are focused on simulating current strategies and provide directions for reduction costs by minimising non-added-value activities in the Brazilian dairy sector. Despite forecasted production costs being simulated and seasonality incorporated as an index factor in the overall scenarios, the research is focused on milk in liquid form.

A Mixed-Integer Programming (MIP) model for scheduling equipment optimisation for fresh dairy products is studied in [131] and [136], a multistage production planning in [151]. The risk of perishability integrating production and distribution plan for perishable products was modelled considering maximising the freshness of the products delivered to the distributors' centres and minimizing the costs related to the supply chain operation [41]. Scheduling for a particular dairy finished product in [147] and a Sales and Operation Plans (S&OP) decision tools for centralised and decentralised management approach of fresh dairy products [148]. Simulation decision support tools based on scenario comparisons are found in [146] where several strategies to determine the optimal condition of a manufacturing environment were tested.

It is observed that all these studies regarding manufacturing production environments are focused on end-products for end-consumers. Based on the literature explored, despite numerous research focused on the dairy manufacturing environment, a significant gap is observed in robust frameworks for decision support considering several factors and challenges identified in this sector such as seasonality combined with limited storage capacity and also risk of perishability, for example. In addition, lean continuous process improvement approaches and therefore pull-type systems are limited. In addition, the impact of CIP and cleaning processes on the manufacturing environment is still waiting to be addressed.

One interesting piece of research addressing a stochastic production planning model for the New Zealand dairy industry was conducted by [139]. Similar to the Irish dairy sector, one of the sources of variability is caused by the uncertainty of milk supply. The effect of supply uncertainty and price–demand curves on contracts were considered in this research since there is a significant impact on production planning.

However, once more, there is no evidence of the impacts caused by CIP or any cleaning procedure in this study.

Decision support based on scenarios focused on sustainability metrics in the manufacturing environment is observed [150]. The model consists of the integration of transportation among farms, dairies, distributors, retails and households and aspects of packing, energy, utilisation, water and waste. Models designed for a specific purpose are found in [134], where the main objective is to compare the energy consumption of several heat treatments. Aspects of sustainability in the manufacturing environment are also observed in [135]. The referred studies are focused on fresh dairy products while the drying bulk-powder production, such as casein and whey, requires a higher volume of electricity.

Current research applying M&S in the dairy bulk powder environment is observed in [127]. In this study, the application of MIP and simulation to identify the best volumes for casein and caseinate were explored. However, it is focused on one manufacturing stage and to support decisions in one specific process environment.

2.6.8. Summary and Positioning of this Research

The studied literature reveals that despite the availability of technology for companies to build and execute their models, little innovation is perceived in the dairy sector. The majority of the research presents a similar approach consisting of the following steps: (i) understanding the problem, (ii) designing the flow, (iii) gathering data and specified parameters for distributions, (iv) creating the simulation model, (v) validating the simulated results, (vi) comparing the results against the defined scenarios or current process.

The scenarios are determined by the authors according to the simulation model designed. Thus, the results presented are totally dependent on the model initially defined. Models capable of generalising a manufacturing environment and defining appropriate scenarios for decision-making processes are non-existent for the dairy sector.

Conversely, Discrete Event Simulation applied for discrete manufacturing such as assembly lines, for example, has evolved to a data-driven approach interacting with real-processes throughout CMSD files in XML format. In addition, the aim of the simulation-based application platform called DREAM is to facilitate the input data phase in simulation applications for decision-making processes. However, the libraries developed are focused on a discrete manufacturing environment. Thus, a significant gap in the literature in exploring advanced technology architecture in the dairy sector is evident.

Regarding applying simulation for supply chain process improvements, from the supply side, the agricultural approach is broadly researched. The influence of market prices on the raw material availability, milk quality, farm milk supply assessment has increased in significance among researchers.

Seasonality is explored for specific cases, such as farmers and finished goods. Little research has been expanded to the dairy bulk-powder manufacturing environment. On the demand side, studies focused on perishability, storage and distribution are mainly concentrated on finished goods for end consumers, once again with little evidence of consideration to bulk-powder manufacturing.

Ultimately, on the manufacturing side, scheduling production flow has been the focus of the majority of the research combining MIP and simulation models for end products. The effect of seasonality is sometimes incorporated through a seasonal index and its impact on the demand fulfilment is partially considered in the research explored.

Literature considering the impact of seasonality and supply variability combining constant interruptions of CIP on the manufacturing environment, production pull-systems, and the management of high volumes of raw material for dairy bulk powder commodities are critical subjects waiting to be addressed.

An exploration of Lean thinking followed by pull-type PCS and Just-In-Time (JIT) systems is conducted in the following sections in order to provide significant background regarding continuous process improvement for this research.

2.7. Lean Thinking

Lean Production Systems (LPS) focuses on minimising several sources of waste such as: defects, overproduction, over-processing, movement, transportation, waiting and inventory. As stated by Ohno [67], waste is originated by insufficient standardisation and rationalisation increasing the inconsistency in the system (mura) and unreasonableness (muri). In other words, uneven processes (mura) result in an overburden system (muri) and consequently increase waste (muda).

This concept has evolved to Lean thinking since it is not restricted to production systems. For Bicheno and Holweg [152], lean thinking consists of identifying what adds value to the customer perspective and systematically improving the process in order to reduce waste or “muda”. Waste is also defined as any activity that absorbs resources but creates no value, such as extra inventories and activity waiting due to an inefficient upstream. For [153] the term *value-added* refers to the activity that transforms the product according to the view of the customer. In addition, the essential principle of a lean mindset is the ongoing elimination of waste.

Bicheno and Holweg [152] state that Lean Thinking can be summarised into five principles: (i) define value by a specific product, (ii) identify the value stream for each product, (iii) make value flow without interruptions, (iv) let the customer pull value from producers, and finally (v) pursue perfection through the continuous process improvement converting *muda* into value. The term *flow* is not only referred to as a physical movement but also as the information and designs essential to run operations requiring continuous improvement in three dimensions: (i) Reducing waste, (ii) Enhancing value, and (iii) Involving people.

Martin and Osterling [154] explore the mapping process activity through the Value Stream Mapping (VSM) methodology which has been adopted as a valuable tool for visualising the material and flow in a work system and classifying non-added-value and added-value activities. The importance of process flow is also observed in the Six Sigma methodology through the SIPOC diagram. SIPOC stands for Suppliers-Input-Process-Output-Customers [155]. It is used to describe the macro steps at the strategic and tactical levels to be used as a starting point for Value Stream Mapping activities.

In a VSM, processes consist of defining and representing each activity in a process box and the inventory between stations and the statistics metrics such as cycle time, changeover, number of operators, percent defective, for example. The objective is to globally improve or optimise the current state, starting at the customer side of the Value Stream, moving up from right to left, from customers to suppliers, and from the material flow to information flow in order to avoid methods that consider individual departments Rother and Shook [156].

The benefits observed from strategies adopted from mature sectors, such as assembly lines, provide a key opportunity to learn the best and established practices as defended by Womack et al. in [157], where “lean production can be applied in every industry across the globe.". However, the lack of management commitment is the first barrier to adopting any continuous process improvement. According to [158] one of the most significant success factors for lean implementation refers to management commitment.

Lean principles have been applied to a variety of sectors as currently observed by [159] through a framework to improve green practices and process innovation. Thus, rather than traditional production metrics such as cycle-time, the referred research is focused on defining sustainable KPIs.

2.7.1. Lean Thinking in the Dairy Supply Chain

In 2007 a report developed by the Food Chain Centre [160] stated that enormous savings could be obtained if the dairy industry applied simple lean principles and improved the relationships along their supply chains. This conclusion was achieved after applying a 4-year pilot program involving 8 companies using the lean thinking approach. The project was completed despite the challenges that stemmed from a natural disbelief that lean thinking could benefit the dairy sector.

Since then, it was observed that little research and practical contribution in applying lean principles in the dairy sector had been conducted. Limited research was found exploring Value Stream Mapping (VSM) in order to identify processes that could be improved for specific products such as [161], [162]. In [161] VSM was explored as a simulation-based methodology to evaluate the cycle-time in a dairy yoghurt processor. The main objective was to identify alternatives to reduce and eliminate energy consumption. As explored, this research is specific for fresh dairy products and has similar drawbacks as observed in the F&B industry such as errors with filling and packaging processes. The initial steps in the raw material supply are briefly

described; however, implications of raw material seasonality are not explored. This raises the question of how lean principles could be appropriately implemented in the dairy bulk powder environment.

Research focused on adopting lean thinking at the farm side is observed in [163] where internal factors that impact farms operations are explored. In addition, a maintenance system to eliminate losses due to breakdowns following lean principles is proposed by [164]. However, in the referred research practical results in implementing lean thinking are limited.

Identifying the key performance metrics, according to lean principles, requires an evaluation based on waste reduction and customer satisfaction. Even though lean principles are widely applied to the discrete manufacturing environment, namely due to its origin in the Toyota Production Systems (TPS), it can be generalised to other sectors in the production-process matrix by following the right methodology and evaluating appropriate performance metrics. In the next section, a detailed investigation regarding pull-type PCS is presented in order to provide significant background for this research.

2.8. Production Control Strategies

As stated by [165], a pull production control mechanism in a multi-stage manufacturing system is a mechanism that coordinates the release of parts into each stage of the system with the arrival of customer demands for final products.

JIT philosophy and Toyota Control Systems are interchangeably used in the literature as a pull mechanism to control the flow of material in the system by Kanbans, also referred to as tokens [166]. Kanban is a mechanism created by the Toyota Production System (TPS) to authorise material within the production flow [67] . The use of the Kanban system to eliminate the interdependency between stages was initially explored by [167] and since then, variations of pull-type were developed as explored in [165] . The conventional "House of Lean" developed at Toyota is based on two pillars: JIT and Jidoka which are regulating mechanisms to control production flow and quality [157]. The referred pillars were later evolved to Continuous Improvement and Respect for people according to the Lean Principles [152].

Pull-type PCS are used for controlling production between flows and are essential in implementing LPS since the flow is pulling according to the customer requirements. The main pull-type PCSs: (i) Kanban Control Strategy (KCS), (ii) Base-stock Control Strategy (BSCS), (iii) CONstant Work-In-Process (CONWIP), (iv) Generalised Kanban Control Strategy (GKCS), (v) Extended Kanban Control Strategy (EKCS) and (vi) a hybrid control combining CONWIP and KCS policy (HKCS) are investigated in this section in order to evaluate how these traditional mechanisms are still being applied in the manufacturing environment and what potential enhancements are achieved. Firstly, the first step consists of identifying the characteristics required by a pull-type system as described as follows.

2.8.1. Push and Pull Systems

The main difference between push and pull production control strategies relies on how the material flow is approved in the system. In a pull-type production system, the raw material is authorised according to the demand whilst in a push systems the raw material is scheduled into the production flow independent of the downstream demand.

Liberopoulos [168] states that pull systems follow three main mechanisms for controlling the production manufacturing: (i) controlling raw part arrivals, (ii) authorising releases based on WIP, and (iii) responding to actual demands. All three main definitions regarding pull systems are summarised as follows:

- ✓ Definition 1: In a pull system, the production is triggered by current demand, while in a push system, the production is anticipated according to a future demand [169][170] .
- ✓ Definition 2: In a pull system, the production is triggered by actual demand for finished products while in a push system the production starts independently of demand [171] [165]
- ✓ Definition 3: In a pull system, the production is limited by WIP volumes, while in a push system, WIP is not controlled [42][166].

An appropriate definition of Make-To-Stock (MTS) and Make-To-Order (MTO) is also essential in determining a push or pull-type system. MTS/MTO distinction is related to whether finished goods are produced to be stocked or to satisfy demand [168]. An alternative replenishment system is identified as Make-To-Forecast (MTF). In an MTF system, production is released to meet forecasted customer demands.

Figure 2.15 illustrates a push system described by [168]. In this example, a primary production system consists of four workstations in series denoted by WSi, $i = \{1, \dots, 4\}$, separated by buffers of infinite capacity, denoted by Pi, $I = \{1, .., 3\}$. Even though there is a demand to be achieved, it is solely controlled for finished goods. The system upstream of P4 is uninformed and disregarded WIP levels for individual stages. In this example, only definitions 2 and 3 are observed since the production is not triggered by demands.

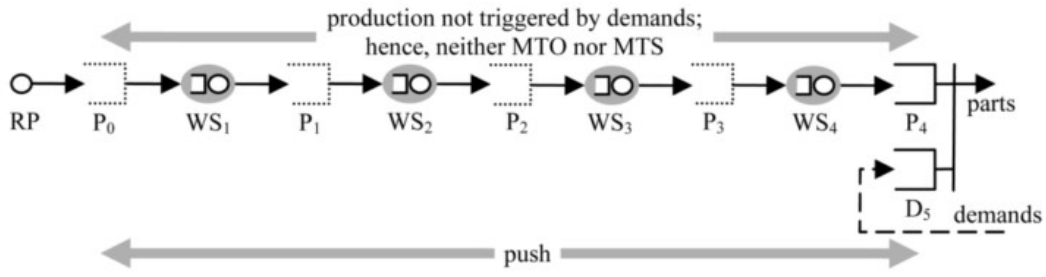

Figure 2.15 – Push System - [168] – Demand for finished goods but no WIP control

Figure 2.16 presents an example of a pull-type system (CONWIP) described by [168]. In this example, definitions 1 to 3 which are driven by customer demands and have a limited WIP are observed and each stage is controlled according to the Production Authorisations (PA).

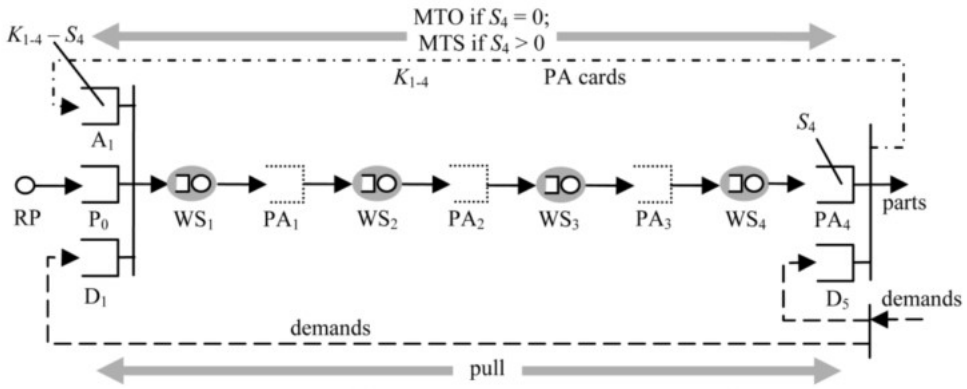

Figure 2.16 – Pull System - [168] – Extended CONWIP - Demand for finished goods and raw material

These two examples provide a vital guideline in understanding the importance of 3 definitions in a pull type production control system. By failing in complying with all these mechanisms a system cannot be deemed as a pull-type system. In the next section, the main pull-type PCS explored in the literature is investigated in order to evaluate the potential benefits of each policy for the dairy bulk-powder environment.

2.8.2. Kanban Control Strategy (KCS)

Kanban Control Strategy (KCS) has been used worldwide to manage the production flow. It is the most well-known pull-type PCS system and several KCS variations have been explored by previous research as found in [172]. According to [172] from the 32 variations of Kanbans systems, 23 or 71% followed the original kanban mechanism. From these 23 variations based on the original KCS system 9 of the overall studies explored had practical development. Therefore, despite the extensive research, there are still gaps in identifying real benefits in the industrial environment.

The main characteristic of a KCS is the authorisation signal to the next stage of the production flow. In this policy, the material flow is controlled by the customer demand. Therefore, the reduction of the waste is the aim of this system since no extra production or excess of inventory is observed without any contribution to fulfil the customer demand.

Figure 2.17 illustrates the KCS system commonly represented in the literature [173]. In this production system, two Manufacturing Processes (MP) in series are denoted by MP, $i = \{1, \dots, 2\}$, separated by Buffers (B) of infinite capacity denoted by B, $i = \{0, .., 2\}$. The current part processed is represented by p whereas k, $i = \{1, .., 2\}$ represents the number of Kanbans in stage i. The available capacity for i stages are determined by the number of maximum Kanbans K, $i = \{1, .., 2\}$. Finally, the customer demand which

triggers the production is denoted by D and triggers the production according to the availability in the last inventory buffer.

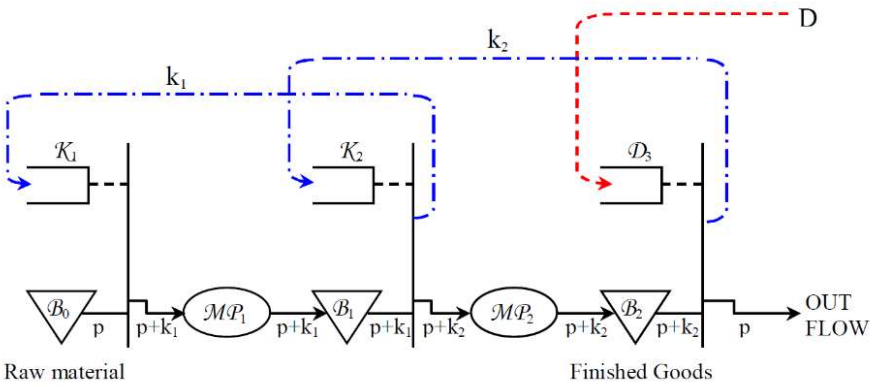

Figure 2.17 - KCS line with two stages [173]

2.8.3. Base-stock Control Strategy (BSCS)

In a BCS strategy, all the production stages receive the demand event at the same time. The main advantage is the fast response to demand requirements and it is considered one of the simplest pull-type [174]. However, it compromises the coordination and dependency provided by previous stages. In addition, it requires an optimum level of safety stock and buffers between stages [175].

Figure 2.18 illustrates the BSC strategy applied to a two-stage manufacturing [173]. In this production system two Manufacturing Processes (MP) in series are denoted by MP, $i = \{1, \dots, 2\}$, separated by Buffers (B) of infinite capacity denoted by B, $i = \{0, .., 2\}$. The current part processed is represented by p. The amount of basestock level (or maximum capacity) in stage i is determined by S, $i = \{1, .., 2\}$. In this system the customer demand D is sent to all three buffer stages by D, $i = \{1, .., 3\}$.

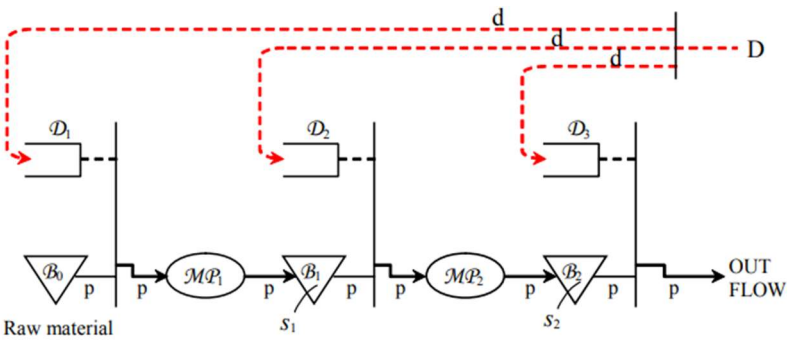

Figure 2.18 - BSC line with two stages in series [173]

2.8.4. CONWIP Control Strategy

CONstant Work-In-Process (CONWIP) is a generalised form of Kanban [176] as a pull strategy alternative for exploration of the benefits of a pull system applied to a variety of manufacturing environments. The authorisation is based on the WIP capacity to control the total inventory in the system. The CONWIP inventory level controls the material flow, and extra material is authorised to enter the system when the demand consumes the current inventory.

There is only one parameter to be optimised denoted by *C*, which simplifies the implementation and maintenance. Conversely to KCS where the demand information travels from the final to the initial stage, CONWIP is instantly communicated to the initial stage and the release rate is adjusted. This is reported as a significant advantage of CONWIP over KCS as there are no information flow delays in communicating the current demand to the initial stage and enabling adjustments to the release wait.

Figure 2.19 presents a system ruled by the CONWIP strategy as described in [173]. In this production system, two Manufacturing Processes (MP) in series are denoted by MP, $\mathrm{i} = \{1, \ldots, 2\}$, separated by Buffers (B) of infinite capacity denoted by B, $\mathrm{i} = \{0, .., 2\}$. The current part processed is represented by p. There is one unique parameter responsible for authorising the amount of COWNIP level (C) (or maximum capacity) in the entire system. The customer demand D is sent to the last stage and authorises the raw material according to the volume defined by C.

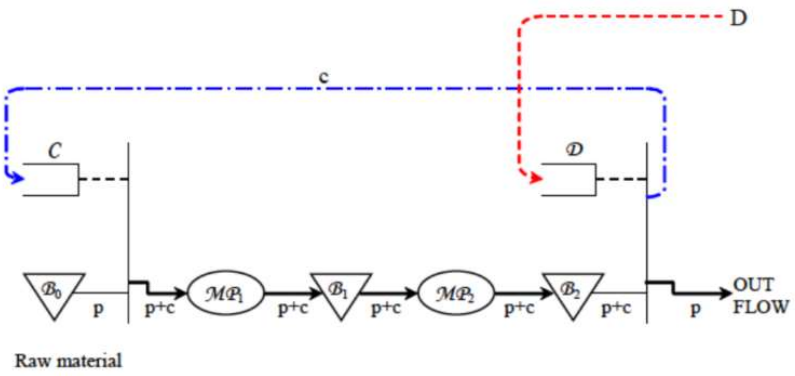

Figure 2.19 CONWIP with two stages [173]

2.8.5. Generalised Kanban Control Strategy

In the Generalised Kanban Control Strategy or GKCS, the demand is communicated to the final stage and each demand signal is assigned to an available Kanban. The demand information can be delayed due to the system of communication between the production stages. This system was initially proposed by [177] where the demand is controlled independently to the stages.

Figure 2.20 illustrates the GKCS mechanism applied to a two-stages of manufacturing as described in [173]. In this production system two Manufacturing Processes (MP) in series are denoted by MP, $i = \{1, \ldots, 2\}$, separated by Buffers (B) of infinite capacity denoted by B, $i = \{0, .., 2\}$. The current part processed is

represented by p. Kanbans are denoted by k, $i = \{1,..,2\}$ and controls each stage i individually. The available Kanbans (or maximum capacity) for i stages are determined by K, $i = \{1,..,2\}$ combined with the demand required for each stage represented by D and triggers all three production by D, $i = \{1,..,\mathrm{D}\}$. In addition, the amount of basestock level (or maximum capacity) in stage i is determined by S, $i = \{1,..,2\}$.

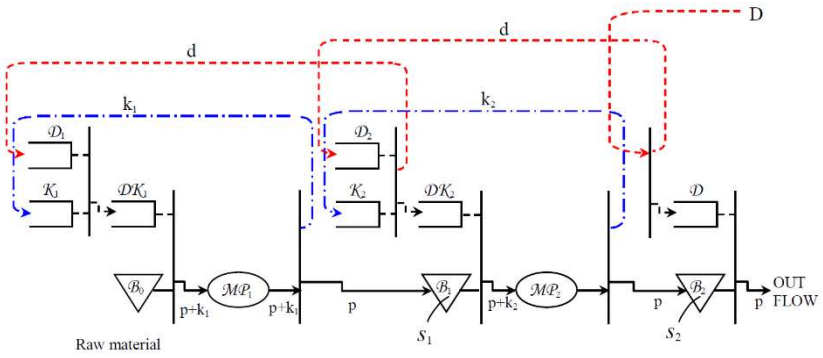

Figure 2.20 - GKCS with two stages [173]

2.8.6. Extended Kanban Control Strategy

In the Extended Kanban Control Strategy or EKCS, the demand event is transmitted instantly to all production stages. In this system [178] Basestock and KCS mechanisms were also merged. In the EKCS, each demand signal is assigned to an available Kanban and the production flow is authorised when the demand, the Kanban and the material are available.

Figure 2.21 depicts the EKCS mechanism for manufacturing two stages. In this production system two Manufacturing Processes (MP) in series are denoted by MP, $i = \{1, \dots,2\}$, separated by Buffers (B) of infinite capacity denoted by B, $i = \{0,..,2\}$. The current part processed is represented by p. Similarly to KCS described in section 4.8.1, k, represents the number of Kanbans in stage I $i = \{1,..,2\}$. The available Kanbans (or maximum capacity) for i stages are determined by K, $i = \{1,..,2\}$ while the amount of basestock level (or maximum capacity) in stage i is denoted by S, $i = \{1,..,2\}$.. The customer demand is represented by D and is communicated to all three production at stages by D, $i = \{1,..,D\}$.

The main difference between the EKCS and GKCS described previously in section 2.8.5 refers to the demand communication. EKCS communicates the demand required independently to all manufacturing stages while in GKCS the signal is assigned to an available Kanban. Therefore, the demand communication to each stage in GKCS can be delayed by lack of inventory and Kanban availability.

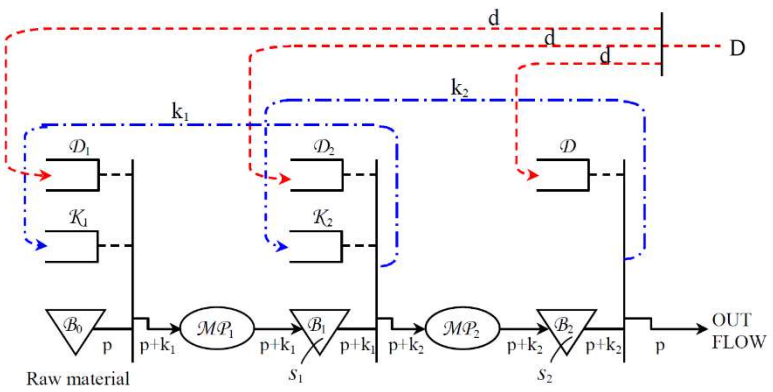

Figure 2.21 - EKCS with two stages [173]

2.8.7. CONWIP/KCS - HKCS

In a pure CONWIP mechanism, the system behaves as a pull system at the end of the line and a push system from the beginning, which can result in increased levels of WIP before the bottleneck. In a hybrid CONWIP and KCS policy or HKCS, WIP is globally and individually controlled at each stage as proposed by [179] and [180]. There is a limited number of Kanbans distributed to each production stage and an overall number of CONWIP as shown in Figure 2.22 as described in [173].

In this production system, two Manufacturing Processes (MP) in series are denoted by *MP*, $i = \{1, \dots, 2\}$, separated by Buffers (*B*) of infinite capacity denoted by *B*, $i = \{0, .., 2\}$. The current part processed is represented by *p*. The number of Kanbans is represented by k, $i = \{1, .., 2\}$ while c the conwip. CONWIP and Kanbans are used to control the maximum capacity within the system. The available Kanbans (or maximum capacity) for i stages are determined by *K,* $i = \{1, .., 2\}$ while CONWIP (C) denotes the maximum capacity by authorising the volumes of raw material to be authorised in the system. The customer demand which triggers the production is represented by *D* and triggers the production at the last stage according to the availability in the last inventory buffer.

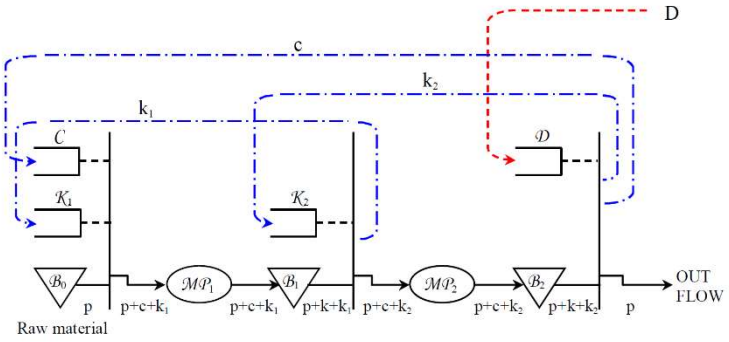

Figure 2.22 – HKCS – Hybrid Kanban-CONWIP [173]

A comparison of three policies KSC, CONWIP and CONWIP-KCS evaluating the results of inventory and backlog levels of each strategy is observed in [179]. The Advantages and disadvantages of each PCS is

summarised in Table 2.4. CONWIP/KCS has been proven by [179] and [180] to be an efficient mechanism since WIP is controlled globally by CONWIP and locally at individual stages by KCS in a discrete manufacturing environment. As observed, the decision for one particular pull-type depends on the industrial environment and complexity; therefore, a trade-off between complexity and precision is fundamental in defining which PCS is more appropriate for each manufacturing sector. Each PCS returns distinct results according to the industrial environment.

Table 2.4 - Production Control Strategies – Summary of Advantages and Disadvantages

PCS	Advantages	Limitations
KCS	Controlled by customer demand and controls WIP at all stages [167]	Delay on demand information at the first stage and may not respond quickly to changes in the demand [167]
BCS	The occurrence of the demand is transmitted to every single production stage [181]	There is a limited guarantee to restrict the number of parts in the system [181]
GKCS	Similar to Kanban, the movement of material is coordinated by Kanbans [177]	The arrival of demand information at a stage can cause delays [177]
EKCS	Demand is immediately disclosed to every stage in the system [178]	The demand information is not synchronized with production stages. It requires the amount of KCS to be at least as large as the basestock levels, limiting its configuration flexibility [178]
CONWIP	Simplified control based on the overall inventory level [76]	The inventory level is not controlled at each stage resulting in a large inventory in the entire system [76]
CONWIP/KCS	Increase the coordination between production stages by Kanbans [179] and demand [180]	An infinite number of Kanbans in all stages increases the system complexity [180]

2.8.8. Dynamic and Adaptive pull-type PCS

Autonomation is defined by LPS as a method of transferring human intelligence to a machine [67] in this context a production system could be automatically adjusted to external and internal conditions according to demand fluctuations, for example.

Dynamic pull-type PCS are examples of autonomous systems to optimise the traditional production control strategy. Adaptive pull-types are proposed to increase the flexibility in selecting the number of kanbans as observed in [165] and [182] for the discrete manufacturing environment. A method for selecting the appropriate pull-type PCS according to an evolutionary algorithm optimisation is proposed by [183]. Several variations of KCS such as combining BaseStock, Kanban and CONWIP BK-CONWIP as explored by [184] and compared to Hybrid CONWIP/KCS were also investigated.

Adaptive mechanisms explored by [185] for KCS where the system is dynamically adjusted according to the inventory and backorder levels and for CONWIP systems are examples of distinct approaches for separate pull-type PCSs as proposed by [186]. Recent research focused on dynamically controlling the system through an Adaptive Generic Kanban Control Strategy is proposed by [187] where the decision on authorising the

flow is based on the service level and [188] for closed-loop supply chains using evolutionary algorithm are examples of the number of heuristics control policies have been proposed in the literature for adjusting the flow of material within in a manufacturing environment. Those systems are applied to multi-stage discrete manufacturing environments and literature examining the benefits of applying such methods to the dairy bulk-powder commodity are waiting to be addressed.

2.8.9. Scheduling and Lean Approach

Scheduling problems have been widely studied in the literature and originally classified in a three-field notation α|β|γ by [189]. The first parameter α defines the Machine Environment, single or parallel processing are examples of Machine Environment parameters. The second parameter β refers to the Job Characteristics where pre-emption and precedence are defined. The last parameter γ defines the Optimality criteria, which usually involves minimising and maximising objectives.

A consistent production-scheduling plan is essential to efficiently transform raw materials into finished products meeting customer demand. In different manufacturing sectors, many studies regarding planning and scheduling problems were found in the literature applying Mixed-Integer Programming (MIP) algorithms. MIP models are used for single and multi-stage planning problems [190] and are widely applied to solve constraints and achieve an optimum criterion.

Scheduling problems are referred to as NP-Complete and are known as “hard” when the computational effort and complexity are unknown [191]. In optimisation problems, a quantitative objective criterion is defined, and the best solution is sought to satisfy all the problem constraints. Problems such as Job Shop and multiprocessor scheduling are classified as NP Scheduling, for example [192]. Several optimisation algorithms such as Simulated Annealing, Threshold Acceptance, Tabu Search and Branch-and-Bound are extensively applied to different NP scheduling problems [193].

According to [152] a detailed scheduling system design is a vital step in Lean implementation. Different processes require different approaches for scheduling solutions and the particularities found in dairy manufacturing must be considered. Examples of scheduling for the dairy sector, as demonstrated in **2.6.7 Simulation to Support Dairy Supply Chain Activities** are usually focused on fresh dairy products.

2.8.10. Summary and Positioning of this Research

In Dairy bulk-powder commodities, even though the demand is defined by contracts and the supply is determined according to the demand as mandatory for a pull-type PCS, internal inventory control is required. In addition, since the market controls dairy commodity prices, operation costs must stay at the minimum level to ensure profitable results for producers.

The previous sections, from 2.8.1 to 2.8.8, provide the fundamental understanding of the pull-type systems widely applied in several manufacturing environments. According to the literature, namely by [179] and [180], hybrid Kanban models provide superior performance in minimising the overall average WIP when compared to single controls. Kanbans have evolved into a new generation with advanced features in controlling inventory as observed in the adaptive and dynamic pull-type PCS. Such flexibility increases the level of control and agility to perceive undesirable changes in the system.

These types of pull systems are essential for manufacturing environments where the variety and complexity of finished products require sophisticated systems. As explored, the dairy bulk-powder manufacturing requires pull-type PCS able to simultaneously cope with seasonal volumes of raw material, stochastic supply deliveries, constant interruptions due to the CIP cycle times, and variability of downstream processes, increasing or reducing the flow according to these criteria.

2.9. Conclusion and Contribution to this Research

This chapter explored the literature focused on the dairy sector, simulation modelling and lean pull-type PCS in order to evaluate what has been conducted regarding innovative solutions to deal with the main challenges of this sector.

The internal stages in the manufacturing and external outbound activities that impact the dairy bulk powder commodity were studied. In addition, common activities in the dairy sector were compared to two production environments with similar processes and also compared to the mass production where mature production control techniques have already been validated. The state-of-the-art in M&S emphasises the significant gap of simulation models towards the particularities of the dairy sector specially to manage production processes.

There is still a deficiency in research approaching seasonality and sources of variability in the dairy environment. The impact of external factors in the manufacturing process is also worsened by internal interruptions caused by CIP cycle times and requires a deep investigation. In addition, the overall average WIP reduction is sought as one of the metrics among all the studies explored in this section. However, in dairy manufacturing, WIP levels must be independently measured for each stage conversely to the overall average WIP reduction conventionally sought. This control is required to avoid the risk of perishability caused when whole milk is processed.

Regarding adopting lean principles, mature principles of LPS pull-type PCS could reduce the impact of such stochastic events since it was proven to benefit several other sectors by previous research presented in the literature such as mass production . However, this shift from a push system to a pull-type PCS requires time, investment and a high level of engagement from key sectors of the company to implement and achieve promised results. Although the methodology is conducted by the subject-matter expert (SME) team, the

support of technologies based on a simulation model would increase the response in comparing a current state process to a proposed lean methodology.

A potential concern in implementing lean principles according to [152] is the alignment of the three following dimensions: (i) waste, (ii) value and (iii) people. Activities to define the current state based on the current process, evaluating the impacts and elaborating a future state map incorporating all the improvements suggested require the total engagement of people. Therefore, a robust decision support framework to evaluate the current state and future state is the first step in incorporating lean thinking and a potential pull-type system in the dairy sector. A framework based on simulations where users could access the interface through a multi-platform such as web-browser or mobiles would reduce the time for testing future states and consequently for evaluating the impact of such changes on their current process.

In addition, little research to date has examined the benefits of lean principles and pull-type PCS based on simulation for continuous process improvement for the dairy environment. According to [76], pull systems reach the same throughput as push systems; however, with less average resources since the material is authorised according to the customer demand. By reducing extra production and overall waste, pull systems have proven the superiority over push systems. This optimisation process is achieved by an appropriate WIP level balancing the flow throughout the production line. In the dairy sector, the raw material supply must be authorised to avoid excess WIP or even exceed the capacity storage since not only is the system restricted by its capacity but also by the processing time.

Supply Chain activities in sectors such as pharmaceutical, as presented in section **2.5 - Comparing Dairy Supply Activities Across Similar Sectors,** were compared to dairy and also have applied M&S for specific processes such as blenders or mixers and mills, chemical reactions and fiction between particles, for example as described in this review for simulation of pharmaceutical processes [194]. A commonly used mechanistic modelling approach for powder is the discrete element method (DEM) which is a method for addressing engineering problems in granular and discontinuous materials, especially in granular flows, powder mechanics [195]. Considering the similarities of the dairy process such as production schedule, specific research is also available as observed in [196]. However, these sector is also dependent on enabling information technologies, such as supply chain tools, manufacturing execution systems (MES). It is also observed that a similar approach observed in dairy such as optimisation of manufacturing processes through simulation assists engineers in dealing with production scheduling and planning [197]. The awareness of the importance of simulation for the pharmaceutical industry is observed in[198], where the application of M&S for decision-making is suggested to improve the communication between stakeholders.

However, the strategies for production control for F&B and pharmaceutical regarding demand and market price are distinct due to the final product manufactured. As previously referred in section **2.5 - Comparing Dairy Supply Activities Across Similar Sectors,** some pharmaceutical manufacturers operate in a batch process, pharmaceutical plants process low production volumes in shared multipurpose pieces of equipment whereas in a continuous environment, similar challenges found in the dairy process are observed due to the

limited storage capacity. However, as described in section **2.5.1 - Supply Chain Activities - Summary and Positioning of this Research** the bulk powder manufacturing environment faces several challenges not observed in other sectors explored despite their similarities in the equipment utilisation. As observed the pharmaceutical sector is applying M&S through a similar approach, or sequence of steps, observed in dairy manufacturing for specific areas. Seasonality and variability of raw material supplied are also external factors particularly identified for dairy manufacturing. Internal factors such as short life span in processing WIP and risk of perishability due to the chemical transformation and high temperature for example are more sensitive when combined to the referred external factors exclusively identified in the dairy bulk environment. Therefore, this research postulates and implements a novel approach to support decision-making processes in the dairy sector as described in Chapters 3 and 4.

CHAPTER 3
RESEARCH METHODOLOGY I – EPMPS - EPILOT MANUFACTURING PLANT SIMULATION FRAMEWORK DEVELOPMENT

3.1. Introduction

The previous chapter highlighted that there is a demonstrable gap in the development and application of simulation-based decision support and optimisation tools, especially regarding dairy bulk powder manufacturing processes.

The previous chapter also established the current state-of-the-art in modelling and simulation for discrete manufacturing environment, application of simulation to the dairy sector and pull-type PCS for controlling the production flow. Key findings indicate that there is a gap between previous research and the real challenges faced by dairy manufacturing with respect to the application of pull-type PCS and continuous process improvement approaches.

Chapter 4 will present and discuss the development of the proposed pull-type PCS for bulk powder manufacturers in the dairy sector whereas the aim of this chapter is then to present the methodology adopted in developing a framework for decision-making processes through a cloud-based simulation architecture. This chapter also elucidates how to adopt the proposed framework as a strategy for implementing continuous process improvement considering the particularities of bulk powder dairy manufacturing.

The main contributions of this chapter; therefore, are derived from: (i) exploring the current processes in three dairy case studies and generalising the dairy manufacturing stages for one specific product. (ii) understanding the potential stochastic events at individual production stages and their potential impacts on the system. (ii) providing a generalised framework for the bulk powder dairy sector with analogous manufacturing stages (iii) designing a robust simulation-based decision support framework compatible with real processes and real challenges faced by dairy manufacturing (iv) visualising current and future state scenarios for continuous process improvement activities.

The study of seasonality and its impact on dairy manufacturing are widely explored throughout this research. With respect to the analysis conducted within dairy manufacturers, seasonality is split between Peak and off-season, which refers to the annual production cycle. However, it was required to redefine seasonality into three periods: (High, Medium, and off-season), in order to investigate the impact of an intermediate volume of raw material between Peak and off-season in the manufacturing environment. Therefore, with respect to seasonality, the term Peak and High season are used interchangeably within this document to refer to the same period in the annual production cycle of the Irish Dairy sector.

3.2. DPTC Dairy Industrial Partners – Case Studies

As stated by Bicheno and Holweg [152], in Lean transformation projects the term *go to the 'gemba'* or workplace is the first step in understanding the current process in order to design the future state or "should be" process. Following this approach, therefore, process mapping was the initial activity performed to elucidate the ongoing process in each case study.

Further insights on the problems with the process flow from a macro perspective were illuminated through the application of complimentary activities such as Measure and Analyse observed in Six Sigma Define-Measure-Analyze-Improve-Control (DMAIC) process. The activities were concentrated on collecting and evaluating the data provided by the industrial partners. A detailed process flow was also required to design a simulation model capable of overcoming the absence of historical information from specific processes and standardising the initial manufacturing processes.

The simulation model was the bridge between the current state and the future state, providing improved results according to the continuous improvement implementation phase. The constraints and the rules which regulate the production flow are also considered as an integral part of the model since the objective is to accurately represent the reality of this environment.

The results simulated were validated with the available operational records. The processes and products demonstrated in all case studies are standardised to guarantee data confidentiality for the Industrial Partners. In addition, the development of a simulation model for specific processes in three Irish Dairy Industrial Partners was identified as a methodology for an in-depth investigation of real challenges faced by this sector.

The dairy activities for each case study were modelled and validated by means of:

i. Interviewing the operators and supervisors to understand the overall production processes for different products and distinct perspectives within the Industrial Partners.
ii. Going to the "*gemba*" and observing the production lines
iii. Collecting and evaluating data for future data analysis
iv. Mapping the current processes using a similar approach applied in the Six Sigma SIPOC diagram
v. Exploring company documents and technical reports available from dairy manufacturers
vi. Evaluating relevant material focused on dairy bulk powder commodities available on the internet
vii. Identifying the Value and Value Stream for each case study
viii. Designing the process model for further simulation
ix. Considering ethical approach in data collection and publications activities keeping the confidentiality of data presented in this research

Ultimately, improvements in their manufacturing processes were suggested and implemented by the industrial partners during this research project as described as follows. The evaluated processes and the

identity of the companies involved in this research project will be generalised in order to keep the confidentiality of the data provided.

3.2.1. Industrial Partner Case Study 1 – Exploring M&S for bottleneck evaluation

The industrial partner is an intermediate milk processor within the Dairy Supply Chain. The company exports to over 30 countries and final products are distributed across 150 countries. The company supplies sectors such as the infant, sports and clinical nutrition product sectors, producing a wide array of commodity products negotiated by contracts previously established as described in section 2.3.2 – Dairy Market Prices.

3.2.1.1. Process Mapping and Data Collection

The initial step consists of defining the value stream for the finished product. Thus, the production flow presented in Figure 3.1 was designed to highlight the main product. The yellow flow represents the value stream for this specific product.

The raw material is received and separated into three other branches (Processes 1, 2 and 3), which are not covered in this specific case study. Process 4.1 produces *Product 4* and also supplies Process 5.1. Product 5 is a by-product originated from Process 4.1 and is represented as a secondary flow. However, despite lower added-value in this process, inefficiencies observed in Process 5.x heavily impact the performance of Product 4.

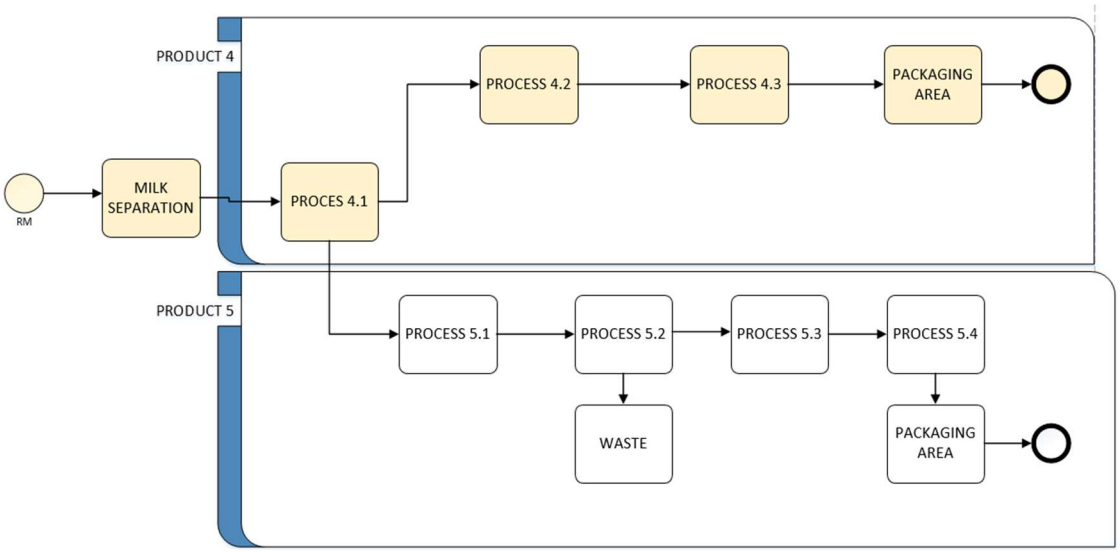

Figure 3.1 – Case Study 1 – Process Map

3.2.1.2. The Problem – Current State

The initial objective consisted of optimising the throughput of *Product 4,* one type of casein, which refers to the most added value end product for this company. The current production flow and schedule were

explored and throughout the *Process 4* validation phase, it was identified that *Product 5,* which refers to the initial phase of the whey transformation, had the potential to cause undesirable upstream bottlenecks in the entire the production flow. The final processed whey and its respective potential branches are by-products of *casein* originated from the ultra-filtration process. Thus, the volume in liquid form to be manufactured by Process 5 is higher when compared to the concentrated form resulting in Process 4.

This high volume of WIP is heavily impacted by unscheduled downtime variability and mis-matched production flow rates. Therefore, to meet the initial objective, the simulation model considered the by-product production flow and its particularities for both products and interactions between the production plants, in this case study represented by Processes 4 and 5.

In addition, Process 5.2 generates large volumes of wastewater to be further treated by the effluent treatment plant, which can also restrict the current capacity of Process 5 and potentially disrupt Process 4 flow. The packaging area is the final manufacturing stage and since the silos have restricted capacity to store the yield, restrictions observed in this process can also increase the level of WIP within the system. Therefore, the main reason for downstream interruption observed in Process 4 is the high level of WIP at Process 5 originated by special and common causes.

Therefore, a simulation model was created for the same operation in IP1, which means that the milk is supplied hourly during the peak season. After processing, part of the yield is packaged, stored and further delivered. The model is focused on reproducing *Process* 4 behaviour, in order to evaluate possible improvements in this production plant. A Discrete Rate simulation model was developed according to the following assumptions and limitations to identify whether the variability in Process 5 is random or due to an assignable cause.

3.2.1.3. Model Assumptions and Limitations

i. The completed model is presented in **Appendix C.1 - Model developed through ExtendSim – Case Study 1**.
ii. The initial stage of the processing flow is continuous and further converted into discrete units - tonnes.
iii. The simulation model was designed to be run by different users such as operators and managers, for example.
iv. The values are informed according to the process flow for each piece of equipment. The integration between spreadsheets as the input to supply external data was also defined. See **Appendix C.2 - ExtendSim and Excel Interface for input process flow information.**
v. The output results were presented through internal graphs available in the ExtendSim package and also by spreadsheet template files.
vi. An internal database was designed to store the quantities provided hourly by each piece of equipment and the production flow.

vii. The historical data was analysed using the StatFit tool to identify which distribution would best represent these stops. Weibull and Exponential distributions were applied to deal with unplanned shutdown disruptions. See **Appendix C.3 - ExtendSim Input CIP**

viii. The stochastic events, namely caused by CIP interruptions, were defined according to a triangular distribution for planned CIP cycle times**.** Due to the fact that CIP time ranges are known, a triangular distribution is more appropriate to simulate the CIP hours with limited ranges based on real processes.

ix. To deal with this range of possibilities, the planned CIP and unplanned downtimes were placed in the three main areas represented by processes 4.1, 4.2 and 5.1 in Figure 3.1.

x. To identify the stops caused by excess of WIP, the silo levels were modelled with indicators to be interrupted due to an excess of the product. The interruptions are measured by hours.

xi. The production is measured in tonnes and it is used to validate and compare further improvements.

3.2.1.4. Validation

A normality and statistical t-test were performed to validate the model against the real process output (see **Appendix C.4 - Checking the normality of Product 4 – Real - Case Study 1** and **Appendix C.5 - Independent t-Test for Product 4 - Case Study 1).** Even though a higher variability presented in the real process is identified, the data provided by the simulated model suggests the difference between means is not statistically significant. However, the high level of variability identified during the validation phase provided meaningful insights regarding the impact of Process 5 on Process 4.

A regression assessment was also conducted comparing the volumes produced by week for 1-Real Production and 2 – Simulated as presented in Appendices **C.6 - Regression Assessment for Real Production and Simulated** and **C.7 - Regression Assessment Real Production Vs. Simulated – Scatterplot.** Through the graph presented in **Appendix 0 -**

Real Production Vs. Simulated for 30 weeks**,** it is possible to observe that the Simulated volumes are concentrated whereas the real production demonstrates volumes below 125 tons for weeks 1,2,3,5,21 and 30. These main of variability identified is caused by the excess of WIP at Process 5; therefore, the entire production flow must be reduced in order to manage the limited storage capacity.

3.2.1.5. Improvements – Future State

The flow of Product 4 was restricted by production flow at Process 5. Thus, in order to provide possible alternatives for reducing the effect of such disruptions, several scenarios were created simulating possible alternatives for future capital investment. The scenarios considered storing the concentration produced by Process 5 for further distribution to an external manufacturer. Therefore, since the capacity of *Product* 5 is restrictive, the disruption caused by this plant on Process 4 would be eliminated. The volumes of the concentrated product provided by this scenario were also simulated. Additional investigation regarding transportation costs and value of concentrated form in the market price would be performed by the manufacturer.

3.2.1.6. Contribution of IP1 to this Research

Due to the restrictions identified in process 4 caused by disruptions and excess of WIP at process 5, it was possible to identify that the dairy bulk powder manufacturing environment is very sensitive to limited storage capacity. Therefore, one of the contributions of this case study to this research was understanding the effect of downstream in creating unpredicted disruptions compromising the entire process. The entire process is compromised since there is no storage buffer available to handle extra production and therefore, also the milk reception is compromised. In addition, insufficient methods and tools for visualising the entire process are observed to support decision-makers in identifying future solutions and the impacts on the current process.

Prior to this investigation, the company had invested in capital equipment to increase Process 4 capacity. By increasing the decanter processing capacity, extra WIP volume was sent to the entire Process 5, amplifying the impact of the current constrained flow since this process was limited in production and storage capacity.

The simulation model provided significant insights regarding which operational problems required more attention and which should be avoided. In addition, where the capital investment would provide improved results. By reducing the restriction in Process 5 investing in drying improvement such as increasing the cyclone drying system capacity, the entire system was enhanced. As explored in section **2.4.5 Drying,** the cyclones are mainly applied for separating product fines from the air leaving spray dryers and fluidized bed dryers in order to increase the yield.

For this company, the model enhanced decisions regarding bottlenecks created by a by-product production originated from *Process 5*, which severely impacted the most added-value product - Product 4. The results by distributing the liquid form to other dairy manufacturers were also explored, as previously mentioned.

As observed, the properties of the raw material influence the number of products in the first production flow and the remains are separated according to a determined criterion by each dairy processor such as:

i. Contracts: A minimum quantity must be achieved according to previously anticipated contracts,
ii. Market price: Products have a high fluctuation in the market price which contribute to improved financial results at specific periods throughout the year,
iii. Internal capacity: Bottlenecks are responsible for limiting process production quantities.

In the IP1 all these criteria impact the production flow and the combination of all these elements will be explored in a multi-objective model in order to evaluate the effectiveness of the current separation process at the operational level. The optimum scenarios are shown in Table 3.1. Results for Product 4 (P4) and Product 5 (P5) production associated with a possible increase in Milk Rate, followed by an increase in the intermediate Silo and Actual Bottleneck capacity, the use a Concentrated Silo and the level of the concentration and total of Disruptions caused in the DSC flow. The results are standardised in order to keep the data confidentiality.

Table 3.1 –Scenarios and main factors for optimising manufacturing process at IP1

Scenario	Product 4 Volume	Product 5 Volume	Milk Flow Increase	Silo Capacity	Actual Bottleneck	Concent. Silo	Level ProdC Litres	Disrup
Scenario 040	2.032	1.807	0.586	1.789	1.225	1	20,493	0
Scenario 101	*1.954*	*1.944*	*2.342*	*–*	*2.449*	*0*	*–*	*4*
Scenario 140	1.954	0.432	2.928	2.683	–	1	200,451	0
Scenario 084	1.722	0.790	1.757	0.894	2.449	1	31,798	0
Scenario 086	1.567	- 0.104	1.757	1.789	–	1	421,313	0
Scenario 057	*1.386*	*1.188*	*1.171*	*0.894*	*1.225*	*0*	*–*	*11*
Scenario 005	*1.283*	*1.504*	*–*	*–*	*2.449*	*0*	*–*	*0*
Scenario 114	1.283	1.078	2.342	1.789	2.449	1	51,232	0
Scenario 042	1.257	1.312	0.586	1.789	2.449	1	27,165	0

All 36 simulation results are shown in Figure 3.2 where the improved conditions are illustrated. The improvements in bottlenecks would increase products Products4 and Product5 in 2 standard deviations. The first factors (1 to 5) demonstrate the region of optimal condition.

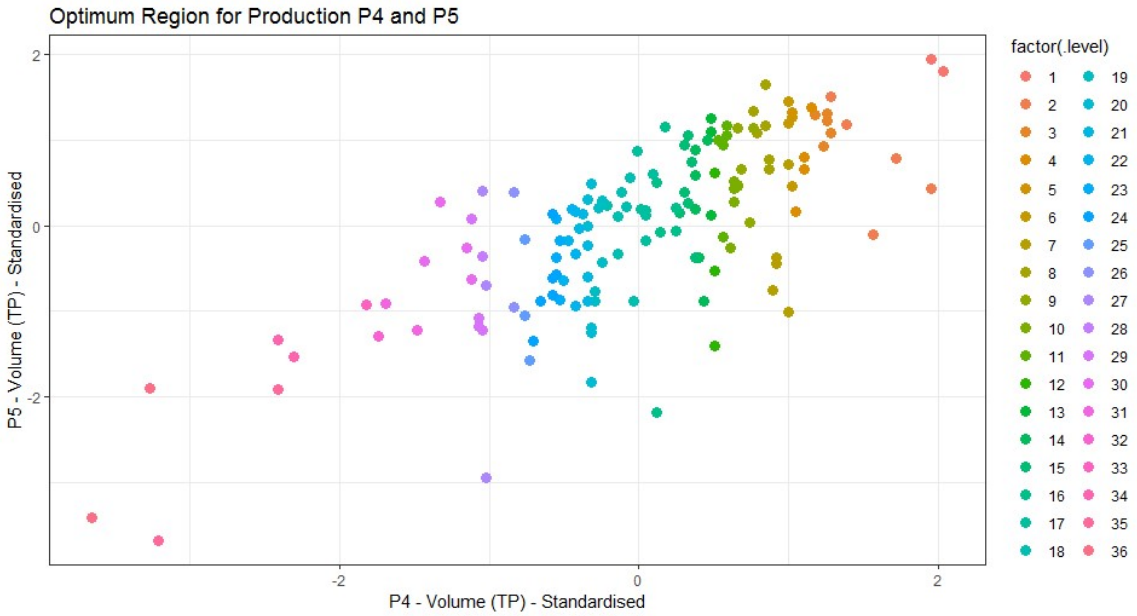

Figure 3.2 – Best scenarios by improving bottlenecks around products P4 and P5 – 36 scenarios

The results produced by this case study were validated by the DPTC team, including the Industrial Partner and published in the **International Conference of Decision Making in Manufacturing and Service (DMMS-2017)** entitled "**MODELLING & SIMULATION AS A STRATEGIC TOOL FOR DECISION-MAKING PROCESS IN THE DAIRY INDUSTRY**" [199] **(see Appendix L.2)** . In addition, the results obtained by expanded research were published in the **International Journal of Decision Making in Manufacturing and Services,** entitled "**MODELLING & SIMULATION AS A STRATEGIC TOOL FOR DECISION-MAKING PROCESS IN THE DAIRY INDUSTRY**" [200] **(see Appendix L.5)**.

The aim of the expanded research consisted of considering the raw material supply within the model in order to evaluate the impact of the initial stages on IP1 processes, contributing to the objectives of this research.

3.2.2. Industrial Partner Case Study 2 – By-Product Processing Analysis

This Industrial Partner is a key connection between other Irish dairy manufacturers. The company processes approximately 200 million litres of intake milk annually. The milk is processed into several dairy bulk powders for export and home markets. Approximately 35,000 tonnes of products are annually manufactured.

3.2.2.1. Process Mapping and Data Collection

The company provides a valuable service in the interconnectedness of the Irish Dairy sector by procuring a by-product from other dairy manufacturers owing to their extra internal capacity to process one specific powder ingredient. Thus, alleviating them of the requirement to invest in capital equipment or in treating the by-product in their effluent-treatment plants.

Investigating the internal manufacturing process, a valuable by-product externally received from other dairies and processed by this company. The production flow in Case Study 2 is illustrated in Figure 3.3. Raw materials RM1, RM2 and RM3 are illustrated as inputs in the figure. The raw material RM1 refers to milk in liquid form and after receipt is separated into several branches of processing, which are aggregated in order to simplify the current production structure. RM2 is exactly the same product resulted from *Process 5.1* but received for other dairies as demonstrated in the diagram. RM3 refers to several packages used for and the finished goods are produced and packaged at the final stages of *Processes* 7.1 and 7.2.

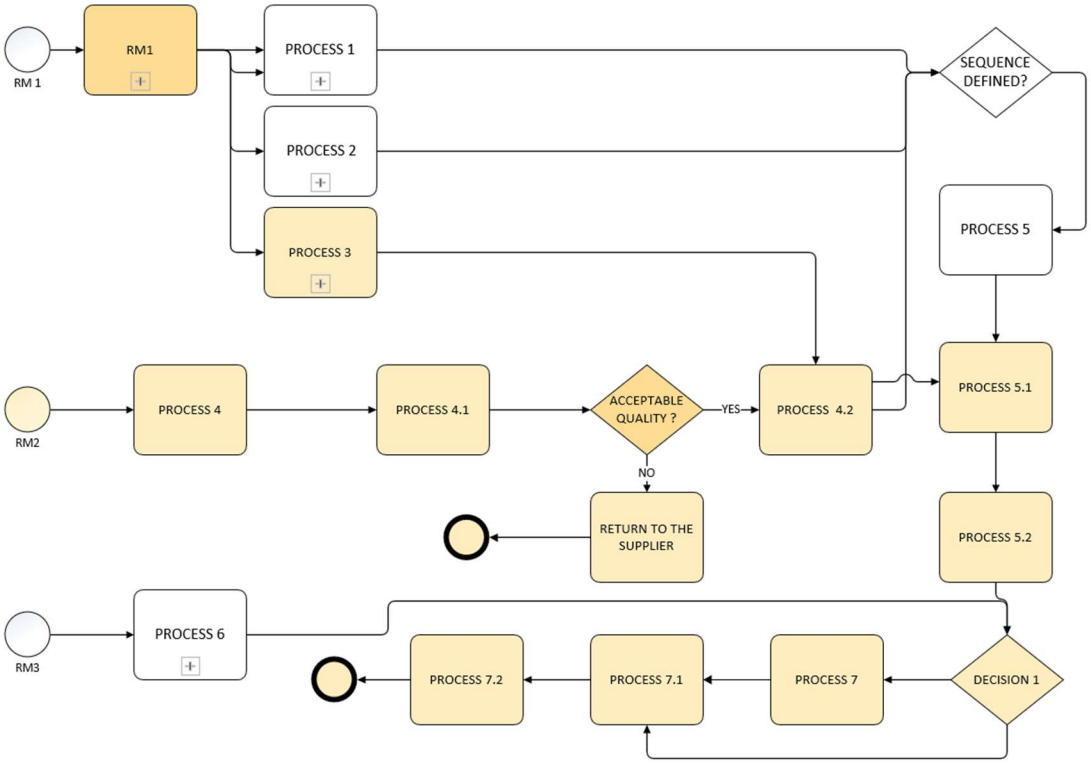

Figure 3.3 – Case Study 2 – Process Flow

3.2.2.2. The Problem – Current State

During the data collection and analysis phase, the following main areas were identified as compromising the current process:

i. The demand contracts are not entirely linked to the raw material supply.
ii. The main bottleneck is the most expensive process and should be optimised since its capacity is shared among other processes.
iii. The planning process ignores the supply variability presented throughout the day.
iv. Essential information is recorded manually in a paper-based system.
v. The decision-making process is compromised by a significant deficiency in data visualisation.

Owing to the fact that this specific dairy manufacturer receives products from other companies, RM2 is a raw material and also a by-product produced by *Process 3* as highlighted in Figure 3.3. Therefore, *Process 4* receives internal by-product volumes from *Process 3* and also external volumes from other manufacturers. The frequency of distribution from suppliers is demonstrated in **Appendix C.9 - Supply Source - Case Study 2** and **Appendix C.10- Frequency of deliveries – Case Study 2.**

By analysing the volume produced at Process 5.2, a high level of instability is presented in Figure 3.4. The mean is concentrated on 83 bags per hour; despite the aim of this company to produce 140 bags per hour, this volume refers to the maximum capacity of such a piece of equipment. The deviation from minimum to maximum volumes demonstrates the presence of the variability in this or in previous processes and requires further investigation.

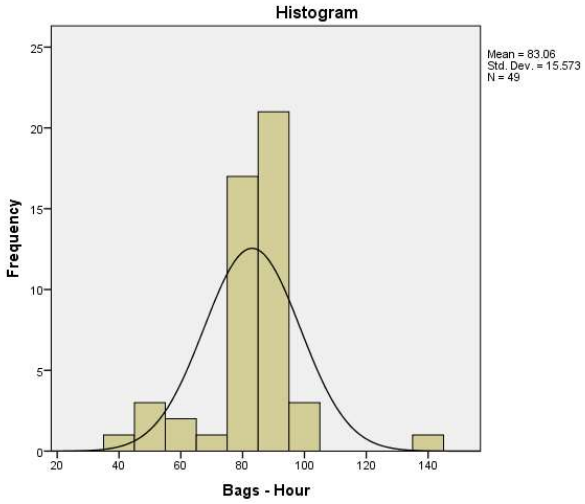

Figure 3.4 – Case Study 2 – RM3 Production Variability

3.2.2.3. Contribution to of IP2 to this Research

A prototype was modelled considering the flow and overall information for the by-product explored. However, the validation of the model developed was not conclusive due to insufficient data provided by the Industrial Partner. Therefore, the investigation for potential improvement was not conducted. However, this case studied provided important insights for the understanding of particular challenges in the dairy sector.

As described this company processes material from other dairies due to the excess of capacity in their facilities. This specific role contributes to a more collaborative approach among the Irish dairy supply chain since it receives pre-processed material and a high level of variability was observed as shown in **Appendix C.9 - Supply Source - Case Study 2** and **Appendix C.10- Frequency of deliveries – Case Study 2.**

As observed the demand contracts are not entirely connected to the raw material supply. Similar phenomenon is observed in the other two case studies and described as a push system as explored in section **2.8.1 - Push and Pull Systems.** In addition, there is a gap in process mapping, data visualisation and

digitalisation. Therefore, the activities developed for this specific case study have contributed to this research in the following understandings:

i. The importance of a collaborative environment among Dairy Manufacturers.
ii. The impact of receiving external intermediate products on internal production processes.
iii. The frequency of supply deliveries might cause internal instability on WIP inventory.

3.2.3. Industrial Partner Case Study 3 – CIP Schedule and Milk Separation

This company processes approximately 1.8 billion litres of milk annually into a range of value-added dairy products and functional dairy food ingredients. The company exports large volumes of bulk powder commodities and dairy products to Europe and several international markets worldwide.

3.2.3.1. Process Mapping and Data Collection

For this specific case study, the initial steps of milk intake and the potential disruption through the system were explored. This company has sufficient capacity to process large volumes of bulk powder and it usually receives milk intake from other dairies. Therefore, the initial step was concentrated on defining the production process flow from supply to the end-customer activities, considering the volume of raw material received hourly.

Process 2, which is the separation process, was investigated for this specific product. In addition, the effect on the intermediate WIP levels in the system and potential bottlenecks caused by extra WIP was also investigated. The raw material is received and separated into several sub-branches under Process 3. However, in order to focus on the value stream product, this process was aggregated to simplify the current production structure.

The most value-added product or the value stream is highlighted in the process flow as illustrated in Figure 3.5. Process 2 also generates a second branch which is out of the scope of this study.

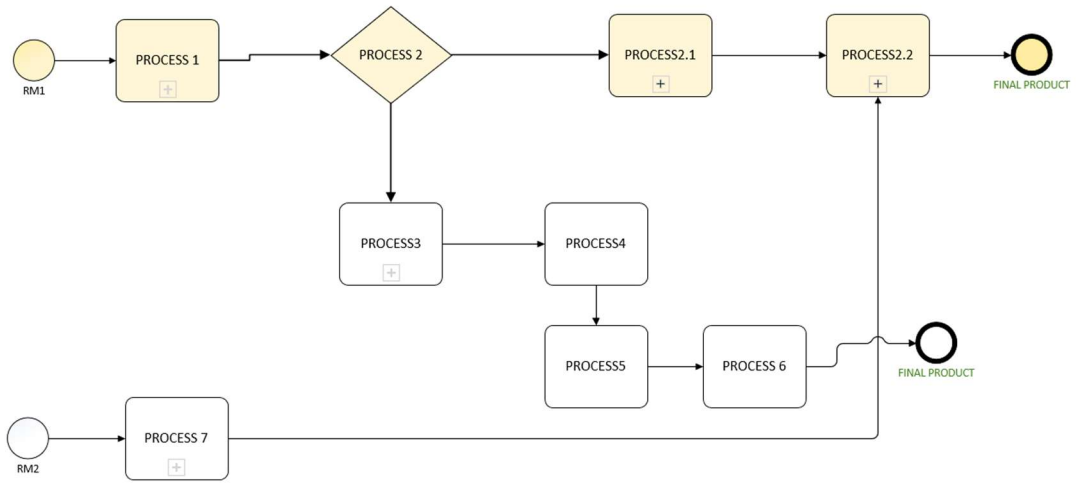

Figure 3.5 – Case Study 3 – Value Stream

3.2.3.2. The Problem – Current State

During long holidays such as Christmas, the shift must be reduced and the impact of the CIP schedules on the equipment utilisation, service and inventory levels must be considered. The industrial partner performs the CIP scheduling process through a complex spreadsheet which is changed constantly. In addition, despite the complexity in formulas and cross-references observed, this manual procedure restricts the equipment to the same schedule reducing the flexibility in increasing or decreasing the capacity hourly.

The main objective of this simulation model is to investigate the potential impact of CIP schedule on the separation process and on the downstream production flow. Conversely to Case Study 1, in Case Study 3, the secondary product has a reduced volume with few restrictions on the main flow. Thus, a simulation model was created to reproduce this behaviour in order to support the decision regarding selecting an appropriate schedule for the current flow.

3.2.3.3. Model Assumptions and Limitations

A tool to support the planning process will reproduce the same behaviour as the current spreadsheets used by the Industrial Partner in this case study. The simulation model interface was designed to support operational and tactical decisions regarding WIP levels at different stages in the production process according to the scheduled plan defined by each piece of equipment.

i. The completed model interface is presented **in Appendix C.11 - Model 2 developed in ExtendSim – Case Study 3** and each process is indicated as illustrated in Figure 3.5.
ii. The model is designed to simulate up to 10 days or 240 hours.
iii. For this case model, only deterministic values are considered, and no stochastic events were incorporated into the model.
iv. The volume supplied hourly is imported from a structured spreadsheet file.

v. General parameters such as: efficiency coefficient for adjustment and proportions required for the separation process are also defined.

vi. Silo capacities for whole milk, skimmed milk, separators, and dryers are easily updated by the user through specific buttons.

vii. The same structure is used for the schedules in distinct spreadsheets indicating which hour each equipment should be ON/OFF.

viii. An internal database was designed to store spreadsheets and the CIP schedule for each piece of equipment.

ix. The internal structure and components are illustrated from **Appendices C.12** to **C.16.**

x. Results calculated by the simulation are also recorded in an internal database and exported to an excel template file called "Results.xlsx" to support decision-makers.

xi. A dashboard in Microsoft PowerBI was built connecting the "Results.xlsx" file see **Appendix C.17 - Power BI – Dashboard for Results Visualisation** in order to provide a visual impact for each process.

xii. The production is measured in litres. The supplied raw milk and the separated total volume were compared between simulated and real production numbers.

3.2.3.4. Validation

A statistical t-test was performed to validate the model against the real process output for Supply Volumes and Process 2 **Appendices C.18 Independent t-Test for Supply Volumes Comparison - Case Study 3** and **C.19 Independent t-Test for Process 2 – Separation Volumes Comparison - Case Study 3,** respectively.

A regression assessment was also conducted comparing the volumes produced by hour for 1-Real Production and 2 – Simulated as presented in Appendices **C.20 - Regression Assessment for Real Production Vs. Simulated** and **C.21 - Regression Assessment for Real Production Vs. Simulated - Scatterplot.** The data is deterministic, and no stochastic distribution was incorporated into the model. Thus the real process data extracted from the industrial partner fits a straight line when compared to the simulation results. In addition, no normality test is required since both datasets (simulated and real) are identical, as shown in Figure 3.6. The results were also validated by the industrial partner.

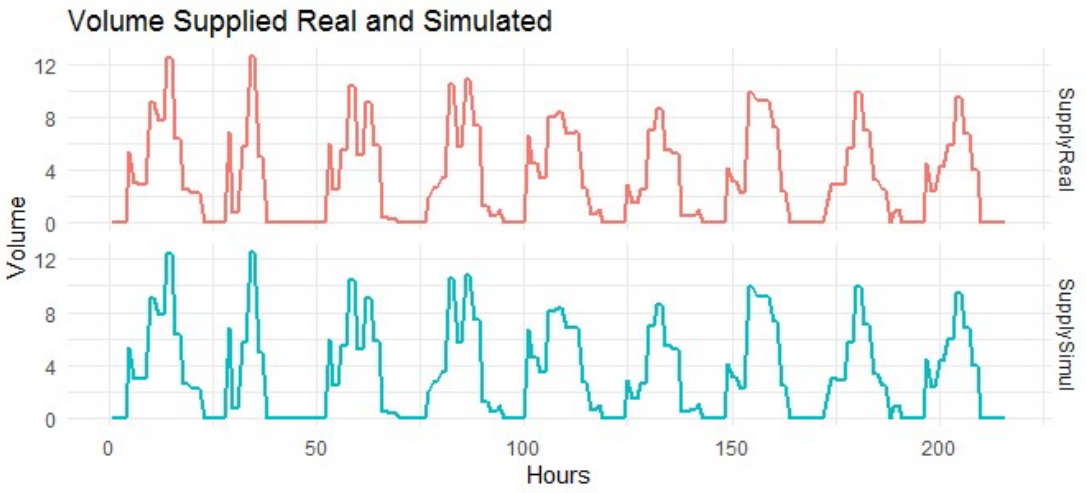

Figure 3.6 –Supply Volumes Real and Simulated – Volumes by Hour

3.2.3.5. Improvements – Future State

The improvements observed in this case study are concentrated on short-term and medium-term decisions, such as rescheduling equipment or accepting more raw material into the system. Tactical decisions are also supported by this study since a potential increase in the volume supplied could be previously evaluated.

Several limitations were identified in the current spreadsheet used by the industrial partner. An example of a schedule for the separation process is presented in **Appendix C.22 Example of scheduling plan for 9 days.** In this example, no flexibility for defining distinct schedules for each piece of equipment is allowed. Thus, extra running hours defined in the spreadsheet do not reflect the real situation in the manufacturing plant. Decisions regarding increasing or decreasing raw material in the system are evidently compromised.

The improvements recommended for this case study considered such a level of flexibility required in this system. The experiment compares the current scenario where all the equipment follows the schedule defined in **Appendix C.22 Example of scheduling plan for 9 days.** A second scenario where one piece of equipment was removed. Ultimately, a third scenario where the running hours were reduced and the second piece of equipment was removed. All experiments were simulated for the same period (216 hours) and the results are presented in Figure 3.7.

The same volume was processed by all three scenarios as presented in each schedule which is represented by the number of lots or end products produced. The utilisation was consequently improved since the running hours were reduced. More importantly, potential reduction of waste such as energy, extra running hours could be managed and ultimately, schedules for reactive maintenance could be simulated during this period.

The model was adopted by the industrial partner during 2018 and 2019 for Christmas shut-down planning purposes.

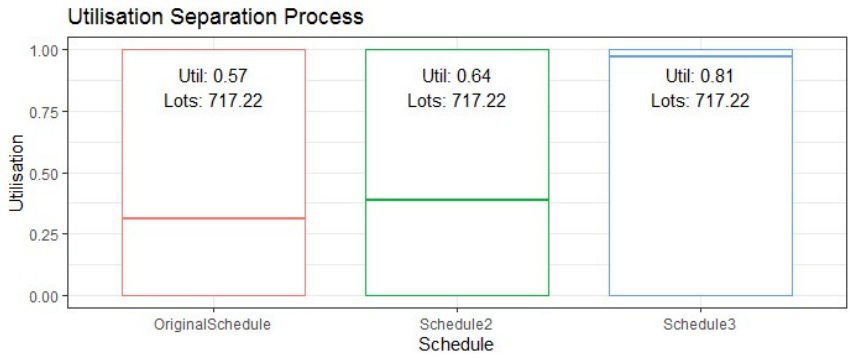

Figure 3.7 –Supply Volumes Real and Simulated – Total Utilisation

3.2.3.6. Contributions of IP3 to this research

The case studies provided an extensive comprehension of the real challenges faced in the dairy environment. From the supply perspective to the finished product produced. In addition, some specific alternatives to avoid radical changes in the production line such as : (i) Varying the number of shifts, (ii) Varying the number of days per week, (iii) Varying the number of hours per day, (iv) Varying staffing levels, (v) Using outside vendors. These strategies are applied to increase the capacity smoothing the WIP and production flow. However, the majority of these strategies are already being applied. The plant operates 24 hours per day seven days per week. Cleaning-in-place (CIP) time processes are carefully planned and predicted and maintenance stops are performed every year due to the lack of appropriate raw material for production.

The impact of CIP cycles and supply variability on the processing capacity as explored in case study 3. The level of WIP at specific stages causes severe disruptions to the upstream production lines, as observed in case study 1 and the shared resources potentially compromise the flow as understood in case study 2. The model developed and a prototype of a dynamic authorisation supply were published in the **International Journal of Mechanics and Production Engineering** entitled **"INDUSTRY 4 . 0 AND THE FUTURE FOR DAIRY SUPPLY CHAINS"** [201] **(see Appendix L.3) .**

In addition, for this case study the integration between data provided by sensors in each piece of equipment was explored since it would provide the required information in a Manufacturing Execution System (MES) and be further processed by algorithms in order to turn raw data into valuable strategic information. The advantage of connecting the production systems is the real time access to avoid any disruption to the production flow, supporting operational decisions in a self-optimisation production line as explored in this research. The structure of the control system of a dairy process line would follow the structure presented in Figure 3.8, incorporating the three decision levels: 1 business planning, 2 management control and 3 operational control.

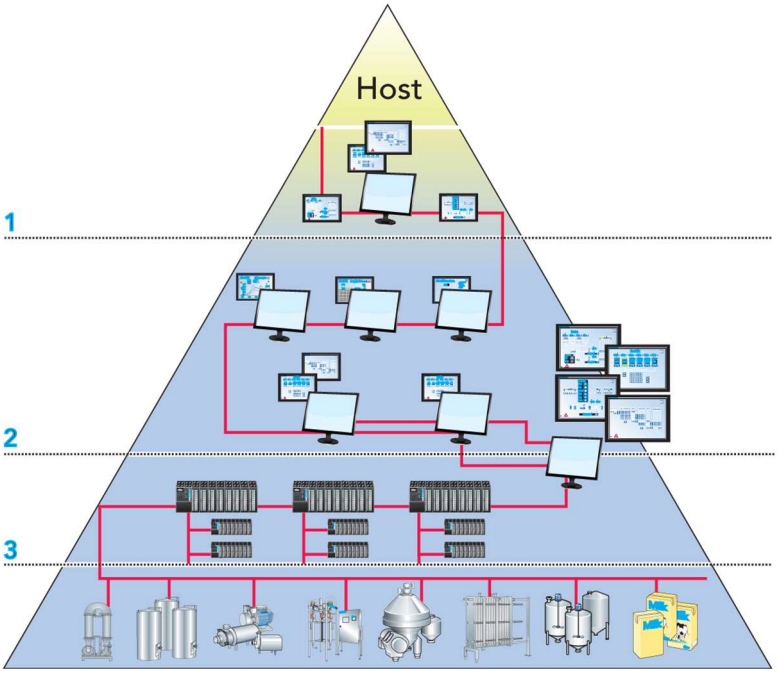

Figure 3.8 – Schematic control system layout for a complete process line

3.2.4. Summary of the Case Studies Contribution to this Research

The case studies contributed to the academic field by exploring simulated scenarios in reducing the effect of by-products in the production line [199], [200] and through a prototype simulation model to explore the effects of a data-driven process authorisation of raw material in the production flow [201]. A summary of all three case studies previously presented is shown in Table 3.2 in order to highlight the contributions to the field.

Table 3.2 – Summary Case Studies

Case Study	Problem	Objective	Main Activity	Metric	Current State	Improvements Achieved?
1	Constant disruptions in Process 4 due to restrictions in Process 5	Maximise the production of Product 4	Investigate alternatives to reduce the restrictions using simulation	Tonnes per week	136 average 21 standard deviations	Results recommending the best scenarios were demonstrated and published [199][200].
2	Several sources of variability in a by-product production plant reduce the capacity of the bottleneck	Optimise the shared main bottleneck	Simulate the sources of variability from raw material to customer demand and the effect on the main bottleneck	Bags per hour	80 average 15 standard deviations	No Conclusions Due to the issues in collecting accurate data However, the supply variability was evident in this Case Study.
3	Challenges in defining schedules for separators and dryers	Maintain the WIP silos balanced and avoid extra volumes	Simulate and visualise the results according to the selected schedule	Trade-off: Equipment Utilisation and total volume processed	50-55% of equipment utilisation	Results demonstrated and applied - The model was adopted by the IP. In addition, a prototype for concepts of Industry 4.0 based on this case study was proposed in [201]

During the analysing and modelling phase, it was also observed that the push production system is commonly adopted among the dairies investigated despite the raw milk dependency on demand defined by contracts. The push system is commonly used to guarantee raw material availability in the succeeding stages. By evaluating these inefficiencies, it is evident that the initial stages in the manufacturing environment would benefit from a generalised decision support framework since dairies face similar challenges due to the fundamental aspects of this environment.

In the next section, all three case studies are generalised into manufacturing stages and the potential sources of the randomness of each stage is fully investigated.

3.3. Initial stages in Dairy Manufacturing - Generalisation

The understanding regarding dairy operations provided by the literature and the three case studies explored are converted into several manufacturing stages. As illustrated in Figure 3.9, the raw material is supplied, stored in silos and further transformed into finished goods. The supply and storage stages are represented by buffer silos (B1) and further processed by Stage 2, which is the separation process as described in section **2.4.3 Separation**. The WIP is then sent to further stages 2.2, 3 and 4 according to the manufacturing environment.

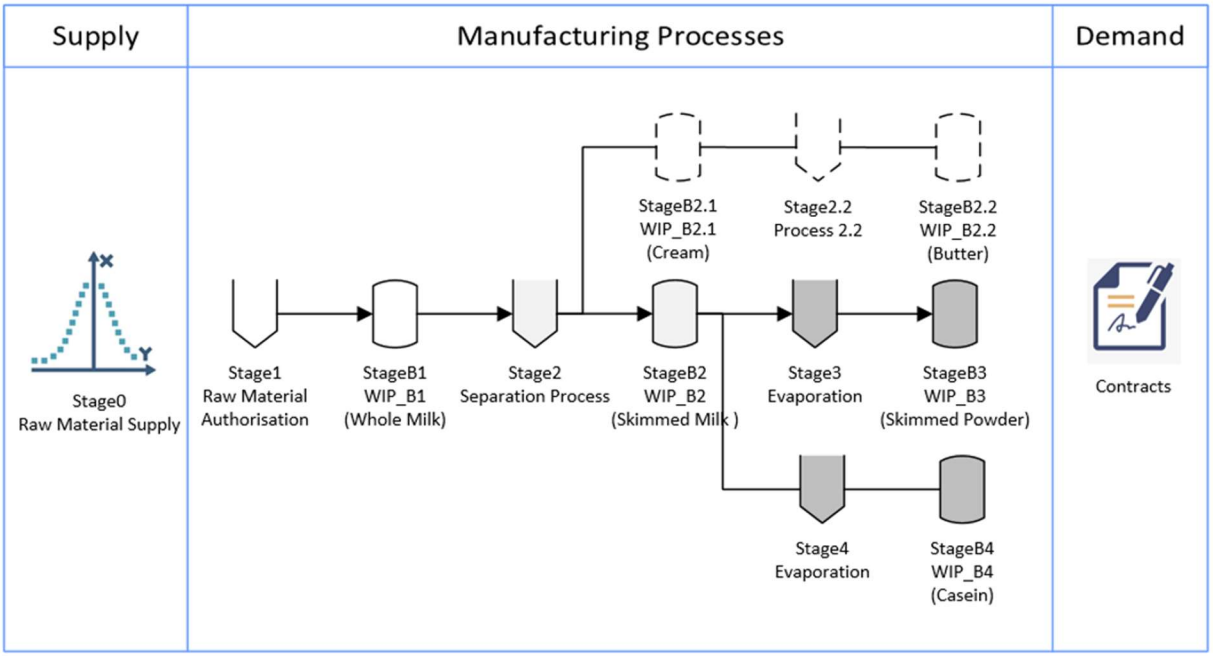

Figure 3.9 –Stages in Dairy Manufacturing

Each stage explored in the Irish dairy bulk powder manufacturing process and illustrated in Figure 3.9 is detailed as follows:

- Stage 0 – Raw material supplied: This stage is an outbound process. The milk is supplied throughout the day and due to the variability in the supply frequency, the production planning process is heavily impacted at the operational level.
- Stage 1 – Raw material reception and storage: At this stage, the reception and authorisation volumes are accepted according to the milk quality. The flow is restricted by Stage B1 capacity. In addition, truck queues are likely to be formed during high seasons.
- Stage 2 – Material Processing and Storage: The raw material is separated according to the separator capacity and at this stage, the WIP is divided into two extra flows: B2.1 fat and B2 skimmed milk.
- Stages 2.1 and 2.2 - Material Processing and Storage: it is the resulting product processed by Stage 2. It is a parallel manufacturing process, which is also restricted by the silo storage capacity.
- Stage 3 – Material Processing and Storage: The product is evaporated, dried, and stored in powder form to be further processed in the packaging area.
- Stage 4 – Material Processing and Storage: This process receives the flow according to specific contracts and the manufacturer's strategy. A similar process is observed in case study 1.

Due to the importance of an efficient process flow for the supply chain, the supply seasonality and the stochastic events on the subsequent stages are explored in this section. Data collected from the case studies for each stage is scrutinised and described as follows:

3.3.1. Stages 0 and 1 –Raw Material Supply and Reception

In the dairy sector, raw material availability is essential to guarantee the production flow in order to fulfil demand contracts. Fundamental assumptions regarding supply are presented as follows:

i. The raw material composition, such as protein levels, varies according to each month. The milk composition affects not only the volume but also the quality of finished products.
ii. During the high season, the raw material inventory stage is restricted by silo and flow capacities.
iii. Queues are likely to be formed during the peak season due to the high volume of supplied milk. Thus, short-term decisions are fundamental to reduce the risk of perishability by accepting extra material on the production flow.
iv. During medium and off-seasons, the production flow is limited by the raw material availability.
v. The supply delivery variability contributes to the increase in the instability of the system during specific periods.
vi. The raw material supply follows several statistical distributions every day increasing the complexity in making predictions.

Figure 3.10 presents the variability caused by seasonality throughout the year in one industrial partner. Months 5, 6 and 7 illustrate the volumes during the high season. Medium season volumes are presented in months 3, 4, 8, 9 and 10 and low volumes during the off-season in months 1, 2, 11 and 12. From the viewpoint of volumes supplied monthly, the variation during high seasons is smaller when compared with the two other seasons. The volume supplied to this industrial partner has a similar distribution shape as was explored in section **2.3.1 - Milk Seasonality.**

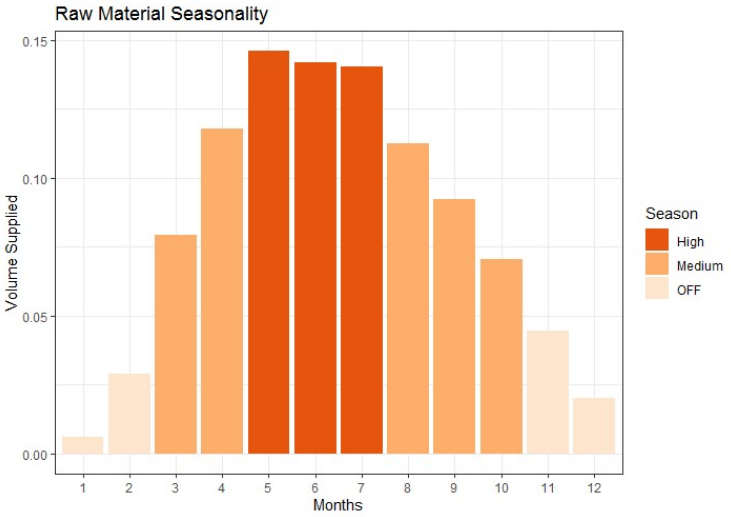

Figure 3.10 – Raw Material Seasonality

3.3.1.1. Comparison of raw material during peak and off-season

The volumes of raw material during peak and off seasons are investigated daily and hourly in order to provide a deep understanding of the pattern and implications for this research.

The processed volumes are then converted into lot sizes for three main reasons: (i) it is based on whether or not the raw material transportation capacity and the suppliers are able to deliver the raw material in fractional lot-size quantities. Thus, it is a significant measurement for transportation efficiency performance; (ii) each stage operates at different flow rates and standardisation according to the supplied volumes simplifies the comparison throughout the production line; (iii) it guarantees the data confidentiality to the Industrial Partners.

During the peak season, the daily raw material supplied reaches volumes higher than 60 lots, as shown in Figure 3.11. In the graphs presented, periods 1 and 2 refer to two selected months for each season. From the viewpoint of volumes supplied daily, the variation is stable and not significant, namely for Period 1 during peak season. However, the variability increases during off-season despite the low volume supplied.

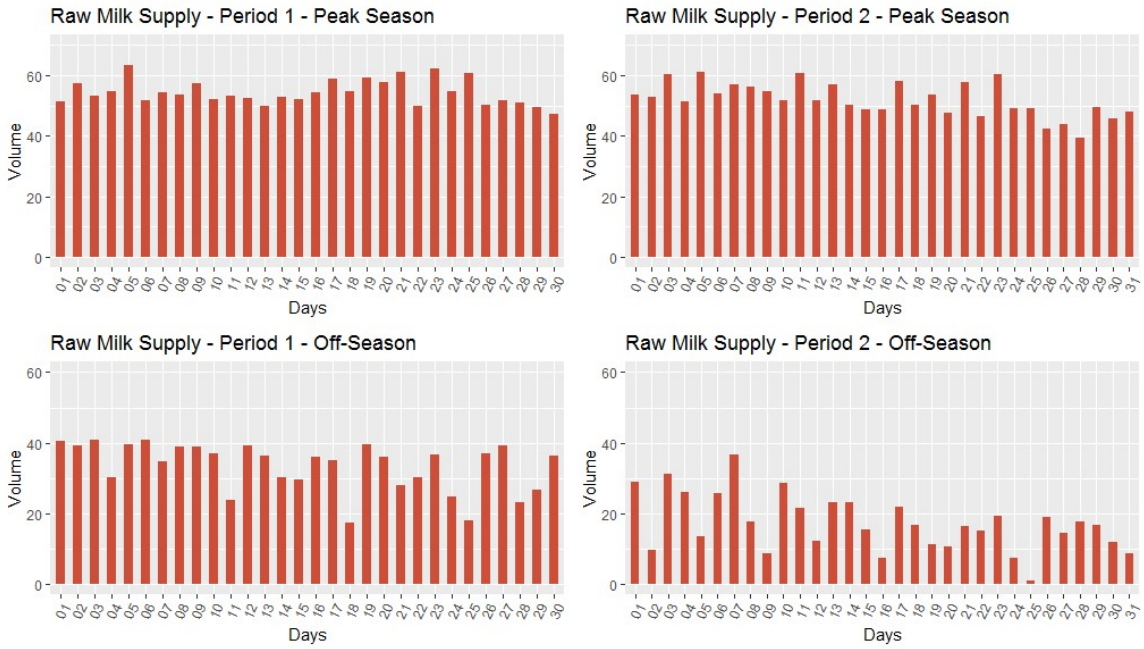

Figure 3.11 – Volume of Raw Material supplied in Lots – Periods 1 and 2 – Peak and Off-season

In order to comprehend the randomness of the supplied volumes, a five-day sample is observable in Table 3.3. The metrics presented in the table such as Mean, Standard Deviation, Minimum, Maximum, Coefficient of Variation, and Skewness for each period were calculated from RStudio functions in addition to Equations (3-1) and (3-2). The statistical distributions were calculated by the StatFit software distributed with a user license agreement with the ExtendSim simulation package.

Table 3.3 – Volume Supplied in Lots – Daily Variability

Days	Mean	SD	Min	Max	CV	Skewness	Most Likely Statistic Distribution (Density Function)
1	1.743	1.115	0.358	4.637	0.640	1.020	LogLogistic,-0.207,12.6,0.243
2	1.963	0.864	0.505	3.995	0.440	0.421	Extreme Value IB,3.9e-002,4.77e-002
3	1.878	1.251	0.608	4.757	0.666	0.868	Inverse Weibull,-8.62e-002,4.43,9.26,
4	1.650	0.869	0.733	3.713	0.526	0.920	Logistic,3.82e-002,4.09e-002
5	1.733	1.157	0.320	4.430	0.668	0.868	Power Function,-8.69e-004,0.153,0.454,

$$CV = \frac{\text{Stage}_0_\text{SD}}{\text{Stage}_0_\text{Mean}} \tag{3-1}$$

$$Skewness = \sum_{h=1}^{H} \left(\frac{RawMaterialSupplied^h - \text{Stage}_0_\text{Mean}}{\sigma} \right)^3 \tag{3-2}$$

The distribution rank was also calculated. For periods where the rank is excessively low, an empirical distribution would be more suitable rather than the distribution suggested. For all four periods, all 30 days were evaluated and are available in **Appendices D.1, D.2, D.3 and D.4.**

The volume of the raw material supplied is illustrated in Figure 3.12 through density function graphs. According to Montgomery and Ruger [202] the Probability Density Function (PDF) is used to specify the probability of a random value x falling within a range of values. Therefore, through density plots it is possible to visualise the daily supply distribution skewness for each period.

The visualisation provided by this graph could assist decision-makers in defining appropriate strategies for storing and processing the raw material received. For example, decisions based on the maximum volume supplied or higher density frequency would result in idle capacities for several days whilst decisions based on the minimum volume would result in queueing time.

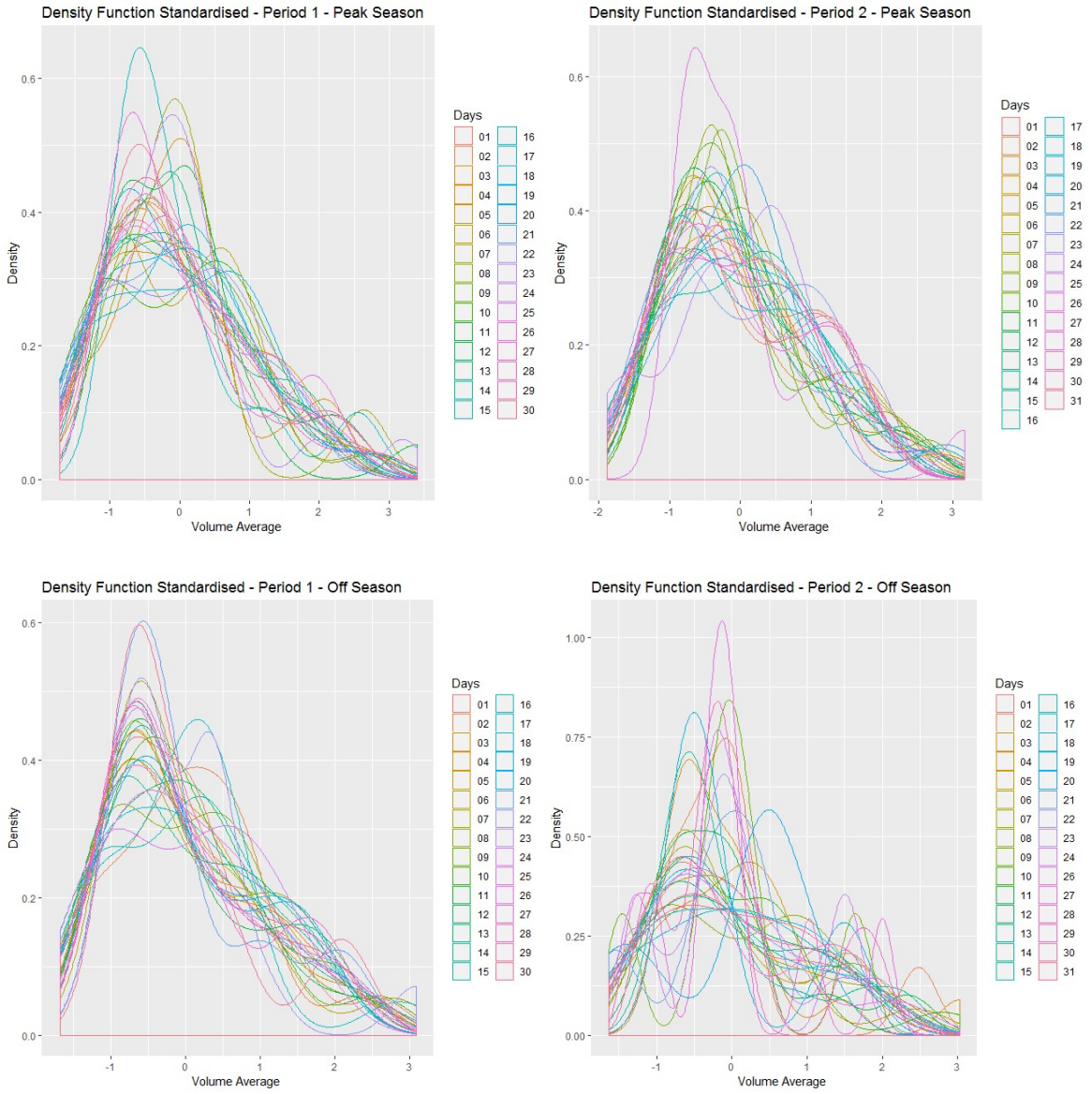

Figure 3.12 – Density Function– Volumes Supplied – Periods 1 and 2 - Peak and Off-season

The same periods and volumes are then illustrated hourly in Figure 3.13 where the variability is evident. The quartiles, low and high limits are shown in the boxplot graphs. The concentration of supply volumes starts at hour 5. It reaches the peak after hour 11 and steadily decreases after hour 16. Similar behaviour is observed in the off-season period, where the concentration peaks between hours 11 and 15.

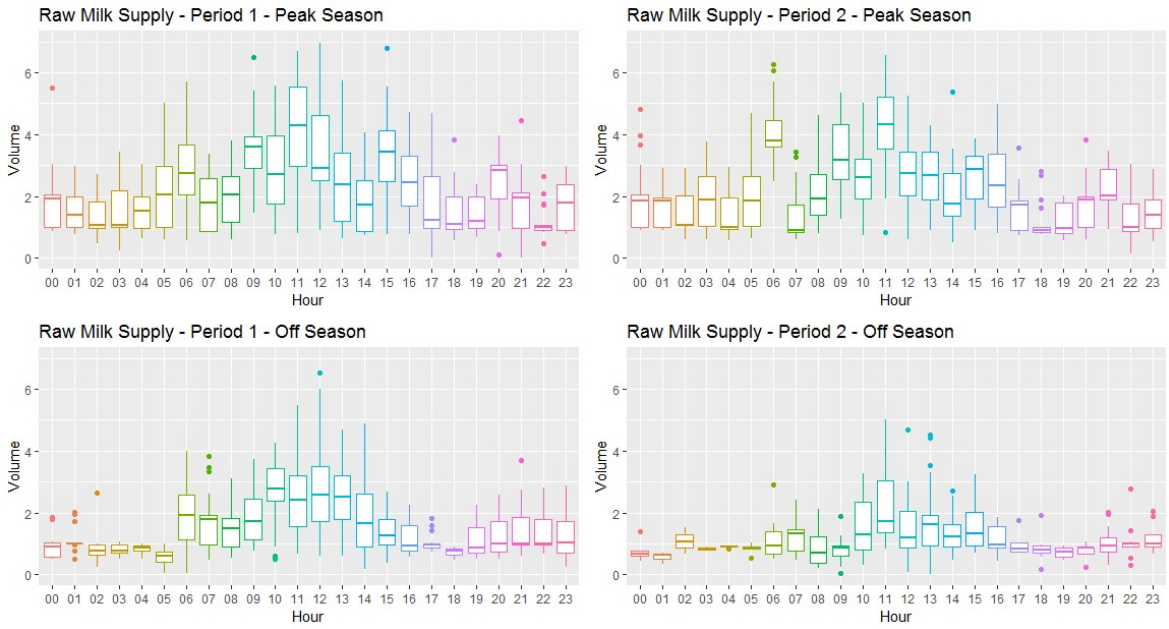

Figure 3.13 – Raw Material Supplied in Lots during the day – Periods 1 and 2 – Peak and Off-season

According to [92] transient and steady-state density functions for a particular stochastic process are conditions for stabilising a process since the distributions from a specific point are similar to each other as presented in Figure 3.14. This property is fundamental for predicting future behaviour in a system or a process and simulation models.

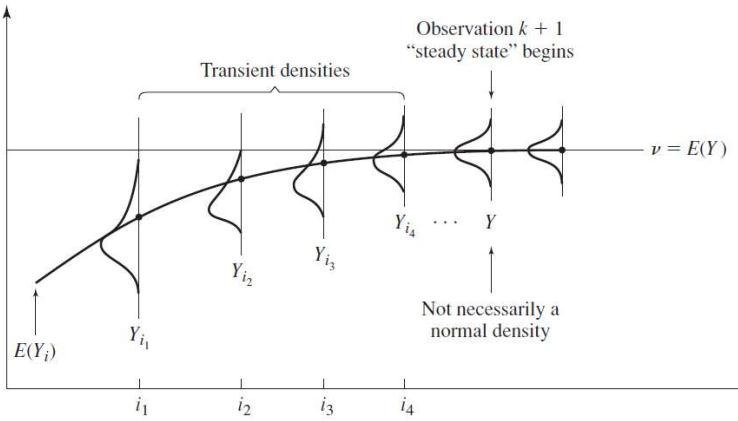

Figure 3.14 – Transient and steady-state density functions for a particular stochastic process [92]

The supply distributions show clear evidence regarding the stochastic behaviour in volume and frequency. It varies daily and the probability that various states will be repeated is not constant. In other words, it is not a stationary process.

This investigation provides an essential understanding for this research concerning the implications of an uneven supply volume on the manufacturing environment. Three sources of stochastic events were identified in the supply stage as follows:

1. The variability caused by seasonality where the volume follows a seasonal pattern.
2. The variability caused by distinct volumes daily supplied.
3. The variability caused by distinct volumes hourly supplied.

Therefore, clearly a different strategy must be adopted since the supply of raw material consistency is compromised. Further analysis of the subsequent stages is required to understand the same level of variability: monthly, daily and hourly.

3.3.2. Stage 2 – Data Analysis

In the Dairy environment, Stage 2 corresponds to the separation process as previously described in section 2.4.3 where the product is separated and solids are removed from the liquid form. At this specific stage, the fat is removed from the whole milk to be further processed. The capacity of this stage can be increased according to the number of pieces of equipment operated concurrently. However, a critical downtime at this stage is caused by CIP cycle-times, consisting of two different variabilities such as **Time to Clean** and **Time between Cleaning**. In order to understand the effects of the sources of variability on the subsequent stages and their impact on the total capacity, an analysis by month, day and hour is performed for this stage.

Firstly, an overall visualisation regarding the utilisation in hours at this stage is presented. Figure 3.15 illustrates the median of utilisation hours during the day. Four categories of utilisation are demonstrated: CIP, WATER, OFF and WORKING. Working hours refer to the running hours, whereas CIP, Water and OFF time represent non-productive hours at this stage. The figure demonstrates the utilisation for all four pieces of equipment (Eq1 to Eq4) at Stage2 for periods 1 and 2 during peak season. The periods presented are the same months analysed in **section 3.3.1.1 - Comparison of raw material during peak and off-season**. The working hours fluctuate from 10 to 15 hours for the periods/months analysed. The time consumed in water and CIP processes have a similar median and vary around 3 hours, whereas OFF hours require more investigation.

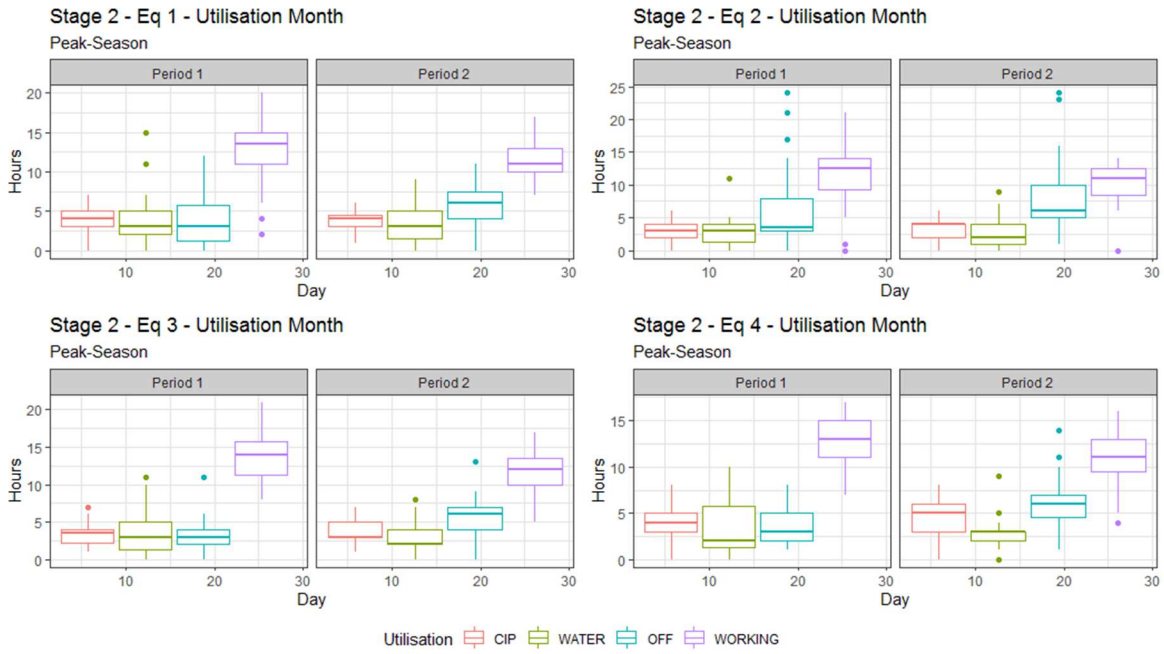

Figure 3.15 – Stage 2 – Boxplot - Equipment Utilisation in Hours - Periods 1 and 2 - Peak-Season

As shown in Figure 3.16, during off-season, the time working is lower for all pieces of equipment (Eq1 to Eq4), which is explained by the reduced level of raw material at Stage 2 being processed. Time consumed by each piece of equipment for CIP is similar, whereas a high level of variability is observed for Water, OFF and Working hours.

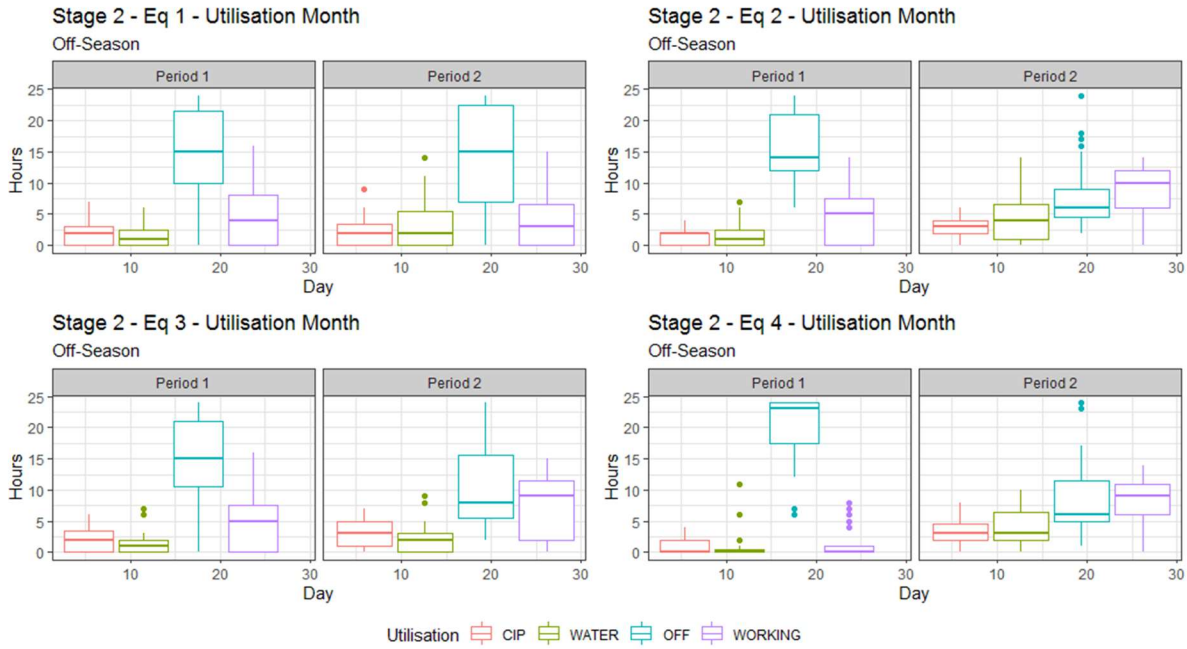

Figure 3.16 – Stage 2 – Boxplot - Equipment Utilisation in Hours - Periods 1 and 2 - Off-Season

The same dataset and pieces of equipment are explored in Figure 3.17; however, in a different type of visualisation. Although boxplots are useful to observe the dispersion of the data given a period of time, the bar graph presented in Figure 3.17 highlights the proportion of the equipment utilisation for each day.

The bar graphs are stacked by utilisation hours. During peak season, the predominant utilisation of each piece of equipment (Eq1 to Eq4) refers to working hours. Equipment 2 (Eq2) remained off for some specific days in periods 1 and 2. In addition, a high level of CIP/Water cycles is observed. The water consumed by the production at this stage plays an important role in maintaining the equipment running and avoiding extra downtimes during the absence of raw material. However, the core product is not being separated during this time. In other words, a non-value-added time is observed for this stage.

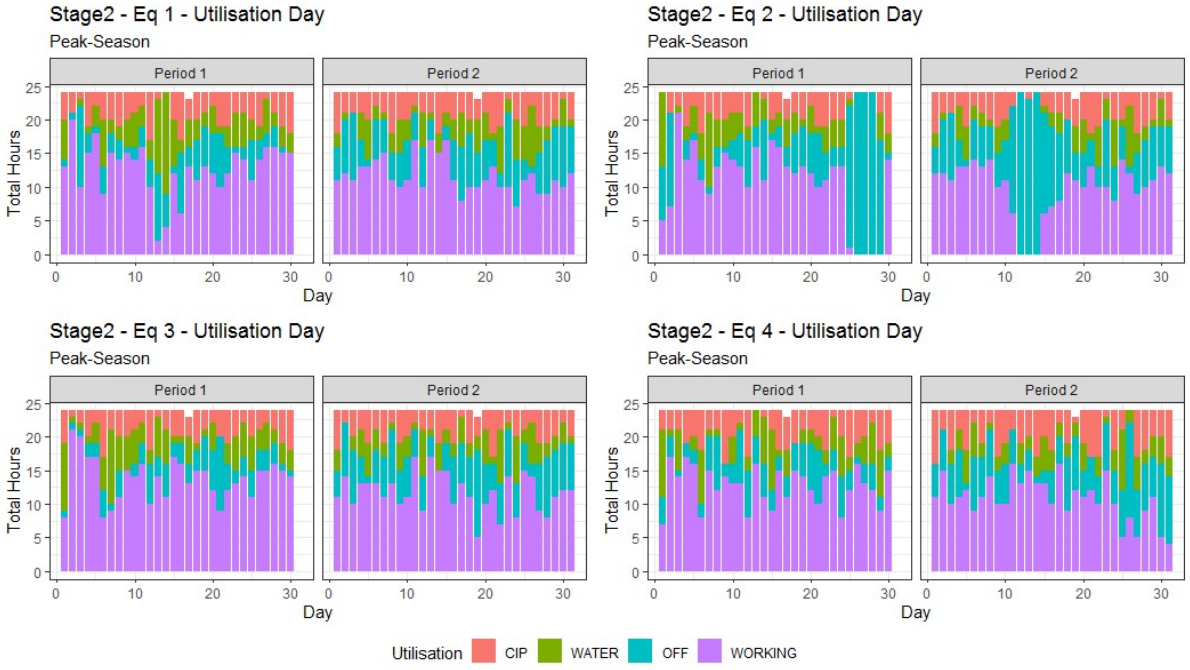

Figure 3.17 – Stage 2 –Equipment Utilisation per Day - Periods 1 and 2 - Peak-Season

During the off-season, all pieces of equipment remained off for some days, as observed Equipment 4 (Eq4) during period 1, for example. Working hours are reduced due to the restriction of raw material availability, as presented in Figure 3.18. Therefore, it is evident that during this season, the manufacturing system is not restricted by capacity but by the absence of raw material.

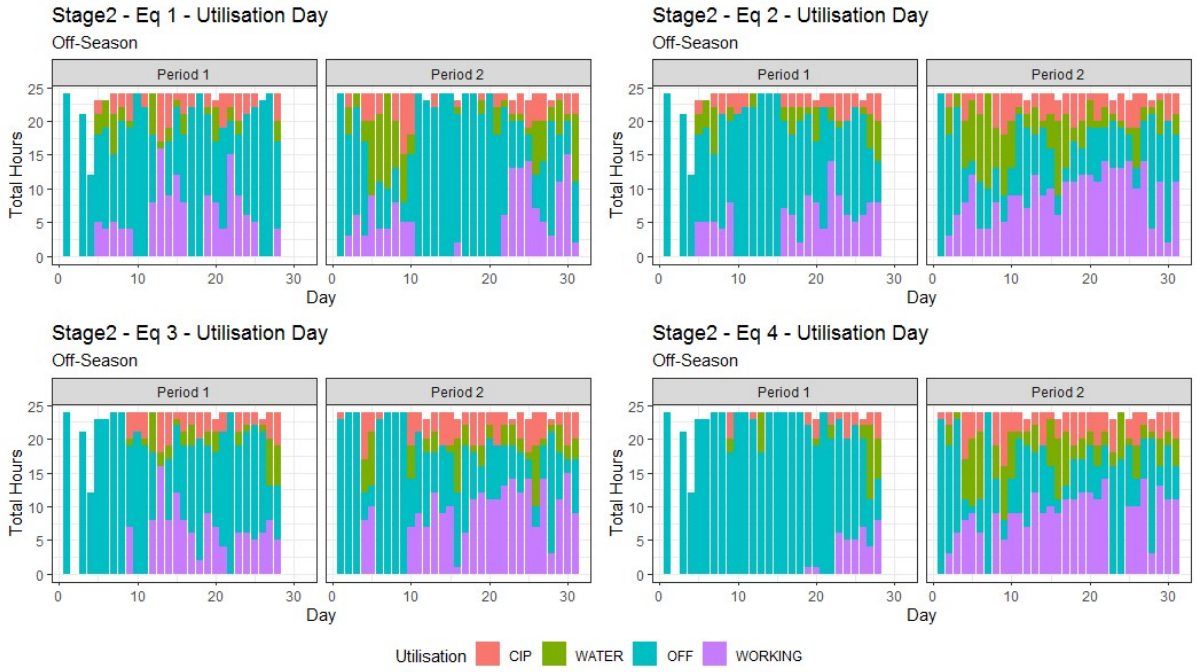

Figure 3.18 – Stage 2 - Equipment Utilisation per Day - Periods 1 and 2 – Off-Season

A final investigation at stage 2 is fundamental to clarify the importance of equipment utilisation and its impact on the separation process. A heat map graph, developed in RStudio, was used to enhance the analysis of the equipment schedule as presented in Figure 3.19 for the first month of the peak season.

The dark blue tiles refer to working hours, while the light blue tiles refer to the non-productive time as previously shown in Figure 3.16. The white periods refer to the absence of data provided by the PLC system records. Days and Hours are demonstrated on x-axis and y-axis, respectively.

The inefficiency for each piece of equipment during the peak season is evident. For example, separator 1 runs for 3 hours on day 6 and only 2 hours on days 13 and 15. Separator 2 runs for 5 hours for the first day and several other short cycle times are observed for separator 3 on days 8, 23 and 24 and separator 4 on days 1, 4, 9,15 and 21.

In addition, as previously illustrated in **Figure 3.13– Raw Material Supplied in Lots during the day – Periods 1 and 2 –**, the peak volume supplied throughout the day is concentrated from hours 11 to 16. Therefore, the separation process should be working consistently in accordance with the WIP levels, optimising the maximum hours per piece of equipment, complying with CIP cycle-times and running according to the volumes supplied during the day.

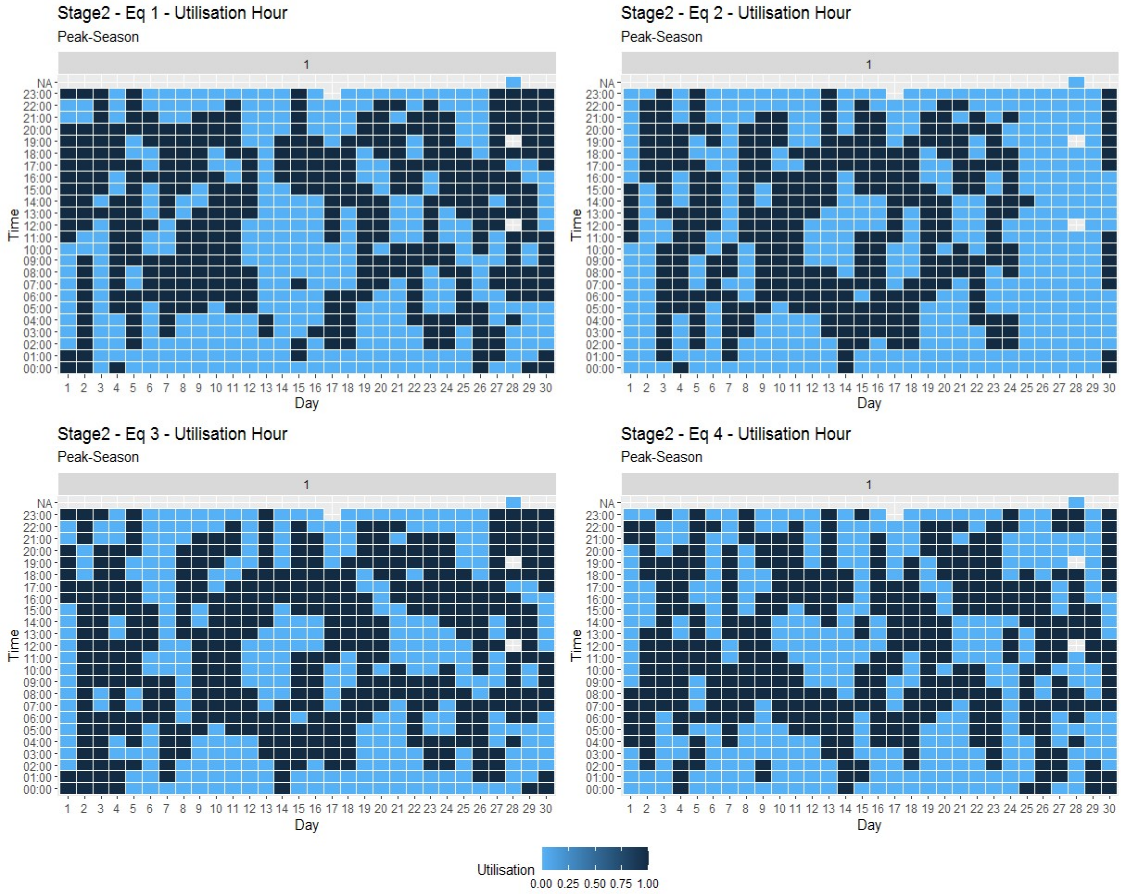

Figure 3.19 – Stage 2 - Equipment Utilisation Hourly - Periods 1 and 2 - Peak-Season

The investigation of the schedules adopted by dairy manufacturers provides essential comprehension regarding the implications of the sources of variability identified at this stage. The defined schedule compromises the flow in both downstream and upstream directions. In addition, CIP is a critical process that reduces the processing capacity and must be efficient in order to avoid the fouling effect as previously described in section **2.4.6 Cleaning-In-Place CIP.**

3.3.3. Stage 3 – Data Analysis

An investigation into the potential sources of variability at stage 3 is required in order to complete the comprehension of the production flow. At this stage, the evaporation and drying processes, as described in sections 2.4.4 and 2.4.5, have the purpose of increasing the product shelf life by reducing the amount of the liquid in the product composition. Similarly, as explored in stage 2, stage 3 capacity is increased according to the number of pieces of equipment operated simultaneously.

Time to Clean and Time between Cleaning are longer at this stage surpassing 24 hours due to the fouling effect explained in section **2.4.6 Cleaning-In-Place CIP** and the same investigative approach is conducted for Stage3. First, an overall visualisation of the productive and non-productive hours for this stage is shown in Figure 3.20 for one piece of equipment and 2 months within the peak season. Working hours refer to the productive hours whereas Caustic, Water and OFF hours refer to non-productive hours in the system. The figure shows the utilisation for one piece of equipment at Stage2 during periods 1 and 2.

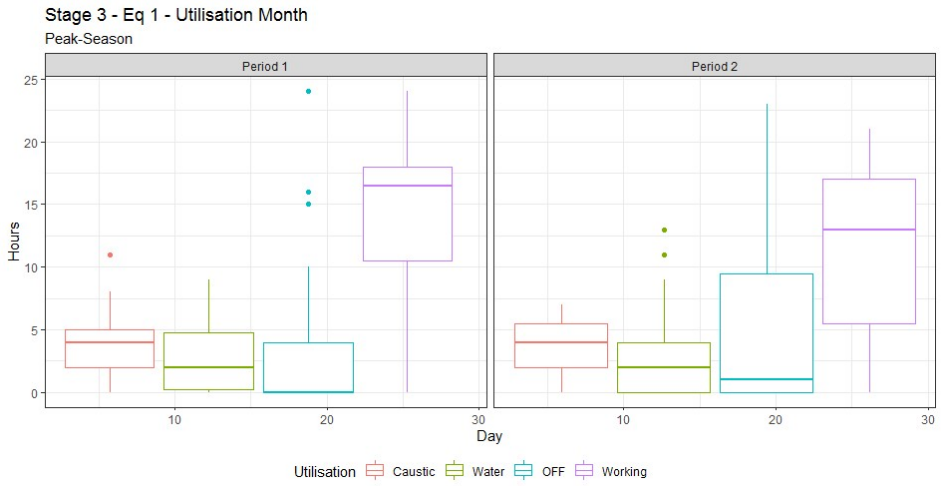

Figure 3.20 – Stage 3 - Boxplot - Equipment Utilisation in Hours - Periods 1 and 2 – Peak Season

Through the graphs shown in Figure 3.21 the utilisation for each day is presented where working and off hours have long cycles when compared to stage 2. Even though similar utilisation hours computed per month are observed at stage 3 as shown in Figure 3.20, two moments where the equipment was turned off for completely one entire day (days 18 and 29) are observed in the graph during Period2. This process is the main bottleneck among dairy manufactures.

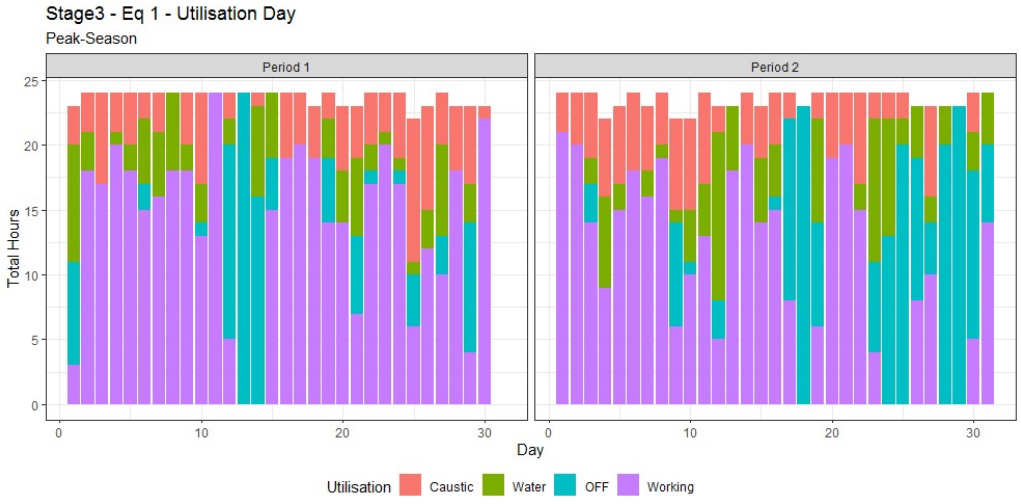

Figure 3.21 – Stage 3 - Equipment Utilisation per Day - Periods 1 and 2 – Peak Season

A similar analysis regarding utilisation per hour is conducted at the evaporation/dryer process as presented in Figure 3.22. The dark blue tiles refer to running hours while the light blue tiles refer to the non-productive utilisation activities. In this visualisation, the number of hours follows the same behaviour observed at stage 2 for each piece of equipment. For example, in the first period, day 15 runs for 4 hours and stops for another 5 hours. Similar behaviour is observed for days 20, 27 and 29. For period 2, for days 10, 12, 22, 27 and 29. In addition, day 10 runs at hour 2:00 while day 12 runs at 17:00 in period 2. One processing hour for this specific stage might represent an abnormal condition at the drying process since it requires high energy consumption.

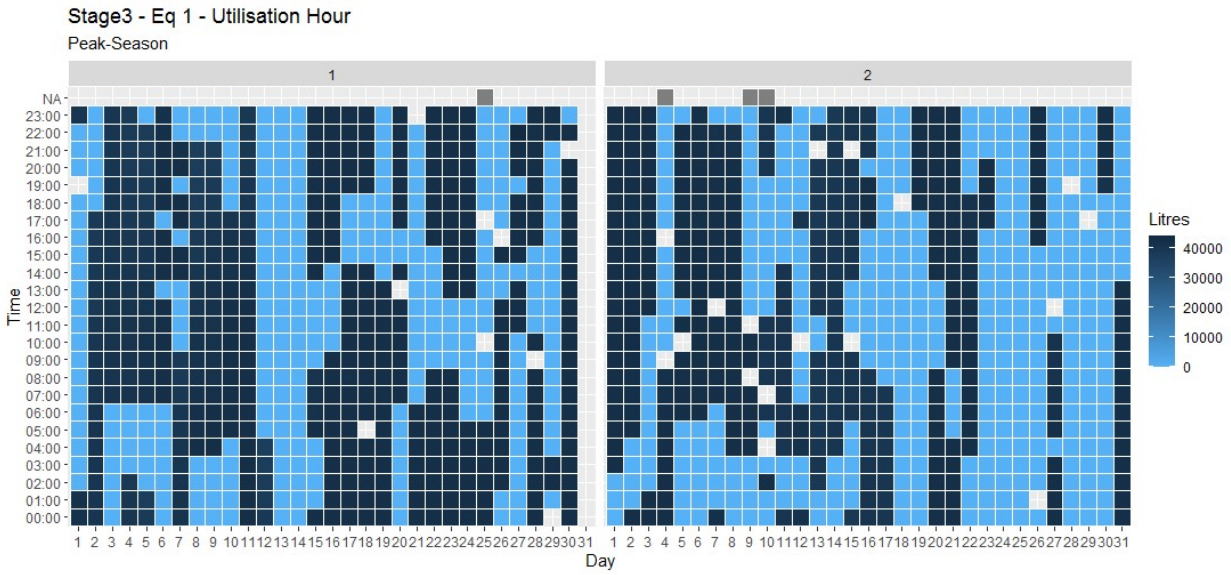

Figure 3.22 – Stage 3 - Equipment Utilisation Hourly - Periods 1 and 2 – Peak Season

Stage 3 is the bottleneck of the production flow as previously presented in Figure 3.9. According to Goldratt [203], in the Theory Of Constraints (TOC), an hour lost at a bottleneck is an hour lost in the entire system and as observed in Figure 3.22 inefficiencies that compromise the entire system are evident.

3.3.4. Summary and Contributions to this research

The main objective of this section was achieved and the fundamental processes in dairy manufacturing were generalised into stages and investigated according to three levels of information. From a macro perspective, stages 2 and 3 present analogous working hours. The median of productive hours relies on 15 hours per day. However, by comparing the activities performed hourly at a more detailed level, it is evident that an appropriate way of visualisation intensifies the inefficiencies observed at each stage.

As observed, seasonality increases intermediate inventory. Thus, the system is restricted by internal storage and processing capacities. The subsequent stages are significantly impacted by the push approach adopted. Therefore, by optimising the WIP levels in order to guarantee customer contract fulfilment, the waste linked to the excess of raw material could be reduced or even eliminated during peak seasons.

In addition, waste of material is likely to be produced due to the authorisation of extra material in the system. For medium and off-seasons, waste of resources such as energy, water and processing time are likely to occur since the further stages must be prepared to receive the raw material. During a temporary shortage, water is processed to maintain the precise temperature of equipment.

Ultimately, a detailed scheduling system design is also essential in lean implementation projects, as stated by Bicheno and Holweg [152] which depends on the type of scheduling environment. For repetitive environments, clear value streams and short changeovers are essential. In the context of dairy powder bulk manufacturing, during the medium season strategy of scheduling the equipment set according to the raw material availability is heavily recommended.

All the data collected and treated in this section refers to spreadsheets extracted from PLC files as shown in **Appendix D.5 - CIP Data Layout – Data collected for one Day**. Each day refers to one file. Therefore, several algorithms were developed in order to upload all files and provide the visualisation for each stage, period and level of information (monthly, daily and hourly). The algorithm developed to present the heat map graph is presented in **Appendix D.6 - Heat Map Algorithm Data Visualisation** where each column represents one individual file. The graphs developed in this section provided important insights into the framework designed. The next step consisted of consolidating the standardised stages into a cloud-based simulation framework to enhance the decision-making process in dairy bulk powder manufacturing.

3.4. ePilot Manufacturing Plant Simulation Framework for Dairy Industry

Developing new products to market is imperative in several sectors. A methodical approach that minimises product quality risks in developing new technologies is also critical. To that end, pilot plants play an essential role in transforming Research and Development (R&D) concepts into commercially viable processes for chemicals, catalysts, fuels and several other products.

Several sectors are challenged by more reliable processes. In addition, potential improvements and experimental studies are able to be managed on a pilot scale. Experiments applied in pilot scales in the chemical sector for new product development is a classical approach as found in [204] where it states that the acquisition of data from the unit process and a review of pertinent factors of the studied process must be undertaken. Examples of research applied in physical pilot plants are found in [205] for dairy wastewater treatment and in [206] in the pharmaceutical sector. In [207] a comparison of Commercial and Pilot Scale production plants is presented, highlighting that the process of knowledge and operational observations are the key objectives aimed in pilot plants.

Similar to physical pilot plants where the primary objective is to demonstrate the process stability of a new production technique, the ePilot Manufacturing Plant Simulation (ePMPS) is capable of demonstrating the results of a specific strategy in the manufacturing environment through simulations. Following this concept, the application of M&S in the dairy bulk powder commodity is presented in this section.

M&S provides an important method of analysing real-world problems through experimentation and testing hypotheses using what-if scenarios. Unlike physical models, through simplified simulation models, initial insights are faster observable, safely and efficiently. Safely since decisions such as increasing capacity levels in any manufacturing environment can be assessed without impacting the current production, for example.

According to the literature explored in [92], models can be mathematically designed in order to evaluate the relationships between variables. However, in real-world problems, analytical solutions can become complex and limited with respect to incorporating variability. A static model represents the state of a system at a particular time, whereas dynamic simulation models are more appropriate to represent a system as it evolves over time, as observed in the manufacturing dairy environment.

The main advantages of is using simulation techniques are: (i) simplified models provide initial insights reducing the risk and undesirable impacts on the production flow, (ii) provides "what-if" analysis, (iii) are cheaper and safer when compared to building physical models such as physical pilots, for example. All these advantages were observed during the case studies conducted as presented in section **3.2 - DPTC Dairy Industrial Partners – Case** Studies**.**

Applying M&S on an enterprise-scale is often called Enterprise Simulation (ES) and it has two main objectives: (i) Providing a strategic view of the business to support decision-making processes; (ii) Enabling the operational level in an enterprise to apply M&S in routine decisions [208]. The interaction between these two objectives is a powerful tool aligning the long-term to the short-term operations in any business process. All these assumptions were carefully studied and used as important insights for the framework designed for dairy bulk powder manufacturing entitled ePilot Manufacturing Plant Simulation (ePMPS).

The main objective of this section is to describe the combination of the state-of-the-art of current technologies as explored in **Table 2.2 – Modelling and Simulation – Summary**, the previous models for solving essential problems in the dairy sector as listed in **Table 2.3 - Research concentrated on Simulation applied to the Dairy Supply Chain** and the case studies presented in section **3.2 DPTC Dairy Industrial Partners – Case** Studies in a generalised simulation model for decision-making processes.

With respect to lean principles, defining several scenarios for each future state by the decision-maker is a powerful resource in any continuous process improvement project. Therefore, the novelty consists of filling the gap identified in previous research where several scenarios are defined for the simulation model by the modeller. Therefore, a comparison of numerous scenarios defined by the decision-maker are provided in the designed dashboard. The model is dynamically adapted to structured files uploaded, allowing performance comparisons from strategic to operational decisions.

After evaluating significant processes in dairy manufacturing, all advantages and drawbacks of simulation packages available on the market including but not limited to Arena, Risk, ExtendSim, Java libraries applied to DES, and Vensim were tested and assessed during this research project. The ExtendSim package was

deemed more appropriate due to previous knowledge and the possibility of working with discrete rate flows that is the nature of the milk processing.

During the simulation building phase, it was identified that programming simulations in conventional languages are still implemented especially due to the availability of a high level of resources provided by specific libraries such as those found in ManPy and a Discrete Event Simulation (DES) cloud-based simulation [123]. However, the complexity of embracing continuous real-world problems such as those found in the dairy environment requires extra effort for coding functions already found in Commercial-Off-The-Shelf (COTS) packages.

The server-hosted simulation structure shown in Figure 3.23 was designed for the innovative framework. In this structure, the user can access the application through any device, the web server communicates to a database and the simulation engine which are hosted in a cloud platform provider. The simulated results are then returned to the dashboard and also csv files.

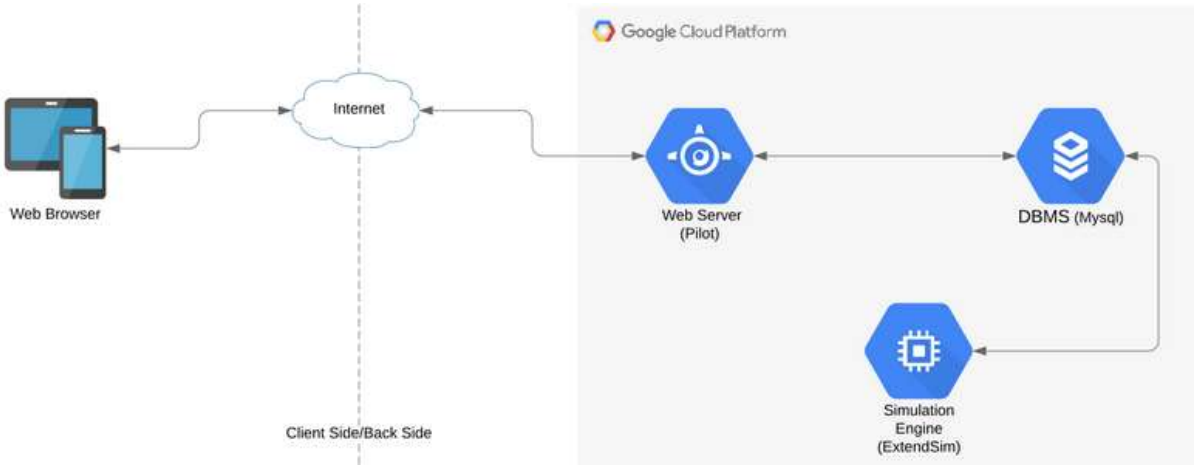

Figure 3.23 – ePMPS Server Hosted Structure

3.4.1. ePMPS Structure

The structure proposed in Figure 3.23 consists of a main layer composed by a web-server and a Database Management System (DBMS) and the Simulation Engine. In this structure, a multi-device platform is available through a web browser for the user. The performed simulation can be visualised in the webpage such as mobiles in the Client Side. In the Back Side, the Web Server (Pilot) receives the uploaded files by the decision maker, verifies the simulation status stored in a Database Management System (DBMS) – MySQL. If the simulation status is “pending”, the Simulation Engine (ExtendSim) runs the simulation model and returns the status as “done”. The database structure and the simulation engine are hosted in a Google cloud platform provider. All the results from the manufacturing environment simulated are then returned to be visualised through the dashboard in the Web Browser interface.

The recommended aspects of the web-simulation proposed by [209] were considered during the development phase such as: (i) The sequence of the input information required to start the simulation. In addition, current state-of-the-art research in web development was adopted such as: (ii) A simplified and commonly used data structure such as a csv file; (iii) End-user waiting progress signalling the simulation is being processed; (iv) A processed result dashboard summary. The integration of a number of mature technologies such as simulation techniques, virtualisation and web service tools were explored during the ePMPS Project. In order to provide an adequate comprehension, the background structure is presented as follows.

3.4.2. User Interface and Security

User Interface (UI) development is also known as Front-End Service (FS) and it has heavily evolved when compared with the last decade. Concerns regarding complexity in interface systems were presented in past research [120]. Declarative UI is currently the most popular approach for web page development. Languages that use a declarative approach eliminate Document Object Model (DOM) manipulation. The DOM connects web pages to scripts or programming languages by representing the structure of a document—such as the Hyper Text Markup Language (HTML) web page—in memory [210]. In a declarative approach, the main advantages are simplicity and the number of instruction reductions.

The ePMPS was designed using JavaScript Object Notation (JSON) and Application Programming Interfaces (APIs) for communicating the results generated by the simulation and the web interface developed. The UI was developed through the component-based library React [211] and the interface structure is presented in Figure 3.24 and further demonstrated in section **3.5.1 - Performing Simulations and Scenarios** .

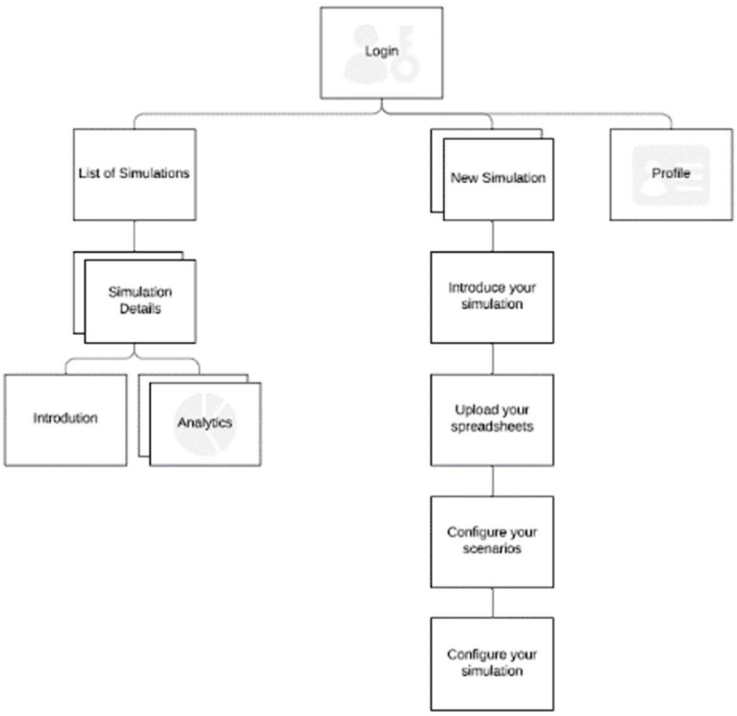

Figure 3.24 – ePMPS - Web Interface Structure

In a cloud-based solution where several users have access, security is of paramount importance regarding data confidentiality. In order to guarantee data confidentiality among the dairies involved in this project, one initial layer of security was added through the user authentication; therefore, only users authorised are able to access the ePMPS platform. The authentication is the first step after accessing the Uniform Resource Locator (URL) where the application is hosted, as presented in Figure 3.25. Thus, each company has a predefined user who will be authenticated in order to guarantee the data protection of each simulation performed in this environment. Moreover, a master profile will set essential information and also provide privileges for the registered users.

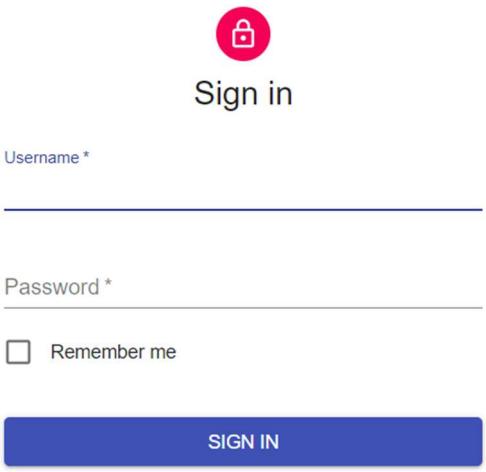

Figure 3.25 – ePMPS - User Authentication

In addition, as described in section **2.6.3 - Cloud Computing and Cybersecurity**, all the cloud computing providers offer data security not only limited to privileges in accessing the application but also the guaranteed infrastructure and encryption techniques for data transferred.

The ePMPS architecture relies on cloud computing, namely Google server. The use of Google as a Cloud Service Provider (CSPs) was decisive, considering SaaS solutions are more reliable in comparison to webpages developed and stored in local hosts. Security tools require manual configuration and exposes the company to constantly being updated. Significantly costs of maintenance infrastructure are reduced by SaaS as a system platform since the data administration, transmission and scalability, as described in section **3.4.6 - Elasticity and Scalability of the ePMPS Framework,** are managed through the cloud for all instances created.

3.4.3. ePMPS Architecture

The infrastructure was built considering a multi-tier architecture as shown in the Unified Modelling Language (UML) Diagram in Figure 3.26. The ***User*** tier saves the simulation data structured in the DB tier through an API as described as follows: (i) The ***User*** tier requests a new simulation form and receives the new simulation form from the ***Browser*** tier, (ii) The ***UI*** *tier* is then allowed to receive the data input. The files are sent and saved into the *DB* tier through the API (*Pilot* tier), (iii) ***DB*** tier then confirms the information with the user through the *Pilot* API, and finally (iv) the new simulation data structure files are sent, stored and confirmed by the ***DB*** tier to the user. The simulation performed is available for visualisation.

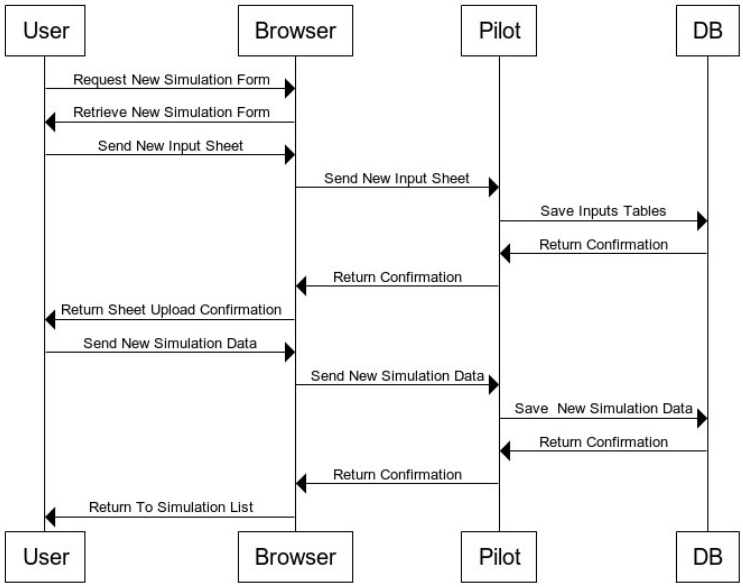

Figure 3.26 – ePMPS - Creating Simulations – Internal Structure

The intermediate process called *ExtendSimAgent* is responsible for checking whether there is any pending simulation stored in the DB that requires processing as shown in Figure 3.27 and Figure 3.28. The communication between the API agent running on the cloud platform and the ***DB*** tier is performed as follows: (i) a scenario is pending, the inputs are sent to the *ExtendSim* model, (ii) the simulation engine is

then performed, (iii) the simulation status is returned, (iv) the agent reads the output results in the *ExtendSim* model and then saves them into the ***DB*** tier, (v) the data stored in the ***DB*** tier is then returned to the *ExtendSimAgent* process.

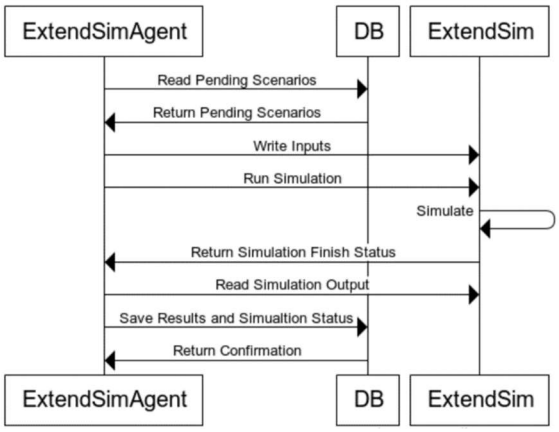

Figure 3.27 – ePMPS - Simulation Communication – Internal Structure

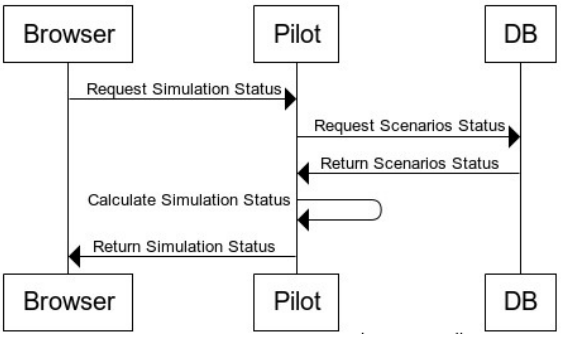

Figure 3.28 –Simulation Communication – Getting Status - ePMPS

The communication between the web page and the webserver is performed through an API developed using Go Language known as Golang [212]. Go Language is a general-purpose programming environment with advanced features such as the availability of a variety of platforms, the robust well-documented standard library, and the focus on best practice software engineering principles. The function *CreateANewProject* is an example of the code performed as presented in Figure 3.29.

```go
// CreateANewProject is used to create a new project with scenarios in database
// It recive a db connection, an opened transaction and the project model populated
func CreateANewProject(db *sqlx.DB, tx *sqlx.Tx, newProject model.Project) (model.Project, error) {
	projectDao := store.BuildProjectDao(db)
	scenarioDao := store.BuildScenarioDao(db)
	projectSaved, err := projectDao.Save(tx, newProject)
	if err != nil {
		return projectSaved, err
	}
	for _, scenario := range projectSaved.Scenarios {
		scenario.Project = projectSaved
		scenario.Status = "Pending"
		_, err = scenarioDao.Save(tx, scenario)
		if err != nil {
			return projectSaved, err
		}
	}
	return projectSaved, nil
}
```

Figure 3.29 – CreateANewProject function - source-code developed - Project.go API

3.4.4. Database Management System (DBMS)

The ability to simulate and compare several scenarios was considered during the ePMPS Framework design. Thus, owing to the DBMS structure it is possible for any simulation application to directly access and store the simulated data and compare multiple scenarios. Queries requesting data from a relational database RDBMS known as Structured Query Languages (SQL) are widely used for information storage [213].

MySQL Enterprise Edition [214] , which is the most popular OS DBMS, was used to store the input information received by the API. The data stored in the internal ExtendSim database model is then transferred through an ODBC connection to the MySQL database structure. After performing the simulation, the *result* table is returned to the web application interface as previously illustrated in Figure 3.26.

The Entity Relationship (ER) Diagram is shown in **Appendix E.1 - Entity-Relationship Diagram – ePMPS**. The structure is divided into three main groups:

1) Project Structure: tables which support the UI such as *company, user, and project.*
2) Input Structure: all the tables referred to as “input”, such as **supply_hour_input**.
3) Output Structure: All the information regarding simulation data such as ***result***, ***skimmed_milk_stock***, and ***whole_milk_stock***.

3.4.5. Dairy Manufacturing Stages in the ePMPS Framework

The manufacturing stages proposed by the ePMPS framework are based on section **3.3 - Initial stages in Dairy Manufacturing.** The structure is divided into two categories as follows:

1) Manufacturing Design (MD) plant files: Through these files, the manufacturing plant is structured. Information such as flows, capacities, and pieces of equipment must be primarily defined.
2) Process Flow (PF) files: Through these files, the daily operation information must be provided such as supply volumes, schedules, variability at the production flow, for example. For finished

good stages, it is possible to incorporate some level of production variability through the average and standard deviation columns.

In Table 3.4 the manufacturing stages are described as illustrated in Figure 3.9. The files are shown in **Appendices E.2 to E.10.** The simulation model engine performs the rules defined by the manufacturing design (MD) and process flow (PF) spreadsheets such as supply frequencies, capacities, flows, set of equipment, and schedules. For MD files, the column Max Capacity refers to the number of pieces of equipment whereas PF files refer to the simulation period. The order of the table follows the type of file MD and PF followed by the sequence of stages in the manufacturing production flow.

Table 3.4 – ePMPS – Manufacturing Stages - File Structure

Type	Stage	Process Description	Spreadsheet Name	File Structure - Appendix	Max Cap
MD	**Stage B1**	Raw Material Storage Silos	RWCapacity	E.2 - Stage B1 – Silos - RWCapacity	10 Silos
MD	**Stage 2**	Separation Process	SeparatorsCapacity	E.3 - Stage 2 – Separation - SeparatorsCapacity	10 Equip
MD	**Stage B2**	Skimmed Milk Storage	SkimCapacity	E.4 - Stage B2 – Silos - SkimCapacity	10 Silos
MD	**Stage B2.1**	Cream Storage Silos	CreamProcess	E.6 - Stage B2.1 – Silos - CreamCapacity	5 Silos
MD	**Stage 2.2**	Churn Process	ChurnCapacity	E.7 - Stage 2.2 – Churn – ChurnCapacity	5 Equip
MD	**Stage 3**	Evaporation Process	EvapCapacity	E.5 - Stage 3 – Silos - EvapCapacity	5 Equip
MD	**Stage 4**	Process 2	Process2	E.8 - Stage 4 – Process 2	5 Equip
PF	**Stage 0**	Raw Material Supply	SupplyHours	E.9 - Stage 0 – Raw Material Supply - Hourly	10 days
PF	**Stages 2, 2.2, 3 and 4**	Separation, Evaporation, Churn	Sep1..10, EvapDryer1..10…	E.10 - Stages 2,2.2,3 and 4 – Equipment Scheduling - Hourly	10 days

The separation process previously described in section **2.4.3- Separation** and analysed in section **3.3.2 Stage 2 – Data Analysis** is partially illustrated in Figure 3.30.

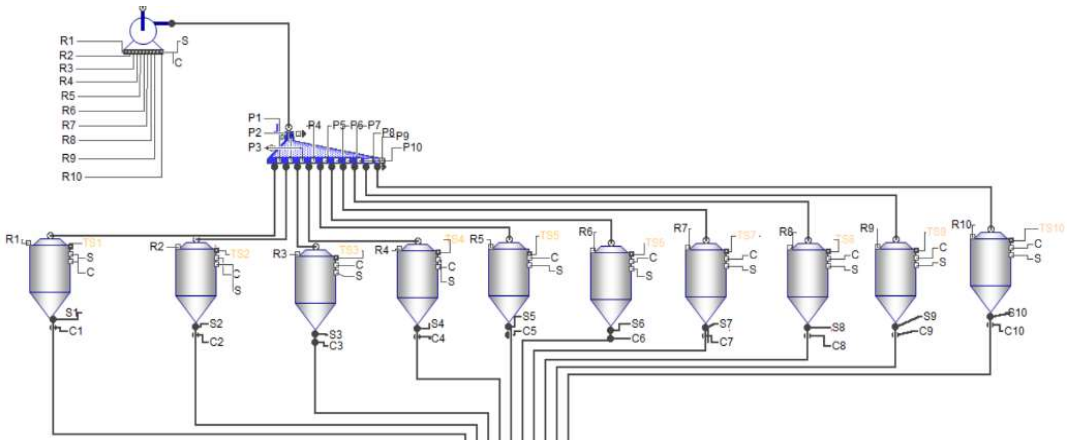

Figure 3.30 – ePMPS - ExtendSim Model – Stage 2 – Separation Process –

3.4.6. Elasticity and Scalability of the ePMPS Framework

Given the cloud structure provided by the framework proposed, characteristics such as Elasticity and Scalability mentioned in section **2.6.5 - Elasticity and Scalability of Cloud Computing** were inherited with

respect to the network and cloud computing environment. From the cloud computing perspective, the framework is scalable in infra-structure and provides a large pool of virtualized resources that can be dynamically adjusted.

Regarding the current design, as previously described in section **3.4.2 - User Interface and ,** several users are able to access the framework and perform their private simulation by testing current and states. The operation structure, such as the number of pieces of equipment, silos capacities for example, as described in section **3.4.5 Dairy Manufacturing Stages in the ePMPS Framework,** the designed framework is capable of incorporating several types of configurations, limited to the structured files. In the proposed pilot version based on a ten-day simulation horizon.

3.5. A Preliminary Experimental Analysis – Case Study 3 under ePMPS Framework

In this section, case study 3 which was fully detailed in section **3.2.3 Industrial Partner Case Study 3 – CIP Schedule and Milk Separation** is now reproduced through the cloud-based simulation framework ePMPS. The same experiment compares the current scenario previously presented in **Appendix C.22 Example of scheduling plan for 9 days,** with a second scenario where one piece of equipment was disabled. Ultimately, a third scenario reducing the running hours and turning off the second piece of equipment was also adopted.

In order to demonstrate the potential benefits of applying the ePMPS framework as a tool for supporting continuous improvement projects, case study 3 was replicated in this platform. In this case study, operational decisions as explored in section **2.2.2- Decision Levels in Supply Chain Management** were simulated. Decisions at the operation level refer to short-term periods and are usually performed daily or weekly. In a continuous process improvement, short-term decisions are faster implemented since capital investments are not required.

3.5.1. Performing Simulations and Scenarios

The framework proposed requires a set of structured csv files to perform the calculation returning the output to the User Interface. The input phase consists of a wizard interface of four steps, from introducing the simulation to the confirmation step, as shown in Figure 3.31.

1. **Step 1 – Introduce your simulation**: This step allows the user to inform the title and the simulation description, as shown in Figure 3.31.

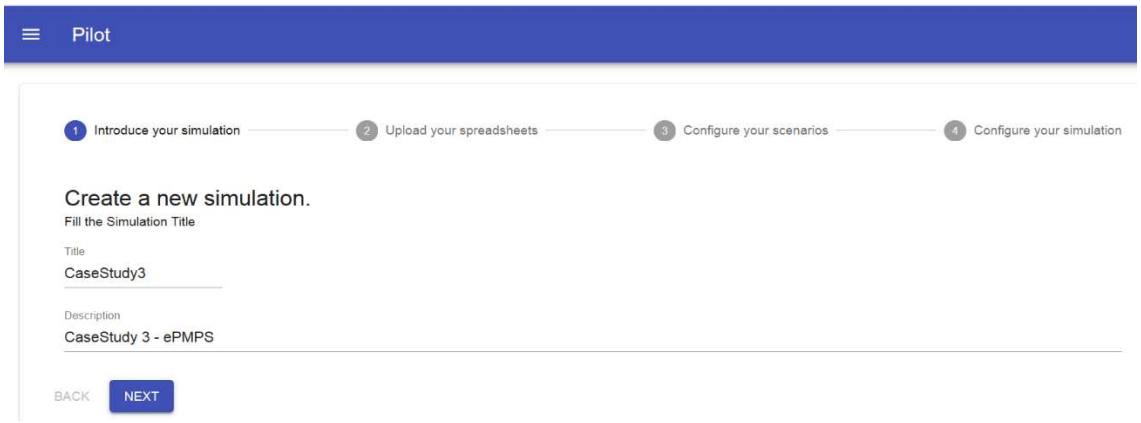

Figure 3.31 – ePMPS - User Interface

2. **Step 2 – Upload your spreadsheets:** In this step, the simulation is created based on the input files as shown in Figure 3.32 and Figure 3.33.

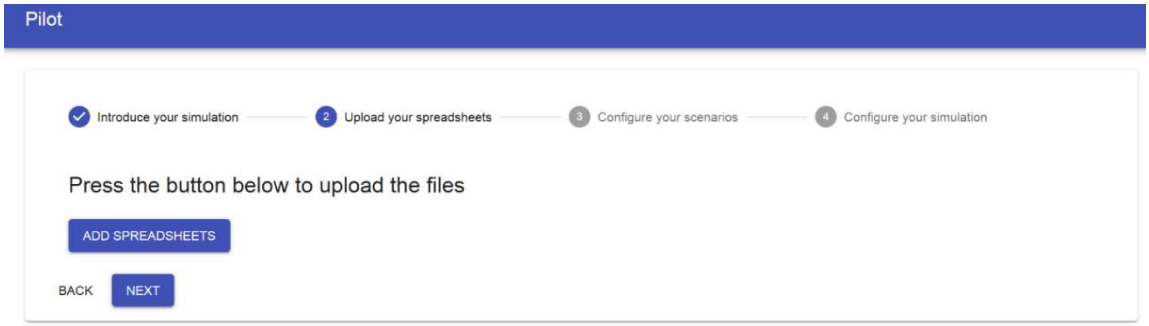

Figure 3.32 – ePMPS - Uploading Files

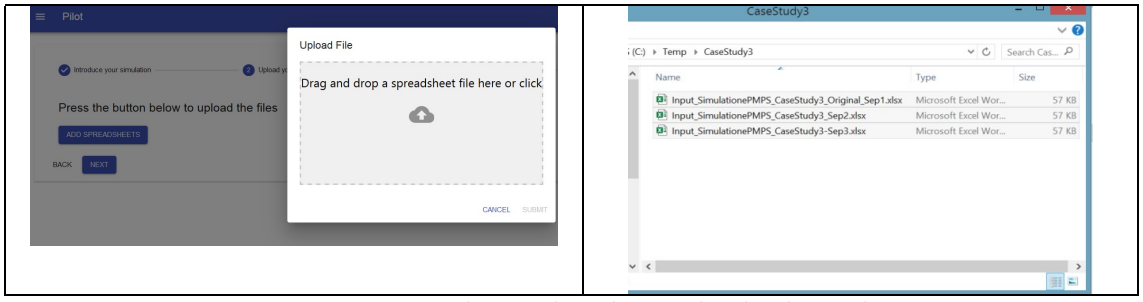

Figure 3.33 – ePMPS - Selecting Files to be considered in the simulation

After uploading the files, it is possible to visualise them as illustrated in Figure 3.34.

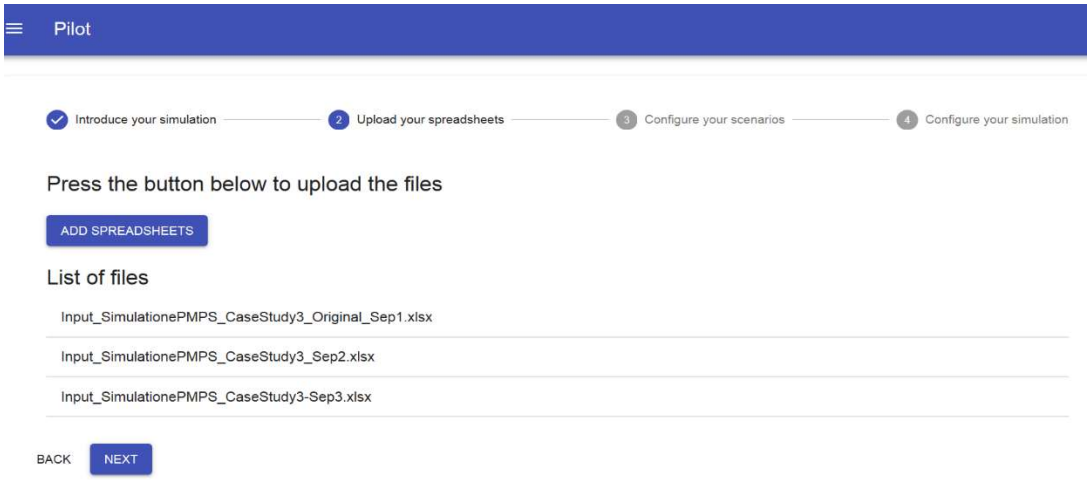

Figure 3.34 – ePMPS - Adding Files to the simulation

3. **Step 3 – Configure your scenarios:** In this step, screen parameters are required to create as many scenarios as needed through the add button (+). In this example, three scenarios are created according to each file, as shown in Figure 3.35.

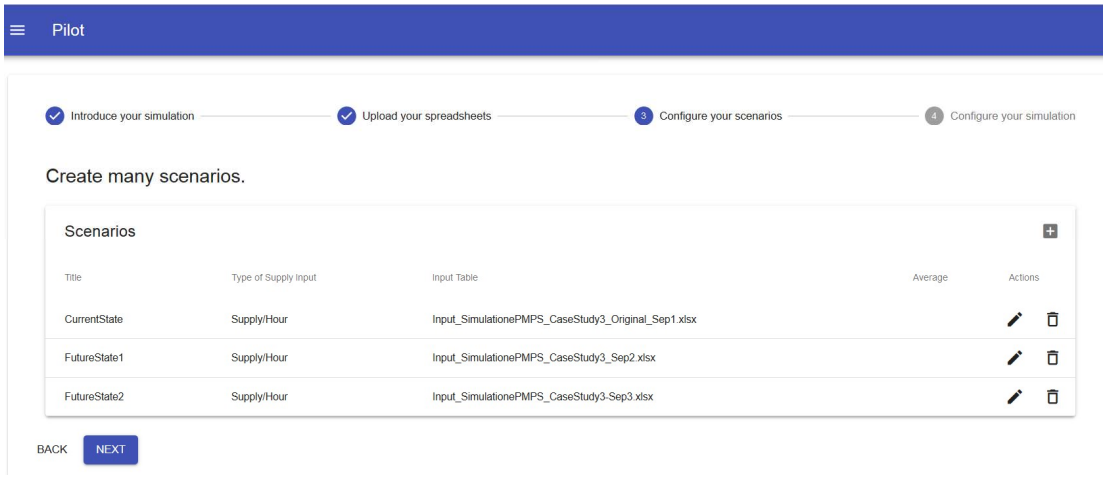

Figure 3.35 – ePMPS - Creating Scenarios for the simulation

4. **Step 4 – Configure your simulation**: In this step, the last piece of information to finalize the simulation is required, such as hours and an optional date for labelling graphs and reports, as shown in Figure 3.36.

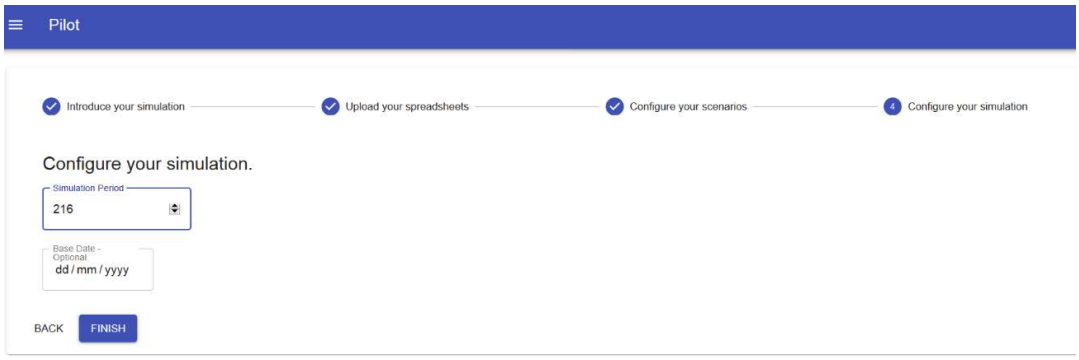

Figure 3.36 – ePMPS - Last step – Finishing the Simulation

After performing the simulation, the cloud-based framework allows dairy companies to consult the scenarios simulated previously through several devices such as mobile phones and tablets. The dashboard and results are presented in the next section.

3.5.2. Visualising the Simulation

In Figure 3.37, a dashboard with the results simulated are presented. However, an explanation about the areas of visualisation is crucial for understanding the purpose of the interface and the sequence of the information available. The interface has four areas described as follows:

- *Simulation Data (1)* : Basic information about the simulation created, title, date, user and description are provided for the user.
- *Scenarios Simulated (2)*: All scenarios simulated are available in this area as a reference for the simulation content performed.
- *Analytics Pages (3)*: Each option or tab refers to a distinct visualisation for the simulation performed.
- *Visualisation (4)*: According to the option selected the graph is demonstrated. The most relevant views for this case study are described as follows.

The ***Results*** page represents the manufacturing stages previously defined in section **3.3 - Initial stages in Dairy Manufacturing - Generalisation.** An amplified view of each graph is presented the appendix for each respective stage as described as follow:

- Total Milk Sourced - (Stage 1) : see **Appendix C.23 Total Milk Supplied – (Stage 1)**
- Total Whole Milk Silos – (Stage B1) : see **Appendix C.24 Total Whole Milk Silos – (Stage B1)**
- Total Milk Separated – (Stage 2) : see **Appendix C.25 Total Milk Separated– (Stage 2)**
- Total Skimmed Silos – (Stage B2): see **Appendix C.26 Total Skimmed Silos – (Stage B2)**

The x-axis represents the number of hours simulated, whereas the y-axis represents the volume processed by the respective stage or stored in silos at stages B1 and B2. All the values are presented in percentage to maintain the data confidentiality.

In the example presented in Figure 3.37, all graphs provide the results for all three scenarios: *CurrentState, FutureState1 and FutureState2* for 216 hours simulated. The simulated period can be visualised by individual days through the ***Filters*** option. Each scenario is described as follows:

- *CurrrentState*: The results demonstrated how the current process is performed .
- *FutureState1*: An increase of 11.5% of the milk supply is simulated, however without any changes in the manufacturing design.
- *FutureState2*: Proposes improvements in the separation schedule.

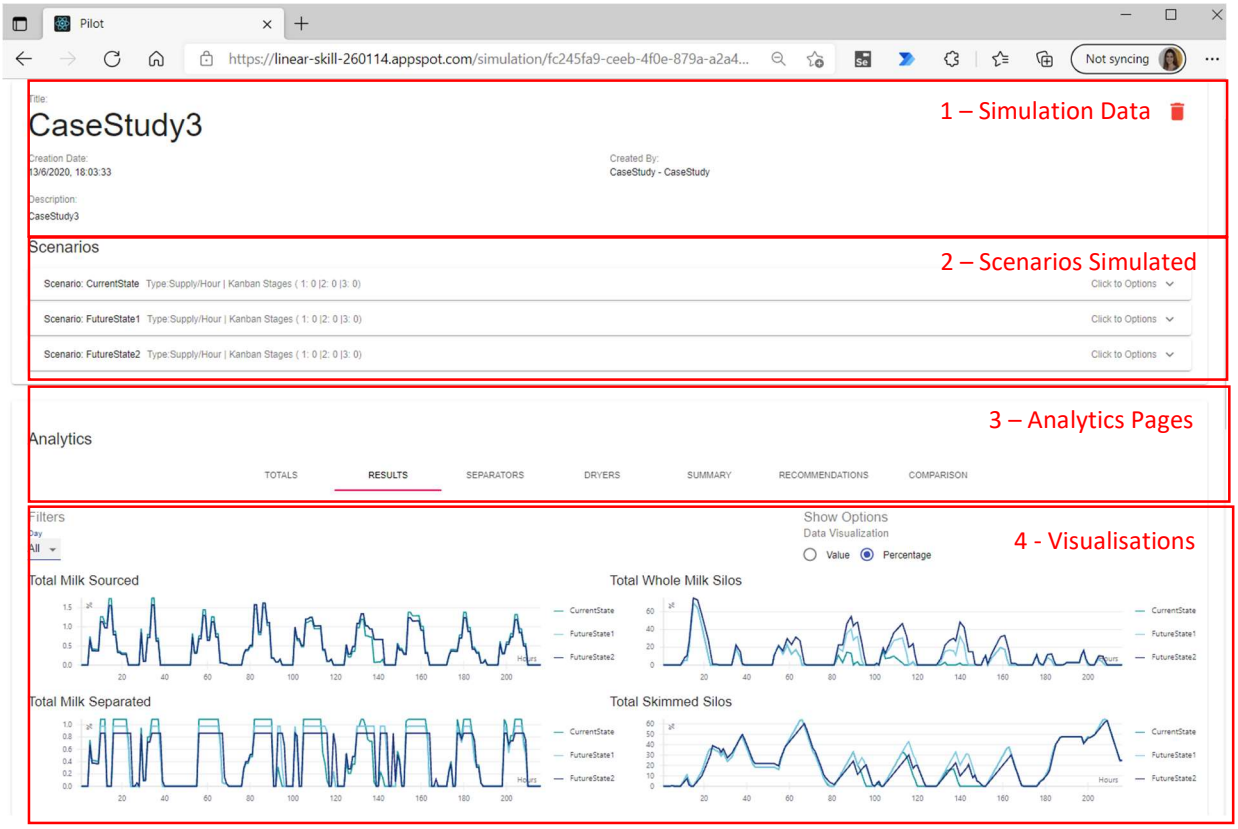

Figure 3.37 – Comparing Current and Future States – Results Dashboard

The ***Separators*** dashboard presents a similar heat map as designed in section **3.3.2 Stage 2 – Data Analysis** showing the equipment utilisation by hours. The schedule for separator 3 is illustrated in Figure 3.38. The idle and starved hours are highlighted as shown in indicating that the material should be available. The x-axis represents the days simulated, whereas the y-axis represents each hour processed by each piece of equipment. All the values are presented in percentage, therefore no volumes are shown in order to maintain the data confidentiality.

The graph is colour-coded to indicate the following statuses:

- Red: Idle hour. The equipment is active, but no material is available.
- Yellow: The volume is processed below its maximum capacity.
- Green: Expected condition.
- Grey: OFF and CIP times are defined by the decision-maker.

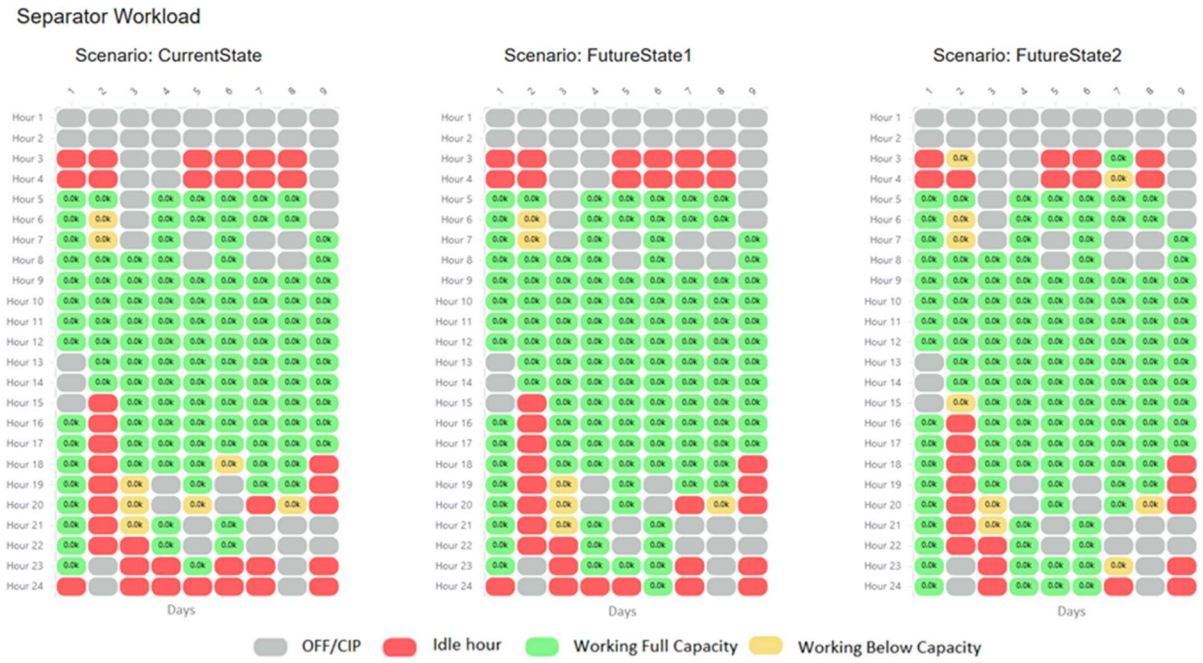

Figure 3.38 – Comparing Current and Future States – Separators (Stage 2) Dashboard

Similar visualisations are used to demonstrate the performance of each stage 3 which refers to the dryer process in the ***Dryer*** dashboard as shown in Figure 3.39. Similarly, the x-axis represents the days simulated, whereas the y-axis represents each hour processed by each piece of equipment. All the values are presented in percentage, therefore no volumes are shown in order to maintain the data confidentiality.

Figure 3.39 – Comparing Current and Future States – Dryers (Stage 3) Dashboard

The ***Summary*** dashboard presents the metrics of the total volumes processed for each day as shown in Figure 3.40. Two main observations can be made: (i) The graph entitled ***"Opening/Closing Stock per Day"*** portrays the WIP stored at stages B1 and B2. The current state presents a traditional push system where no inventory is observed at Stage B1 (Whole Milk Silos). (ii)The volume is sent to the next stage (StageB2) as observed by the Skimmed volume, while in scenarios *FutureState 1* and *2* the flow is partially restricted, and the material is partially sent to the next stage due to the reduction of processing material at Stage 2. The volumes shown in the graph entitled ***"Total Supplied and Separated per Day"*** are identical, for scenarios *CurrentState* and *FutureState1* as is expected since no changes in the equipment utilisation was performed whereas scenario *FutureState2* demonstrates some variation between supplied and Separated for day 6.

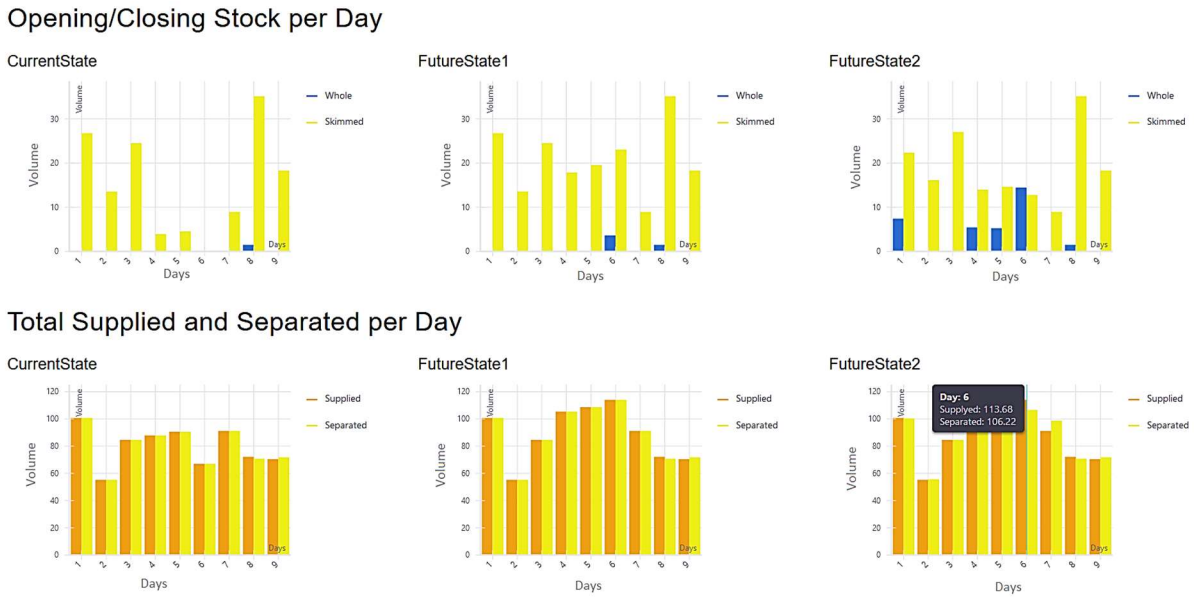

Figure 3.40 – Comparing Current and Future States – Summary Dashboard

Two extra graphs are available as shown in Figure 3.41. In the graph entitled ***"Total Separated – Skim and Process 2"***. Process 2 has no volume since it refers to the Casein production and it is following the same process as was explored in section **3.2.3 - Industrial Partner Case Study 3 – CIP Schedule and Milk Separation**. Therefore, no extra branches were simulated.

In the ***"Separator Utilisation"*** graph it is possible to observe the waste of running extra resources to produce the same volume of skimmed milk (see *Current State and Future State1*). By rescheduling the equipment set as proposed by *FutureState 2* the enhancement is evident as observed in the graph.

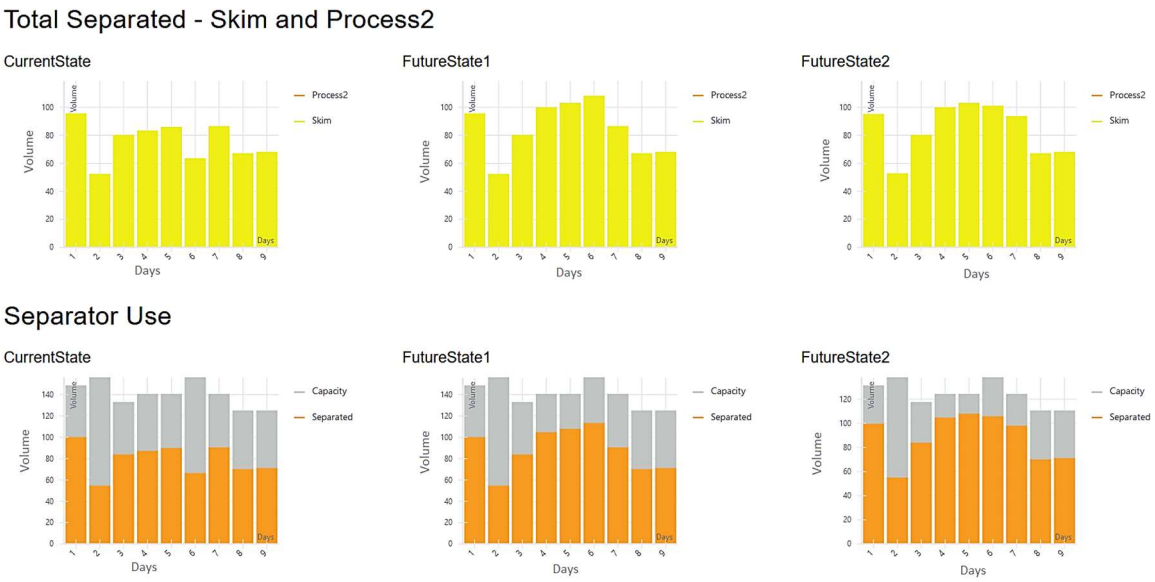

Figure 3.41 – Comparing Current and Future States – Summary Dashboard – Total Separated

In the ***Comparison*** dashboard, all key performance metrics for scenarios *Current State* and *Future State 2* are also compared. *CurrentState* and *FutureState2* suggest that by adding 11.5% of raw material supply, a similar increase is observed at the bottleneck: the drying process at Stage 3. The WIP at both stages 1 and 2 is slightly increased. In addition, the separation process was improved by 26%, as shown in Figure 3.42.

Metric	CurrentState	FutureState2	Variation
Total Supplied (L)	717	800	11.503%
Total Separated (L)	717	800	11.503%
Total Skim (L)	663	742	11.819%
Total Cream (L)	36	40	11.503%
Total Process2 (L)	0	0	0%
Total Utilisation Separators %	56.76%	71.544%	26.047%
Total Utilisation Dryers %	81.256%	90.859%	11.819%
Total CIP Separators (Hours)	708	708	0%
Total Average WIP Stage 1	0.052%	0.128%	145.238%
Total Average WIP Stage 2	0.21%	0.216%	2.753%
Total Waste	0	0	0%

Figure 3.42 – Comparing Current and FutureState2 scenarios simulated - Metrics

FutureState2 is not limited to operational decisions such as equipment reschedule, but also refers to decisions at the tactical level referring to mid-term horizons. FutureState2, this case study exemplifies two levels of decisions: (i) operational short-term decision based on optimising available resources and (ii) mid-term decisions by simulating a potential increase in the raw material supplied. It was observed that despite the current design presented in the in CurrentState scenario, dryers operating at 81% of utilisation on average; however, improvements could be achieved by increasing the raw material supplied. Decisions regarding increasing raw material, namely during Christmas, involve outbound decisions. Consequently, by simulating an increase in the supply volumes at a specific hour and comparing them to current processes, fundamental drawbacks could be avoided.

The dashboards provide significant insights for supporting decision-makers in identifying potential waste caused by extra running equipment during the manufacturing process. In addition, the graphs are effortlessly accessed through several devices such as mobile or tablets as shown in **Appendices E.11 and E.12 - Mobile Dashboard Vertical Visualisations.**

The examples of this case study are available in **https://linear-skill-260114.appspot.com/** (User: **CaseStudy** and Password: **CS#3dptc**) Project Name: **CaseStudy3**

3.6. Conclusion and Contributions to this Research

The Industrial Partners case studies provided significant contributions to this research in understanding the real processes and the particularities found in the dairy environment. The models were developed to attend specific requirements for their operations and the results then were further validated.

Even though only Case Study 3 was demonstrated as a Proof of Concept (POC) for this research project, the most valuable streamflow was identified for each case study, since all dairies receive the raw milk and store it in a similar process flow. Therefore, all case studies contributed to standardising the initial dairy manufacturing processes generalised into stages as all dairies shared similar challenges from the raw material reception to the final bulk powder ingredient produced. Process 2 as observed in the visualisations and available as an input in the spreadsheet files and refers to the Casein process explored in case studies 1 and 2.

Furthermore, the sources of variability such as milk seasonality and the stochastic events impacting the subsequent stages were investigated. The total volume received monthly suggests that not significant variation at each stage impacts the upstream processes. However, comparing activities by hour at a more detailed level, the inefficiencies observed at each stage are evident.

Simulation-based on new capital investment is possible by enabling extra pieces of equipment, simulating new scenarios, and evaluating its impact on the current flow. The preliminary analysis and results presented by the ePMPS framework concentrated on data provided by case study 3.

This preliminary experiment demonstrated new possibilities for dairy bulk powder manufacturing in visualising the benefits and drawbacks of future states in a continuous process improvement through the developed cloud-based simulation - ePMPS framework. In addition, the performance of individual stages was visually demonstrated in the dashboards and a comparison between the current and future state-provided powerful insights for decision-making processes.

The main contributions of this chapter were achieved: (i) model the dairy sector into similar manufacturing stages; (ii) provide insightful comprehension of the significant stochastic events at each production stage; (iii) investigation of the main sources of variability of this sectors as internal and external factors that impacts the manufacturing process such as: limited storage capacity between manufacturing stages, constant interruptions caused by CIP process, perishability due to the short life span of raw material, seasonality which dictates the volumes available to be processed and internal and external stochastic events commonly found in the dairy sector.(iv) design a robust framework compatible with the real process and real challenges faced by Dairy Manufacturing (v) visualise current and future state scenarios for continuous process improvement projects, allowing the accessibility for dairies manufacturers through a cloud-based structure with a user-friendly interface for the subject-matter expert (SMEs).

The next step consisted of consolidating the standardised stages according to Lean principles in order to enhance the decision-making process for this sector. As stated by Womack and Jones [63], pulling the system according to the customer's demand is required in order to pursue perfection. Therefore, an investigation of the adequate pull-type PCS for dairy bulk powder manufacturing is conducted in chapter 4 as follows.

CHAPTER 4
RESEARCH METHODOLOGY II – IMPROVING THE CURRENT DAIRY PROCESSES BY PULL-TYPE PRODUCTION CONTROL STRATEGIES

4.1. Introduction

In the previous chapter, the structure for the cloud-based simulation framework to support this research in the dairy bulk powder manufacturing was described. A proof of concept (POC) is an elaboration of a method in order to demonstrate its feasibility and it was developed to replicate the initial stages in the dairy environment through the ePMPS. In addition, by comparing the results from current and future states through the dashboard presented, an innovative method to pursue continuous process improvement best practices was achieved.

The next step consists of implementing a pull-type system according to the customer requirements. Therefore, the methodology described in this chapter consists of maximising customer value and minimising one of the most common waste observed in the dairy sector: unnecessary WIP levels. Identified in chapter 3 through the case studies. In order to achieve these objectives, appropriate metrics must be defined in order to guarantee the accomplishment of a performative manufacturing system.

By transforming the current push flow into an appropriate pull-type PCS as explored in section **2.8.1 - Push and Pull Systems**, an investigation of the main PCS such as CONWIP, KCS, and CONWIP/KCS and the requirements for adapting each strategy to dairy manufacturing are presented. Each of the three inventory control strategies was simulated in scenarios grouped by three distinct periods randomly selected as the control group.

This research tests the dairy environment designed to analyse the optimum performance boundaries through a series of simulations aimed to define the appropriate pull-type PCS considering all the challenges highlighted such as seasonality, supply variability and CIP interruptions, particularities intrinsic to this sector.

4.2. Performance metrics

The performance metrics used for comparing all experiments are described as follows. Periods refer to as $h = \{1, \dots, H\}$ and manufacturing stages refer to as $s = \{1, \dots, S\}$.

I. The total supply during H as shown in equation (4-1)
II. The sample mean raw material supplied as shown in (4-2) [202]
III. WIP for individual stage *s* as shown in equation (4-3)
IV. The sample mean WIP for each stage s as shown in equation (4-4) [202]
V. The sample standard deviation of WIP for each stage s as shown in equation (4-5) [202]

VI. The Supply-Accuracy for measuring the raw material authorized in the system according to the raw material planned shown in equation (4-6)

VII. Service Level Agreement (SLA) is calculated for the final stage as shown in equation (4-7)

VIII. The Separation Rate is the ratio of the total processed at stage 2 by the total raw material authorised by stage 1 (4-8)

IX. Total Produced according to the theoretical capacity (4-9)

$$\text{Stage}_0\text{Sum} = \sum_{\text{h}=1}^{\text{H}} \text{RawMaterial Supplied}^h \tag{4-1}$$

$$\text{Stage}_0\text{Mean} = \frac{\text{Stage}_0\text{Sum}}{\text{H}} \tag{4-2}$$

$$\text{Stage}_s\text{WIP}^h = \sum_{s=1}^{S} \text{Stage}_s\text{WIP}^{(h-1)} + \text{Stage}_{(s-1)}\text{Authorised}^h - \text{Stage}_{(s+1)}_\text{Authorised}^h \tag{4-3}$$

$$\text{Stage}_s\text{Mean} = \frac{\sum_{\text{h}=1}^{\text{H}} \text{Stage}_s_\text{WIP}^h}{\text{H}} \tag{4-4}$$

$$\text{Stage}_s\text{SD} = \sum_{s=0}^{S} \sqrt{\frac{\sum_{\text{h}=1}^{\text{H}} (\text{Stage}_s\text{WIP}^h - \text{Stage}_s\text{Mean}^h)^{\,2}}{(H-1)}} \tag{4-5}$$

$$SupplyAccuracy = \frac{1}{H}\left(\sum_{h=1}^{H} \frac{\text{RawMaterial Autorised}^h}{\text{RawMaterial Supplied}^h}\right) \tag{4-6}$$

$$Service\ Level\ Agreement = \frac{1}{H}\left(\sum_{\text{h}=1}^{\text{H}} \frac{\text{Stage}_S\text{Authorised}^h}{Demand^h}\right) \tag{4-7}$$

$$SeparationRate = \frac{1}{H}\left(\sum_{h=1}^{H} \frac{\text{Stage}_1\text{Sum}^h}{\text{RawMaterial Autorised}^h}\right) \tag{4-8}$$

$$\text{Stage}_s_Utilisation = \frac{1}{H}\left(\sum_{h=1}^{H} \frac{\text{Stage}_s\text{Authorised}^h}{\text{Stage}_s Capacity^h}\right) \tag{4-9}$$

All the WIP stages evaluated are also computed according to the maximum capacity reached by the system. Equations (4-6) to (4-9) refer to performance ratios. Even though Forecast-Accuracy is usually sought for a demand-driven process [9], the Supply-Accuracy metric was designed to evaluate the overall supply authorisation in the system and the compliance with the raw material planned.

The Supply Accuracy index, presented in Equation (4-6), is the ratio between the raw material authorized in the production system and the total supply planned. A value close to 1 indicates that all the planned raw material was accepted, and no short-term decisions are required to control unforeseen supply delivery causes. Supply Accuracy lower than 1 indicates a poor supply plan unable to receive the volume planned.

According to the Lean and Six Sigma principles, the Voice of the Customer (VOC) must be heard and translated into key performance indicators (KPI). To guarantee that the process improvement agrees with customer requirements, as stated by Schonberger [1], the customer SLA is the main link between the current process and the customer requirements, while inventory levels are essentially controlling the internal performance process. Through the SLA metric, demand is well managed and linked to the customer

requirement, allowing lower safety stock investment whereas still maintaining customer service levels as stated by Sanders and Reid [9]. Quality metrics such as Critical To Quality (CTQ), costs and also customer satisfaction are out of the scope of this research and are suggested as potential directions for future research.

According to Montgomery [202] , sample means and sample standard deviations are a point of the estimator of the population. The sample mean is a reasonable estimate of the population mean, μ. However, for samples variances the number of degrees of freedom is used $(n-1)$ in order to compensate for the lack of information about the population.

Lead time is one of the performance metrics widely measured for LPS. It refers to the time from when an order is received to its fulfilment. Optimising this time is sought as part of the strategy to guarantee customer satisfaction since it also improves financial metrics such as cash-flow. Considering the dairy manufacturing environment, WIP levels could perform an equivalent role since, in accordance with Little's Law [86], [215], the reduction of WIP levels also decreases the inbound throughput.

4.3. Research Space Assumptions

The assumptions and limitations to the simulation model developed, as described in Chapter 3, were improved to perform the investigative study of three pull-types PCS in the Dairy Environment. The initial stages of the manufacturing process are explored in this section as follows:

I. The manufacturing stages examined in sections **3.3.1, 3.3.2** and **3.3.3** were modelled. These three stages represent an entire added-value flow from supply reception to the drying process including intermediate buffer silos. The capacities and flow rates for each piece of equipment were defined according to the referred sections.
II. There is a limited capacity for WIP storage between the raw material supply, manufacturing processes and the final product storage.
III. The location of the main constraint is non-stationary and varies throughout the year:
    a. During the peak season, the production flow is heavily limited by the production rates and storage capacity.
    b. During medium and off-seasons, the raw material supply is the main restriction requiring a reduced set of equipment to process the material flow.
IV. Interruptions for CIP accomplishment are defined according to a Triangular Distribution for each stage. As observed for all dairy manufacturers, the stochastic events mainly caused by CIP interruptions were defined according to a triangular distribution due to the fact that CIP time ranges are known, a triangular distribution is a simplified method to simulate the CIP hours with limited ranges based on real processes.

V. Metrics for evaluating and comparing the system performance are previously described in section 4.2.

VI. The system is measured by lot sizes to simplify the overall comparison and to preserve the confidentiality of the Industrial Partners' data.

4.4. Simulating and Analysing the Current Production System

The initial experiments described in this section provide valuable insights regarding the consequence of the stochastic supply deliveries on the current process to be further investigated under the three main pull-type PCS. Additionally, the volumes supplied are steadily increased to illustrate the impact of extra volumes on the main performance metrics.

The two main objectives of this section are:

1) To investigate a potential influence on SLA derived from supply variability
2) To evaluate the effect of extra levels of inventory on the overall KPIs.

4.4.1. Simulating the Daily Supply Variability

The simulation framework ePMPS was enhanced to calculate the metrics previously defined. The model considered the original data and the real supply volumes as fully explored in section **3.3.1.1 Comparison of raw material during peak and off-season.**

Using the original manufacturing processes and validated data from the Industrial Partners, the same condition was replicated on the ePMPS framework. From all the days observed, six different days were randomly selected from the original production and simulated as shown in Table 4.1. The table is sorted by the **SLA** column. The total volume, **Stage0_Sum** column, represents the total daily volume supplied. Even though day 6 has a higher supply volume when compared to day 1, the **SLA** performed slightly below.

Table 4.1 - Supply Volumes Simulated – Original Values

Period	Stage0 Mean	Stage0 SD	Stage0 Sum	StageB1 Mean%	StageB1 SD%	StageB1 Max%	StageB2 Mean%	StageB2 SD%	StageB2 Max%	Supply Accuracy	SLA	Separation Rate	Stage2 Util
D2	2.635	1.652	63.250	9.328	13.618	44.691	8.199	6.318	20.200	1.000	0.845	0.928	0.630
D5	2.547	1.534	61.139	6.925	12.022	43.037	8.196	6.606	19.931	1.000	0.818	0.936	0.614
D1	2.387	2.041	57.293	9.851	15.470	53.035	7.613	8.210	25.379	1.000	0.817	0.982	0.603
D6	2.531	1.318	60.751	7.930	12.420	43.691	8.147	7.069	25.377	1.000	0.805	0.955	0.622
D4	2.456	1.647	58.932	8.640	13.137	48.621	5.446	6.142	20.685	1.000	0.751	0.907	0.573
D3	2.272	1.440	54.520	5.393	8.611	28.916	3.912	5.281	17.578	1.000	0.730	0.966	0.565

The volumes supplied are also demonstrated in Figure 4.1 where it is possible to observe that day 1 (D1) presents a higher volume of milk received at hour 12 despite the lower volume supplied for this day (*Stage0Sum*) in Table 4.1.

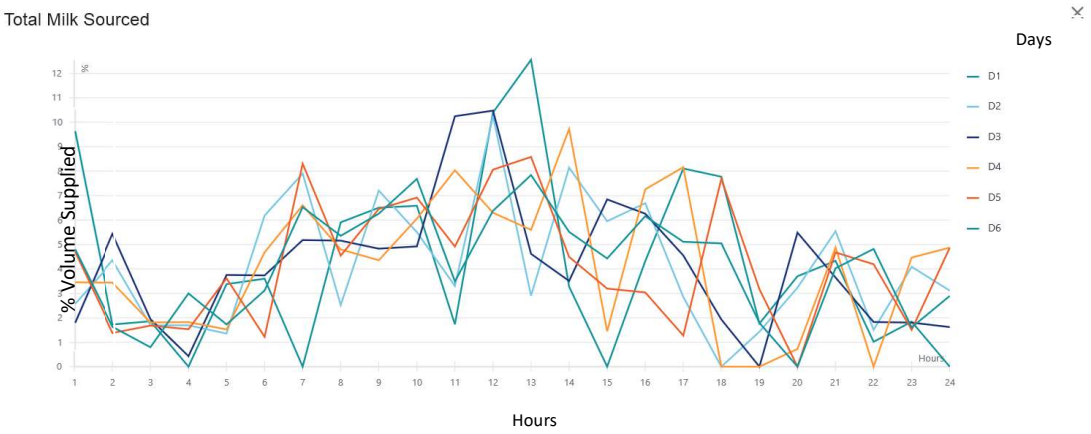

Figure 4.1 – Stage 1 – Raw Milk Supplied and Authorised - Simulation 6 Days – ePMPS Framework

Figure 4.2 demonstrates the next stage within the manufacturing production. After receiving the milk supplied, 53% of the storage capacity in the whole milk silos (Stage B1) was utilised on day 1 while 43% on day 6. The maximum values are also available in Table 4.1. However, the graph illustrates the exact moment where the maximum utilisation is reached providing clear evidence about the impact of supply variability on internal operations.

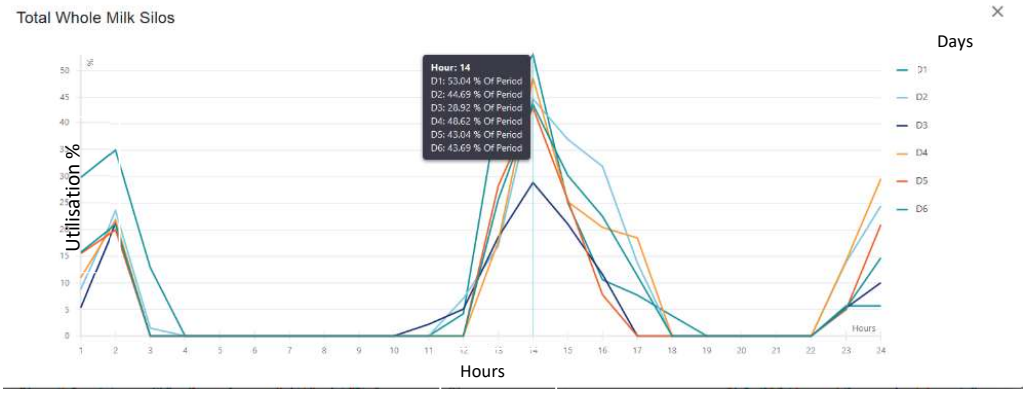

Figure 4.2 – Stage B1 – Whole Milk Silos Utilisation - Simulation 6 Days - ePMPS Framework

In Figure 4.3 the correlation between all the key performance metrics evaluated in this process. Even though the total volume has a significant impact on SLA, a strong correlation between **SLA** and **StageB2_Mean** (0.96) is shown, which is justified by the amount of material available to be processed at Stage 2. The same pattern is observed between **SLA** and **Stage2_Utilisation** (0.95).

An important relationship is also evident when comparing Maximum and SD values. A strong correlation between **StageB2_SD** and **StageB2_Max** (0.92), and **StageB1_SD** and **StageB1_Max** (0.97) suggests that the unpredictability is related to Maximum WIP levels. However, correlation does not imply causation and further investigation is required.

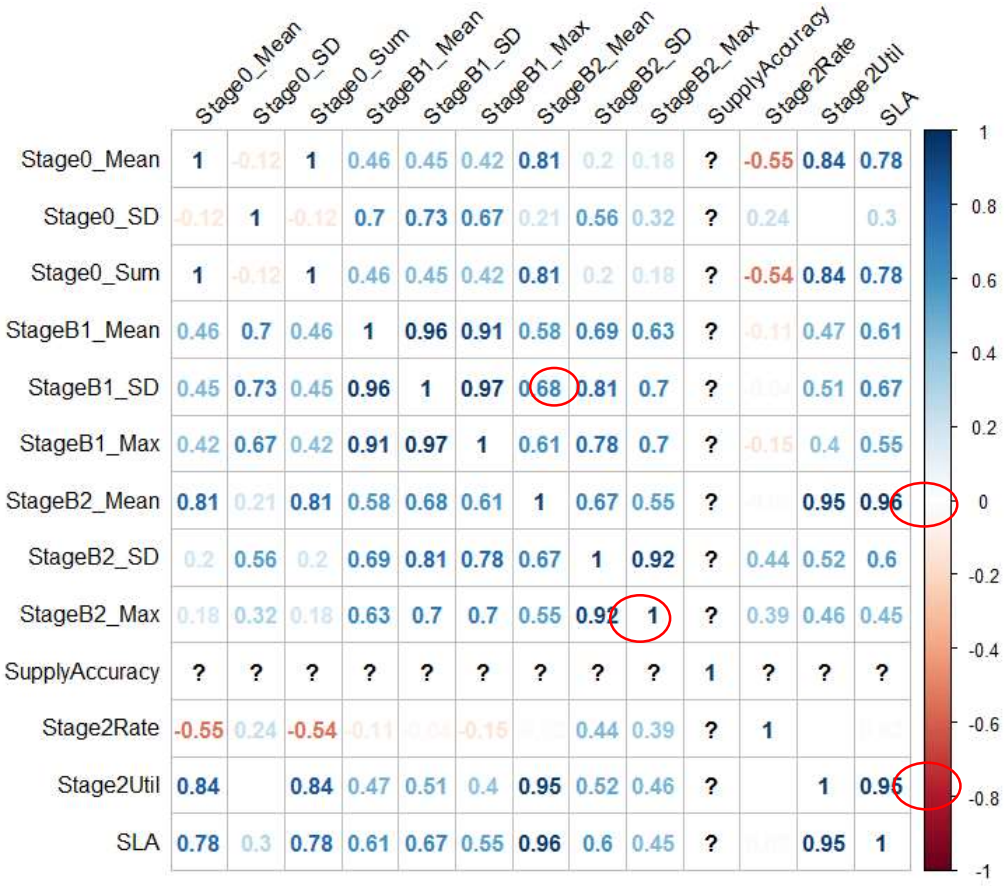

Figure 4.3 – Correlation - Original Data Simulated for 1-Day period

The results shown in Table 4.1, considered current production from different averages and daily supply volumes. Thus, under identical supplied volumes an analysis is required in order to evaluate the impact of supply delivery on the overall performance metrics. The main objective is to investigate at what extent extra volumes improve the SLA metric.

4.4.2. Investigating Supply Distributions under Identical Volumes

The behaviour of each production day previously simulated in Table 4.1 is then replicated under identical supply volumes. In addition, CIP cycles are also considered under identical conditions. Each day has a steady increase in the volume supplied and the impact on the overall performance metrics is examined.

The traditional conflicting metrics investigated for pull-type PCS in section **2.8 - Production Control Strategies** such as **Average WIP** and **SLA** is shown in Figure 4.4. This figure presents individual graphs for each volume supplied, starting at 53.57 lots and gradually increasing by 3.57 lots. Through this graph, two essential observations must be highlighted:

1) As suggested in the correlation between **Stage B2 Mean %** and **SLA**, by increasing the average WIP at **Stage B2** an increase in **SLA** is observed; however, this trade-off is restrictive since the average WIP volume is limited by up to 30% capacity utilisation on average.

2) Day 1 shows a higher performance for volumes lower than 60.71 lot sizes while day 3 has improved performance for volumes higher than 60.71 lot sizes. Day 6 performed poorly for the majority of the volumes lower than 75 lots.

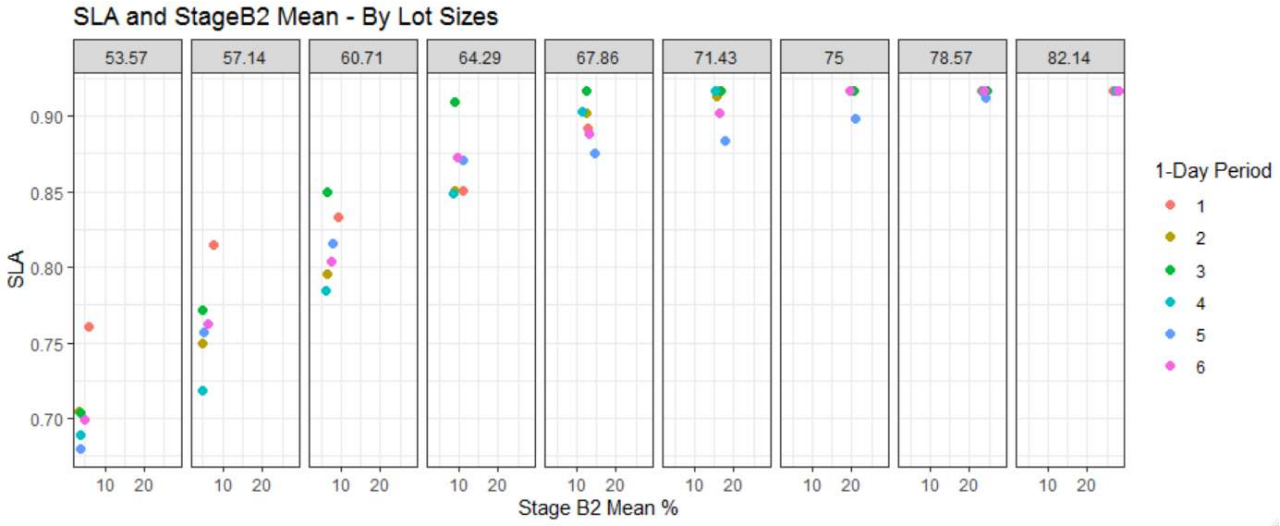

Figure 4.4 –WIP average - Stage B2 and SLA

Figure 4.5 presents the relationship between the computed metrics **Stage B2 Max%** and **SLA**. In this graph, three valuable pieces of information are elucidated:

1) Even though **Stage B2 Mean %** is maintained below 30% for all lot sizes, as shown in Figure 4.4, **Stage B2 Max %** achieved a higher silo capacity utilisation as shown in Figure 4.5.
2) Supply volumes higher than 75 lot sizes, as observed in periods 1, 2 and 4, for example, did not improve **SLA** performance but increased the inventory level.
3) A high level of variability is observed for volumes below 67.86 lot sizes, providing evidence that the supply distribution would influence the **SLA**.

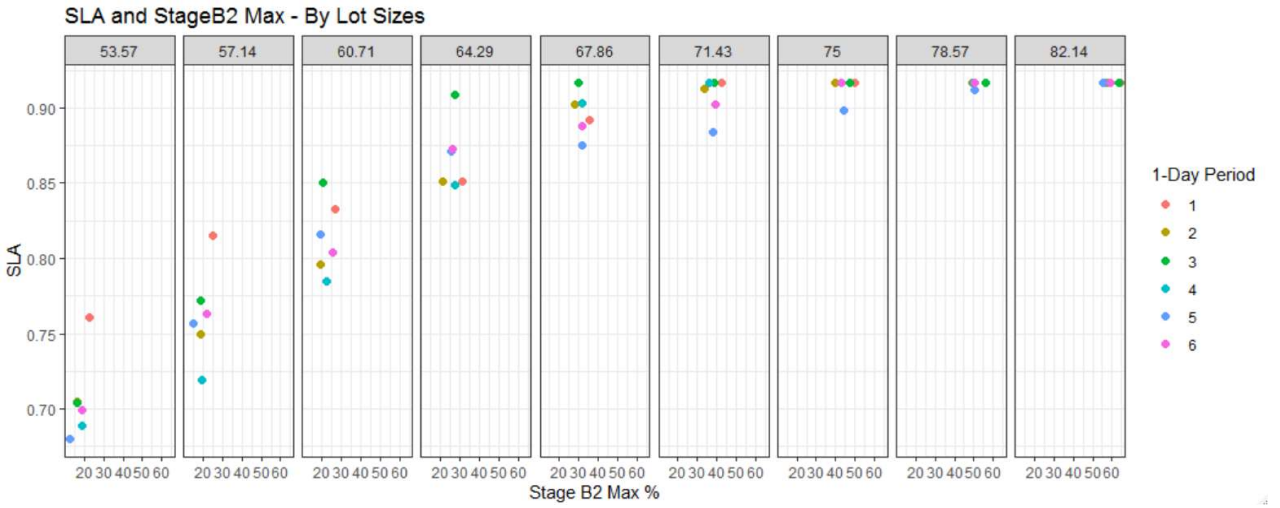

Figure 4.5 –Maximum WIP - Stage B2 and SLA

As observed for both measures **Stage B2 Mean %** and **Stage B2 Max %,** despite the same volume supplied and intermediate buffer capacities, the variability identified in each period impacts the **SLA** metric. In addition, by comparing metrics **Stage B2 Mean %** and **Stage B2 Max %** traditionally sought by [168], [184], [216]–[218] must be investigated in the bulk powder environment.

For all simulated scenarios, the Supply Accuracy metric reached 100%, indicating that the total volume planned was authorised and processed by the system. However, the simulation experiments considered a unique day and no initial inventory was added. The effect of extra volumes produced by more than one day period must be fully explored.

4.4.3. Selecting 3 Supply Periods for the Control Groups

Complementing the previous analysis of the impact of supply variability on dairy performance metrics, three periods of 5 days were replicated into identical supply levels and CIP cycle times in order to create the control group for further comparison.

The first investigation consists of evaluating the level of variability of three different groups of 5-day periods provided by the Industrial Partners. The boxplot graph in Figure 4.6 illustrates all 5-day periods and the volume of raw material supplied. As observed, each day presents distinct maximum limits and median. In addition, extra outliers for Period 3 are also observed. The values for each period are summarised in Table 4.2.

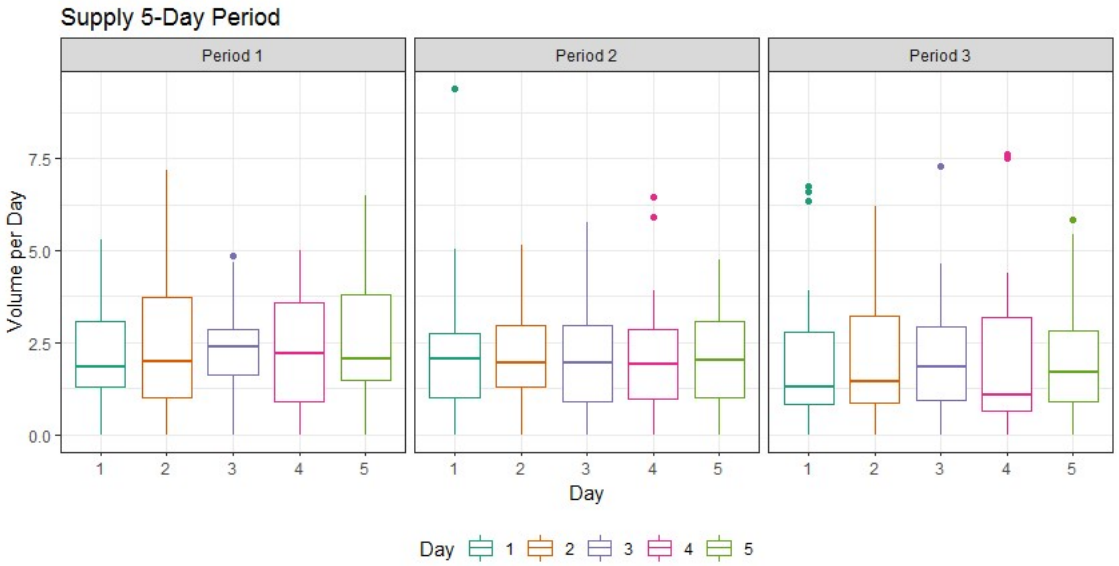

Figure 4.6 – Volume of Milk Supplied in Lots per day - 5-day Period – Original Data

Table 4.2 - Volume of Supply 5 in Lots per Period - 5-day Period - Summary

Period	Mean	SD	Min	Max	CV	Skewness	Most Likely Statistic Distribution (Density Function)	Rank
1	2.615	1.483	0.156	7.194	0.567	0.678	Johnson SB(-2.99e+003, 2.52e+005, 1.12, 1.15)	97.2
2	2.351	1.478	0.190	9.406	0.629	1.492	Weibull(1.58e+003, 1.65, 7.21e+004)	67.1
3	2.402	1.782	0.090	7.621	0.742	1.149	Inverse Gaussian(-1.57e+004, 2.1e+005, 8.3e+)	72.5

Figure 4.7 illustrates the distribution in an aggregated form in order to examine the statistical significance among the three selected periods. In the boxplot, the aggregated values are observed while in the second graph the average -/+ (3sd) shows similar distributions.

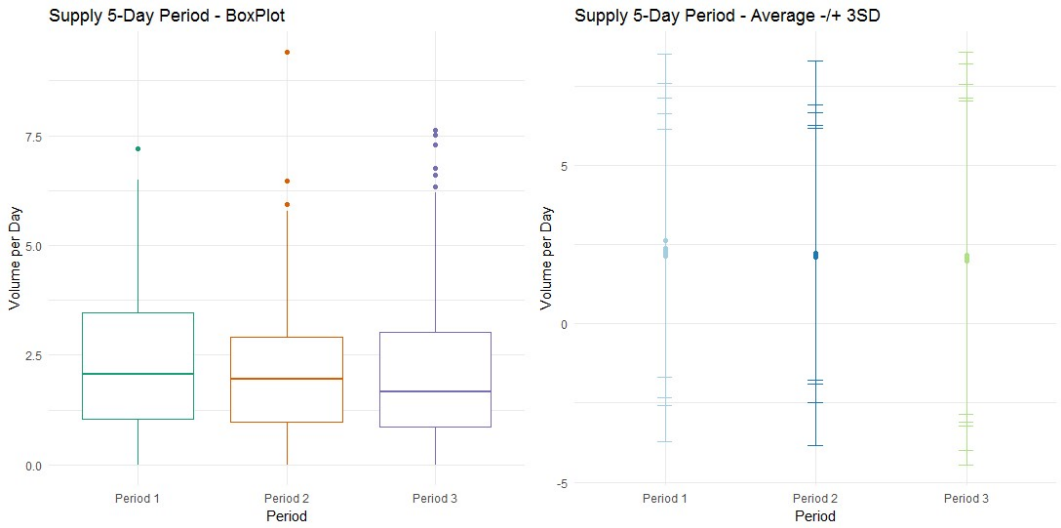

Figure 4.7 – Supply 5-day Period – Boxplot

By increasing the sample size to 120 observations, which refers to 120 hours simulated, the normality assumption was initially expected which would facilitate the identification of a distribution curve for supply volume deliveries. However, as previously observed in Figure 4.7 and in the QQ-plot shown in Figure 4.8, the evidence that the data is not normally distributed is presented.

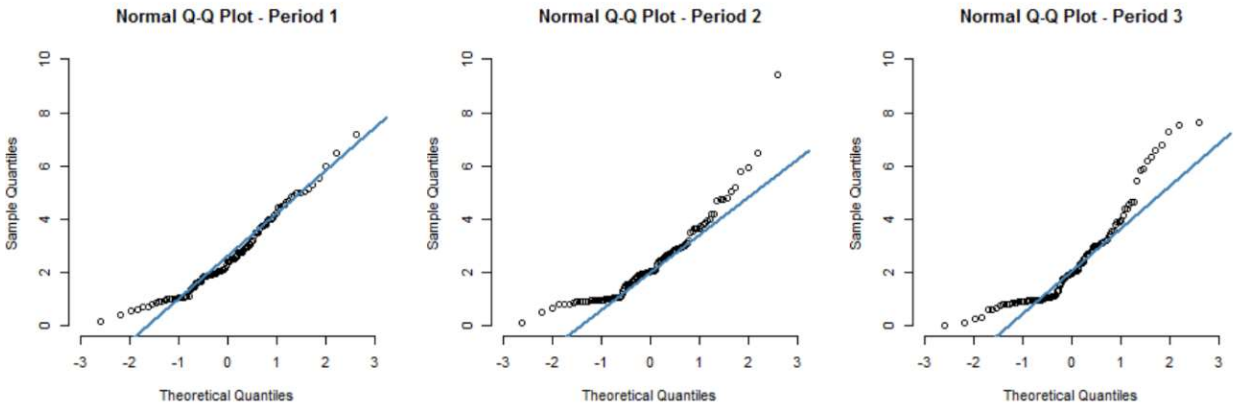

Figure 4.8 – Supply 5-day Period – Normal QQ-Plot

Two normality tests were performed through the SPSS software package in order to complement the visual analysis presented in Figure 4.8 and to confirm whether or not the periods are from a normally distributed population. Kolmogorov-Smirnov (KS) test quantified the distance between the empirical distribution (all three periods) and a normal distribution based on a frequency while the Shapiro-Wilk (SW) [219] test computes the difference according to the rank or position of the data [220]. Both tests KS and SW, returned a p-value less than ($p<0.05$) as shown in Table 4.3, providing evidence that the periods are not normally distributed.

Table 4.3 – Kolmogorov-Smirnov and Shapiro-Wilk - Normality Tests

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Period1	.127	89	.001	.948	89	.001
Period2	.125	89	.002	.886	89	.000
Period3	.135	89	.000	.890	89	.000

a. Lilliefors Significance Correction

Outliers are usually the main cause of bias and some techniques are suggested by [220] to reduce the potential source of bias including but not limited to trimming, winsorizing and transforming. However, all outliers identified in this production environment correspond to the real supply delivery and cannot be ignored in this analysis. It must be understood and properly managed.

The data and the code programmed in Rstudio to conduct this analysis and illustrated in Figure 4.7 and Figure 4.8 are available respectively in **Appendices F.1 - Supply Volumes per Day** and **F.2 – 5-Day Supply Validation – Rstudio Algorithm Graphs.**

4.4.4. Simulating 3 Periods - Examining the impact of CIP variability on downstream processes

The aim of this section is to evaluate the impact of combining the supply distribution frequency and variability on the downstream manufacturing flow; stages 1, 2 and 3. The simulation consists of replicating the three periods previously defined in section 4.4.3 and examining the impact CIP variability as follows:

1. Type 1 - Stochastic CIP and Supply: CIP cycle-time interruptions and supply variability at all stages.
2. Type 2 - Stochastic Supply : events exclusively at the supply stage.

In the stages previously presented in Figure 3.9 –Stages in Dairy Manufacturing, a triangular probability distribution was incorporated as shown in Table 4.4. Stage 0 is not presented in this table since no CIP is considered at this stage.

For all other stages, the parameters are referred to as minimum, most likely and maximum hours for CIP, respectively. The triangular distribution is commonly used when the data is restrictive. The method consists of deriving the geometric argument involving triangles [221]. The values are defined according to the current policies at the Industrial Partners investigated.

Table 4.4 – CIP Variability - Probabilities for each stage

Event	Stage (s,S)	Probability	Unit
$C_{s^{min}}$	2	Triangular (1.5,2,2.5)	Hours
$R_{s^{max}}$	2	Triangular (8,9,10)	Hours
$C_{s^{min}}$	3	Triangular (2.5,3,4)	Hours
$R_{s^{max}}$	3	Triangular (30,32,35)	Hours
$C_{s^{min}}$	4	Triangular (8,10,12)	Hours
$R_{s^{max}}$	4	Triangular (70,72,75)	Hours

All three periods were replicated for the following lot-sizes: 53.57, 57.14, 60.71, 64.29, 67.86, 71.43, 75.00, 78.57 and 82.14. The impact of CIP variability on WIP and SLA performance at stages B1 and B2 is illustrated in Figure 4.9. The SLA is slightly impacted by the CIP variability, however the results are intensified when combined with the supply deliveries as observed in **Period 3 – Stage B1 Max% - SLA**.

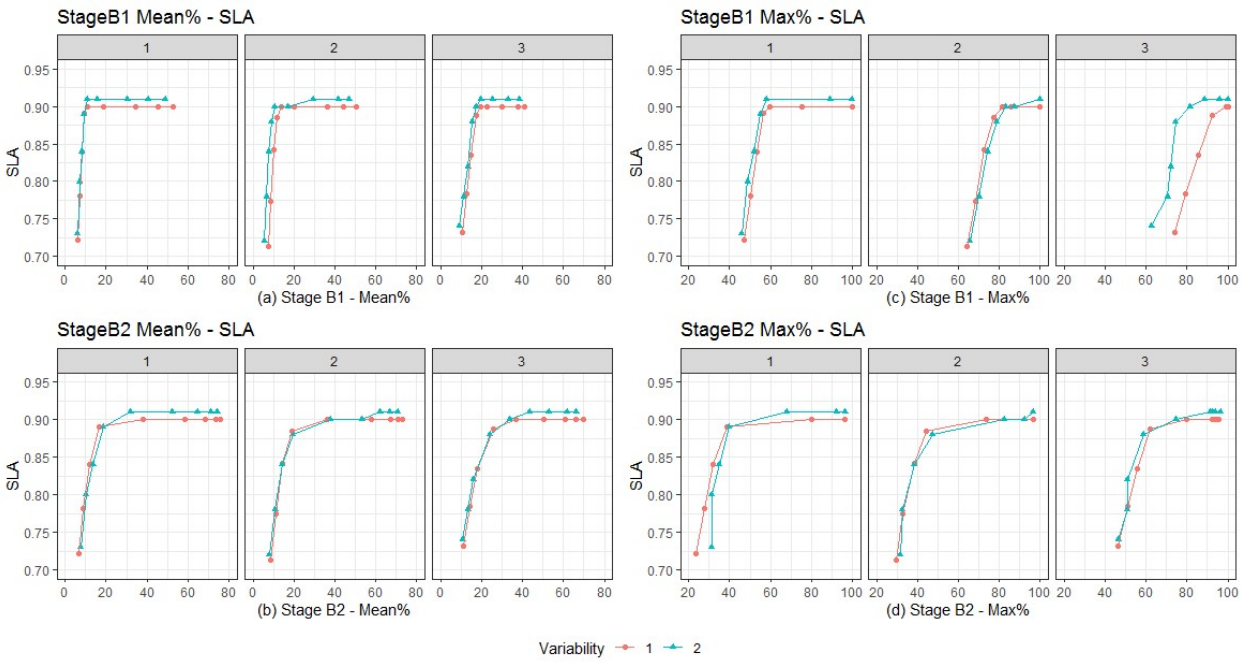

Figure 4.9 – The impact of CIP variability on WIP and SLA performance

Through Figure 4.9 it is possible to observe that SLA performs slightly higher when solely the supply variability is considered. Periods 1 and 2 perform equally for both levels of variability. In period 3, the desirable **SLA** has not reached a WIP level lower than 100% storage capacity utilisation at stage 1.

In conclusion, the CIP cycle-time incorporated at all manufacturing stages contributes to a significant impact on WIP levels when combined with stochastic volume supplied distributions. The following steps consist of creating a control group for implementing the pull-type PCS based on variability type 1 where both stochastic events are considered.

The data corresponding to variability type 1 is shown in Table 4.5, Table 4.6 and Table 4.7 for periods 1,2 and 3, respectively. Table 4.5 shows SLA performance improving according to the volume supplied. However, for volumes higher than 67.86 lot sizes no improvements in the overall metrics are observed.

Table 4.5 - Data Simulated for Period 1

Lot	Stage0 Mean	Stage0 SD	Stage0 Sum	StageB1 Mean	StageB1 SD	StageB1 Max%	StageB2 Mean%	StageB2 SD%	StageB2 Max%	Supply Accuracy	SLA	Separation Rate	Stage2 Util
53.57	2.23	1.54	267.86	5.37	9.28	37.75	6.77	7.17	27.58	1.00	0.72	1.00	0.58
57.14	2.38	1.64	285.71	6.21	10.33	40.27	9.66	8.39	33.47	1.00	0.78	1.00	0.61
60.71	2.53	1.74	303.57	7.22	11.47	42.79	14.09	9.45	39.35	1.00	0.84	1.00	0.65
64.29	2.68	1.85	321.43	8.41	12.71	47.11	20.65	10.63	45.23	1.00	0.88	1.00	0.69
67.86	2.83	1.95	339.29	9.89	13.99	54.37	38.39	16.71	72.66	1.00	0.90	1.00	0.73
71.43	2.96	2.05	355.08	16.94	19.66	88.23	59.13	25.64	93.88	0.99	0.90	0.98	0.74
75.00	2.96	2.15	355.29	30.36	26.72	100.00	69.13	25.52	96.46	0.95	0.90	0.97	0.74
78.57	2.96	2.20	355.67	38.97	29.14	100.00	74.27	24.44	96.46	0.91	0.90	0.97	0.74
82.14	2.97	2.25	356.00	46.76	28.30	100.00	76.69	22.97	96.46	0.87	0.90	0.97	0.74

In Table 4.6, the same behaviour is observed. SLA performance improves according to the volume supplied and for volumes higher than 67.86 lot sizes no improvements in the overall metrics are observed.

Table 4.6 - Data Simulated for Period 2

Lot	Stage0 Mean	Stage0 SD	Stage0 Sum	StageB1 Mean	StageB1 SD	StageB1 Max%	StageB2 Mean%	StageB2 SD%	StageB2 Max%	Supply Accuracy	SLA	Separation Rate	Stage2 Util
53.57	2.23	1.59	267.86	5.85	10.83	43.35	6.92	7.46	30.22	1.00	0.71	1.00	0.58
57.14	2.38	1.69	285.71	6.79	12.12	48.10	9.62	8.74	36.75	1.00	0.78	1.00	0.61
60.71	2.53	1.80	303.57	7.82	13.50	52.85	13.36	9.95	43.29	1.00	0.84	1.00	0.65
64.29	2.68	1.91	321.43	9.11	15.03	57.60	19.52	11.46	49.82	1.00	0.89	1.00	0.69
67.86	2.83	2.01	339.29	10.57	16.73	62.34	37.77	18.26	73.41	1.00	0.90	1.00	0.73
71.43	2.95	2.14	354.27	16.52	22.55	100.00	58.59	27.15	95.67	0.99	0.90	0.98	0.74
75.00	2.95	2.22	353.68	32.59	27.62	100.00	68.16	27.90	96.46	0.94	0.90	0.98	0.74
78.57	2.95	2.23	354.38	44.48	31.31	100.00	71.89	26.87	96.46	0.90	0.90	0.97	0.74
82.14	2.96	2.23	354.91	50.01	30.35	100.00	74.28	25.81	96.46	0.86	0.90	0.97	0.74

Ultimately, in Table 4.7 SLA stops improving for supply volumes higher than 67.86. This period requires more WIP at both stages when compared to periods 1 and 2.

Table 4.7 - Data Simulated for Period 3

Lot	Stage0 Mean	Stage0 SD	Stage0 Sum	StageB1 Mean	StageB1 SD	StageB1 Max%	StageB2 Mean%	StageB2 SD%	StageB2 Max%	Supply Accuracy	SLA	Separation Rate	Stage2 Util
53.57	2.23	1.98	267.86	7.39	12.63	50.62	10.92	11.81	46.51	1.00	0.73	1.00	0.58
57.14	2.38	2.12	285.71	9.18	14.45	55.85	14.07	12.92	50.76	1.00	0.78	1.00	0.61
60.71	2.53	2.25	303.57	11.39	16.75	61.71	17.99	13.69	51.85	1.00	0.84	1.00	0.65
64.29	2.68	2.38	321.43	13.96	19.57	69.98	25.78	14.30	58.89	1.00	0.88	1.00	0.69
67.86	2.81	2.48	337.27	16.50	21.95	72.12	36.82	17.95	70.32	0.99	0.89	1.00	0.72
71.43	2.93	2.55	351.15	20.08	23.50	79.04	54.42	25.16	92.42	0.98	0.90	0.99	0.75
75.00	2.99	2.61	358.14	28.35	29.65	100.00	64.40	26.07	96.46	0.96	0.90	0.97	0.74
78.57	2.99	2.61	359.27	37.14	32.53	100.00	68.83	24.92	96.46	0.92	0.90	0.96	0.74
82.14	2.99	2.73	359.04	41.23	34.22	100.00	72.27	23.70	96.46	0.87	0.90	0.96	0.74

Additionally, in the results presented, the Supply Accuracy index varies according to the period simulated, highlighting divergences between the material planned and authorised. Supply Accuracy is decreasing which indicates that the planned supplied volumes are not being completely processed into the system.

This performance index also represents the effect of trucks queueing before the weighing process. The weighing process occurs before the raw material test and reception. The decision to accept extra raw material compromises not only the storage silo capacity, but also the entire downstream processes.

The rejection of raw material due to the lack of capacity at the first stage is also often presented in real processes. The added value of raw milk is lower when compared to the processed WIP, which has received special processing and temperature treatment. Thus, the decision to transfer the extra raw material between dairies is a common practice in this sector as previously described in section **3.2- DPTC Dairy Industrial Partners – Case** Studies**.**

The same presented in Table 4.5 to Table 4.7 is also depicted in Figure 4.10. The graphs illustrate the WIP level for both stages 1 and 2 showing the moment when SLA reaches the maximum desired result.

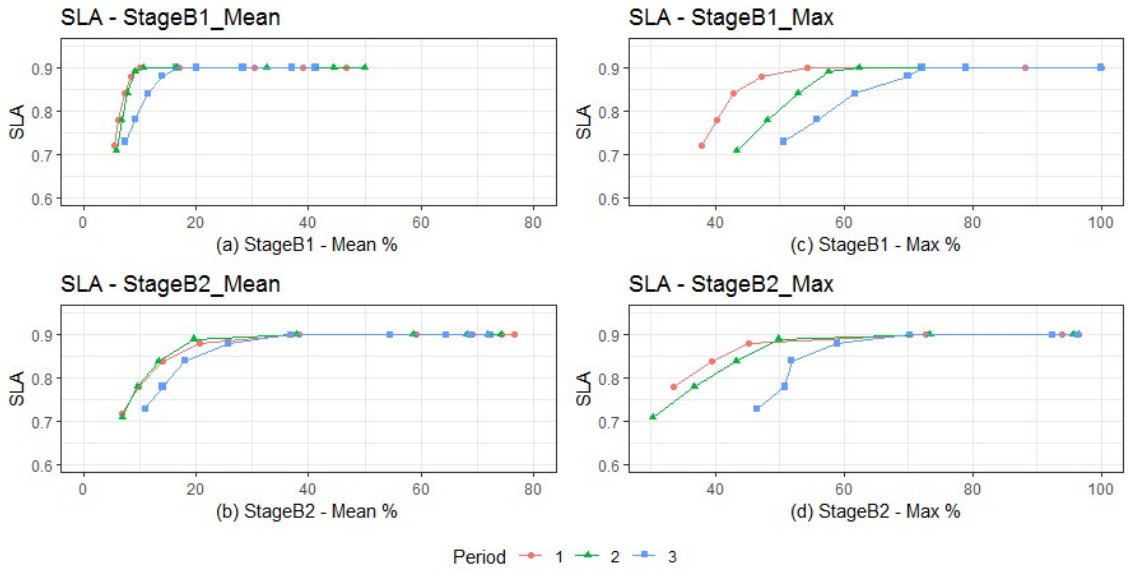

Figure 4.10 – SLA Results simulated Periods 1,2 and 3

Periods 1 and 2 require 10% WIP average at stage B1 to reach the desired SLA. For stage B2, the average for all three periods behaves similarly. However, by analysing the maximum WIP level reached by stages B1 and B2, it is noticed that the first period reaches an improved performance by storing less than 60% of silo capacity while periods 2 and 3 require more than 70% of silo capacity at stage B2 whereas stage B1 requires more than 70% of silo capacity for all three periods.

An additional comparison for equipment utilisation at **Stage2** and **SLA** metrics is shown in Figure 4.11. Despite increasing equipment utilisation, the SLA is improved at a certain level, after reaching 70% of utilisation no enhancements in SLA metric is observed. This stage often presents a higher processing time and it is the main process responsible for the consumption of water and energy owing to the CIP cycle times.

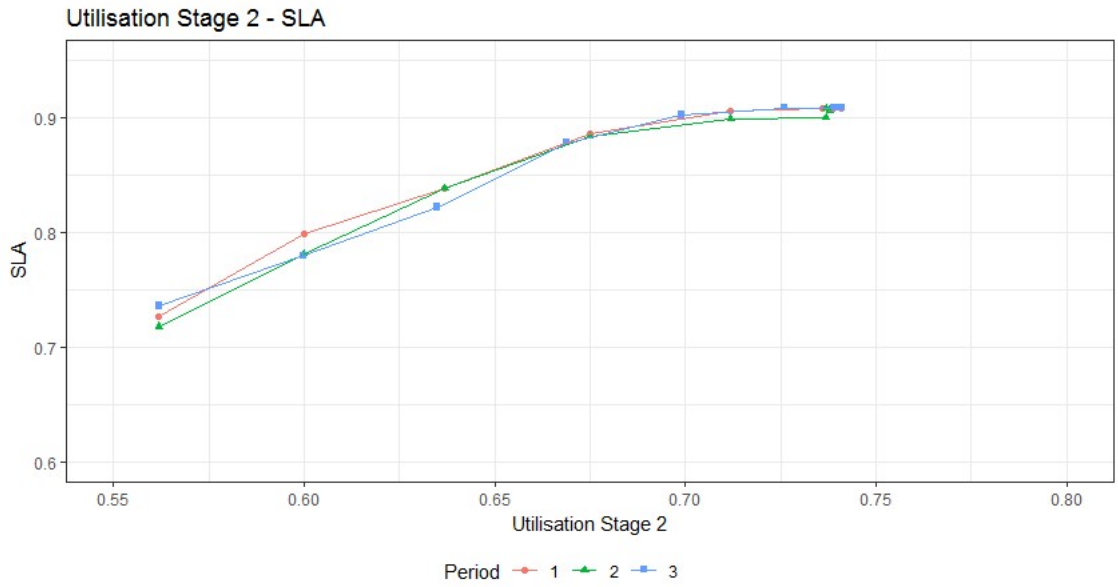

Figure 4.11 – SLA and Stage 2 Utilisation

4.5. Exploring push and pull systems in dairy manufacturing

As evidenced in the literature review presented in Chapter 2, in a pull-type PCS, three mechanisms for controlling the production manufacturing must be considered as stated by Liberopoulos [168]: (i) how the raw part arrivals are controlled, (ii) how the authorisation between stages is managed, and (iii) whether the system is responding to actual demands. This section examines these three assumptions with respect to dairy bulk powder manufacturing challenges.

The main objective of this section for this research is to fully comprehend the concept of push and pull systems and investigate in which conditions such systems are suitable for dairy bulk powder manufacturing. Table 4.8 presents the behaviour of a push system as illustrated in Figure 2.15. The condition was adapted for dairy manufacturing stages where the Supply Authorisation is referred to as Stage_1 which is limited by the WIP capacity at Stage_1.

The volumes are standardised into lot-sizes and Stage_2 processes 9 lots per hour while the main bottleneck has a lower capacity of 7 lots at Stage_3. The demand is 7 lots and all three examples receive the same amount of raw material in order to emphasise the implications on dairy manufacturing.

No initial inventory is considered in period $(h-1)$. This situation is also observed during medium and off seasons and demonstrates the impact of supply variability on the entire process. Period *h* receives 12 lots, which are sent directly to Stage_1 to be separated. Wip_Stage_{Bs} Columns reflect WIP levels stored in the silos. In the first hour, the SLA was reached; however, the WIP level Wip_Stage_{B2} starts increasing due to the push system behaviour.

Table 4.8 – System 1 – Supply is pushed in the system to achieve the demand – no WIP control

SYSTEM 1 – Push - no CIP									
Period	Supply	Stage_1	Wip_Stage_{B1}	$Wip_{\text{Stage}_{B1}}/Capacity$	Stage_2	Wip_Stage_{B2}	$Wip_{\text{Stage}_{B2}}/Capacity$	Stage_3	SLA
$h-1$									
h	12.00	12.00	3.00	0.15	9.00	2.00	0.13	7.00	1.0
$h+1$	8.00	8.00	2.00	0.10	9.00	4.00	0.27	7.00	1.0
$h+2$	5.50	5.50	-	-	7.50	4.50	0.30	7.00	1.0
$h+3$	8.00	8.00	-	-	8.00	5.50	0.37	7.00	1.0
$h+4$	7.00	7.00	-	-	7.00	5.50	0.37	7.00	1.0
$h+5$	3.00	3.00	-	-	3.00	1.50	0.10	7.00	1.0
$h+6$	6.00	6.00	-	-	6.00	0.50	0.03	7.00	1.0
Total	**49.50**	**49.50**	**-**	**0.04**	**49.50**	**0.50**	**0.22**	**49.00**	**1.0**

In a push system, the production initialises independently of current demands and the WIP is not controlled. Therefore, despite the assumption that production is initialised to achieve contracts as observed in the dairy environment, this assumption is not sufficient in defining a pull system.

In the second example, the system is controlled by the final stage Stage_3 as demonstrated in Table 4.9. In this example, the supply is driven by demands and the rate of supply was set equally to the demand rate. The supply is controlled and limits to the system are set. The variability heavily impacts demand fulfilment. In this case, only 7 lots are authorised to the system and it is clear a level of WIP is required to absorb the stochastic behaviour observed in the supply side, otherwise the SLA is impacted by insufficient raw material.

Table 4.9 –System 2 – Demand is controlled for finished goods and Supply – no WIP control

SYSTEM 2 – Pull – no CIP – no WIP									
Period	Supply	Stage_1	Wip_Stage_{B1}	$Wip_{\text{Stage}_{B1}}/Capacity$	Stage_2	Wip_Stage_{B2}	$Wip_{\text{Stage}_{B2}}/Capacity$	Stage_3	SLA
$h-1$									
h	12.0	7.00	-	-	7.00	-	-	7.00	1.00
$h+1$	8.00	7.00	-	-	7.00	-	-	7.00	1.00
$h+2$	5.50	5.50	-	-	5.50	-	-	5.50	0.79
$h+3$	8.00	7.00	-	-	7.00	-	-	7.00	1.00
$h+4$	7.00	7.00	-	-	7.00	-	-	7.00	1.00
$h+5$	3.00	3.00	-	-	3.00	-	-	3.00	0.43
$h+6$	6.00	6.00	-	-	6.00	-	-	6.00	0.86
Total	**49.**	**42.50**	**-**	**-**	**42.50**	**-**	**-**	**42.50**	**0.87**

The objective here is to initially investigate the current operations and the drawbacks of implementing a simplified pull system in this environment, as presented in Table 4.10. The system allows some level of inventory at stage 1 where it is possible to observe that the level of WIP supports the SLA or demand fulfilment.

Table 4.10 –System 3 – Demand and Supply controlled – WIP is controlled

SYSTEM 3 – Pull – WIP control									
Period	Supply	Stage_1	Wip_Stage_{B1}	$Wip_{\text{Stage}_{B1}}$ /Capacity	Stage_2	Wip_Stage_{B2}	$Wip_{\text{Stage}_{B2}}$ /Capacity	Stage_3	SLA
$h-1$									
h	12.0	12.00	5.00	0.25	7.00	-	-	7.00	1.00
$h+1$	8.00	8.00	6.00	0.30	7.00	-	-	7.00	1.00
$h+2$	5.50	5.50	4.50	0.23	7.00	-	-	7.00	1.00
$h+3$	8.00	8.00	5.50	0.28	7.00	-	-	7.00	1.00
$h+4$	7.00	7.00	5.50	0.28	7.00	-	-	7.00	1.00
$h+5$	3.00	3.00	1.50	0.08	7.00	-	-	7.00	1.00
$h+6$	6.00	6.00	0.50	0.03	7.00	-	-	7.00	1.00
Total	**49.5**	**49.50**	**0.50**	**0.20**	**49.00**	**-**	**-**	**49.00**	**1.00**

A summary comparing all three systems is presented in Table 4.11. It is possible to observe that an inefficient production control creates an unstable manufacturing environment. In a push system as performed by System 1, the WIP at Stage_2 increases the risk of perishability as described in sections **2.4.1 - Milk Reception and Storage** and **2.4.3 - Separation**. An ideal condition is presented by System 3, where at different stages, the supply variability is mitigated by the intermediate WIP at Stage_1. Nevertheless, no disruptions caused by CIP cycle-times were incorporated into this simplified example.

Table 4.11 – System Results – Summary

	Units	System 1	System 2	System 3
Total Supply	lots	49.50	49.50	49.50
Total Stage1	lots	49.50	42.50	49.50
Total Stage2	lots	49.00	42.50	49.00
Supply Accuracy		1.00	0.86	1.00
SLA		1.00	0.87	1.00
WIP/Cap StageB1 (Average)		0.04	-	0.20
WIP/Cap StageB2 (Average)		0.22	-	-
CIP cycle-time	hours	-	-	-

Keeping the sequence simplified, an example considering CIP times at Stage 2 is demonstrated in Table 4.12 where system 3 fails to maintain the same performance results.

Table 4.12 –System 3 – Demand and Supply controlled – WIP Stage1 and CIP Times

SYSTEM 3 – CIP at times h+3 and h+4									
Period	Supply	Stage_1	Wip_Stage_{B1}	$Wip_{\text{Stage}_{B1}}$ /Capacity	Stage_2	Wip_Stage_{B2}	$Wip_{\text{Stage}_{B2}}$ /Capacity	Stage_3	SLA
$h-1$									
h	12.00	12.00	5.00	0.25	7.00	-	-	7.00	1.0
$h+1$	8.00	8.00	6.00	0.30	7.00	-	-	7.00	1.0
$h+2$	5.50	5.50	4.50	0.23	7.00	-	-	7.00	1.0
$h+3$	8.00	8.00	5.50	0.28	CIP	-	-	-	-
$h+4$	7.00	7.00	5.50	0.28	CIP	-	-	-	-
$h+5$	3.00	3.00	1.50	0.08	7.00	-	-	7.00	1.0
$h+6$	6.00	6.00	0.50	0.03	7.00	-	-	7.00	1.0
Total	**49.50**	**49.50**	**0.50**	**0.20**	**35.00**	**-**	**-**	**35.00**	**0.7**

A controlled level of inventory at Stage_2 mitigates the material unavailability caused by this disruption as shown in Table 4.13.

Table 4.13 - System 3 – Demand and Supply controlled – WIP Stage2 and CIP Times

SYSTEM 3 – CIP at times h+3 and h+4									
Period	Supply	Stage_1	Wip_Stage_{B1}	$Wip_{\text{Stage}_{B1}}/Capacity$	Stage_2	Wip_Stage_{B2}	$Wip_{\text{Stage}_{B2}}/Capacity$	Stage_3	SLA
$h-1$									
h		12.00	3.00	0.15	2.00	0.13		7.00	1.00
$h+1$	8.00	8.00	2.00	0.10	4.00	0.27		7.00	1.00
$h+2$	5.50	5.50	-	-	4.50	0.30		7.00	1.00
$h+3$	8.00	8.00	8.00	0.40	CIP	-		4.50	0.64
$h+4$	7.00	7.00	15.00	0.75	CIP	-		-	-
$h+5$	3.00	3.00	11.00	0.55	-	-		7.00	1.00
$h+6$	6.00	6.00	10.00	0.50	-	-		7.00	1.00
Total		**49.50**	**10.00**	**0.35**	**-**	**0.10**		**39.50**	**0.81**

In both examples, periods $(h+3)$ and $(h+4)$ are stopped in order to run the CIP for 2 hours impacting on the SLA performance. Even though the SLA was decreased due to the CIP times in these examples it is possible to observe that some level of WIP at Stage_2 is essential to maintain the production flow as shown in Table 4.14.

Table 4.14 – System Results – CIP Times

	Units	System 3 – Wip_Stage_{B1}	System 3 – Wip_Stage_{B2}
Total Supply	lots	49.50	49.50
Total Stage1	lots	49.50	49.50
Total Stage2	lots	35.00	39.50
Supply Accuracy		1.00	1.00
SLA		0.71	0.81
WIP/Cap StageB1 (Average)		0.20	0.35
WIP/Cap StageB2 (Average)		-	0.10
CIP cycle	hours	2.00	2.00

Following the same strategy of maintaining WIP at Stage_{B1} and Stage_{B2} levels independently, and in addition, by combining the CIP schedule, a final comparison was performed in order to comprehend the impact of CIP starting at different periods. This example demonstrates the most challenging aspect of dairy manufacturing.

As observed in Table 4.15, the CIP schedule has a significant impact on SLA performance. In this table, 2 hours for CIP were considered several times. In schedule 1, for example, CIP cycle starts at hour h. Other metrics are also impacted by CIP cycles such as the Utilisation. The ideal scenario for this case is performed by Schedule number 5 where an improved SLA performance is achieved and the WIP is controlled at both stages: Stage 1 and Stage 2.

Table 4.15 – PCS Results – CIP Times (MTTR) and Starting Time (MTBF)

Schedule CIP Starts (Stage 1)	1 h *to* $h+1$	2 $h+1$ *to* $h+2$	3 $h+2$ *to* $h+3$	4 $h+3$ *to* $h+4$	5 $h+4$ *to* $h+5$	6 $h+5$ *to* $h+6$
Total Supply	49.50	49.50	49.50	49.50	49.50	49.50
Total Stage1	49.50	49.50	49.50	49.50	49.50	49.50
Total Stage2	35.00	37.00	39.00	39.50	40.50	40.50
Supply Accuracy	1.00	1.00	1.00	1.00	1.00	1.00
SLA	0.71	0.76	0.80	0.80	0.83	0.83
WIP/Cap StageB1 (Average)	0.64	0.51	0.38	0.31	0.21	0.12
WIP/Cap StageB2 (Average)	0.29	0.21	0.17	0.16	0.17	0.20
CIP cycle	2.00	2.00	2.00	2.00	2.00	2.00
Utilisation Stage1	0.71	0.71	0.71	0.69	0.67	0.64

This analysis is imperative for this research in understanding the impact of production strategies combining the accomplishment of mandatory CIP cycle-times. Three major stochastic events must be managed in Dairy Manufacturing:

- Supply Variability in volumes and frequencies
- CIP times: Mean Time-to-Repair (MTTR) or Cleaning Time and Mean Time Between Failure (MTBF) or Time Between Cleaning
- Independent level of WIP for each manufacturing stage

4.6. Modelling pull-type PCS for Dairy Manufacturing

Markov Decision Process (MDP) has been widely applied in manufacturing systems such as analytical models with multiple product classes [222], WIP level control for Discrete Event Models (DEM) [223] and pull-type PCS in DEM models as adopted by [224] to represent the actions and the states of the manufacturing system.

Thus, a similar approach was adapted for dairy manufacturing processes to represent each stage in the continuous flow, an MDP model requires 4-tuples (S,A,P_a, R_a) as follows:

(i) S is a finite set of states,

(ii) A is a finite set of actions available from state S,

(iii) P_a is the probability that action A in stage S at time t will lead to stat s' at time $t+1$. $P_a(s,s') = Pr(st+1 = s' | st = s, at = a)$,

(iv) R_a is the immediate reward after transitioning from stage s to state s', according to action A.

Similar to [224] the production trigger, production objective and the actual production quantity for each stage were calculated and described as follows:

I. The production trigger is the amount of milk to be processed to achieve the customer demand. From the Supply Chain perspective, the production trigger is responsible for balancing outbound and inbound processes flow based on the forecasted or actual demand.

II. The production objective is the amount of milk that the stage is capable of producing according to the production trigger, maximum production capacity, and the inventory levels responsible for balancing inbound processes.

III. The production quantity is the amount of milk processed by each stage according to the production objective and production reliability; CIPs and downtimes.

In an MDP model, stochastic events increase the system variability and the majority of models explored considered demand as a probabilistic event. In the dairy bulk powder manufacturing production flow, several sources of stochastic events were verified. Thus, in order to facilitate the modelling process, a discrete interval for processing time and quantities was adopted. However, an important consideration in comparison to the MDP model studied relies on the fact that the WIP is transformed from a liquid into powder form. Therefore, a unit of measure conversion is required for the model at different stages. Table 4.16 provides the notation used.

Table 4.16 - Notation in MDP models modified to accomplish dairy manufacturing processes

Notation	Description
s	Production stage where 1 ≤ s ≤ S
P_s	Production centre at stage s
h, H	Production period in hours where 1 ≤ h ≤ H
D_{min}	The Minimum demand quantity
D_{max}	The Maximum demand quantity
D^h	The actual demand in period *h*
A_s^h	The production trigger for stage *s* in period *h*
PO_s^h	The production objective for stage *s* in period *h*
PA_s^h	Production Authorisation simplified for KCS, CONWIP, CONWIP/KCS, EKCS, BKCS for stage *s* in period *h*
$P_{s^{min}}$	The minimum production capacity of stage *s*
$P_{s^{max}}$	The maximum production capacity of stage *s*
P_s^h	Production quantity for stage *s* in period *h*
I_s	The output inventory of stage s
$I_{s^{max}}$	The maximum inventory capacity to store the production of stage *s*
I_s^h	Inventory held in the output buffer of production for stage *s* in period *h*
$\{B_s^h\}$	The set of inventories held in the output buffers of the immediate predecessors of stage *s* in period *h*
SI_s^h	The sum of inventories held in the output buffers of stages parallel to, but with stage number greater than, production stage *s*
K_s	The number of Kanbans allocated to production stage *s*
CC:	The cap on total inventory allowed in CONWIP and CONWIP/KCS
DC_s^h	Number of demand cards held at stage *s* in period *h* in BSCS and EKCS lines
IL_s	The initialization stock level for stage *s in* BSC and EKCS lines
$IL_{s^{min}}$	The minimum initialization stock level for s stage *s* in period *h* in BSCS and EKCS lines
U_s	Unit of Measure for stage s
$C_{s^{min}}$	The minimum time for CIP cycle for *s* stage
$R_{s^{max}}$	The maximum time running for *s* stage
R_s^h	Running hour *h* at stage *s*
R_s^h = $\begin{cases} 1, & \sum_{h=1}^{H} R_s^h \geq C_{s^{min}} \\ 0, & \sum_{h=1}^{H} R_s^h < C_{s^{min}} \end{cases}$	Subjected to $C_{s^{min}}$
R_s^h = $\begin{cases} 1, & \sum_{h=1}^{H} R_s^h < R_{s^{max}} \\ 0, & \sum_{h=1}^{H} R_s^h \geq R_{s^{max}} \end{cases}$	Subjected to $R_{s^{max}}$

4.6.1. Production of Each Stage for Dairy Manufacturing

A production flow considering a 3-stage system as previously presented in section **3.3 - Initial stages in Dairy Manufacturing - Generalisation** was modelled for the dairy bulk-powder environment. The production of stage s in period h, P_s^h relies on the interval $[P_{s^{min,}} P_{s^{max}}]$ and the maximum inventory capacity of stage *s* is $I_{s^{max,}}$ with stages as $s = \{1, \dots, S\}$. It is also impacted by the Unit of Measure U_s where the liquid form is converted according to this factor, thus $\mathrm{P_s^h}$ refers to the production yield converted at stage *s.*

The state transition process are determined in equations (4-10) and (4-11) as follows:

$$\mathrm{I_s^h} = \mathrm{I_s^{(h-1)}} + \mathrm{P_s^h} - \mathrm{P_{(s+1)}^h} \quad s = 1, \dots, S-1 \tag{4-10}$$

$$\mathrm{I_S^h} = \mathrm{I_S^{(h-1)}} + \mathrm{P_S^h} - \mathrm{D^h} \tag{4-11}$$

The inventory level of stage *s* in period *h* is denoted by I_s^h and the current stage *s* verifies the previous inventory stage represented by $I_{(s-1)}^h$. The constraints in the production stage *s* in period *h* are shown in equation (4-12) , where the component$(I_{s^{max,}} - I_s^h)$ limits the downstream processes according to the inventory level. In this case part of the equipment set processes the material which decreases or increases the processing capacity.

$$P_{s^{min,}} \ll P_s^h \ll \left\{P_{s^{max}}, I_{(s-1)}^h, I_{s^{max,}} - I_s^h\right\} \tag{4-12}$$

The production are limited by the capacity at $P_{s^{max}}$ stage, by the previous stage inventory $I_{(s-1)}^h$, and also by the kanban control $(I_{s^{max,}} - I_s^h)$.

4.6.2. Demand Uncertainty

The demand for dairy bulk powder commodities is based on contracts previously accorded by the customers, uncertainty for future demand is mitigated and the production is defined according to these contracts. However, some level of variability is expected when orders are cancelled, recall due to product quality specifications below the minimum acceptable requirements, rework at the production process, and new urgent demand occurs. However, due to the nature of the dairy bulk powder commodity sector, this variability was not incorporated into the model.

4.6.3. Notation for pull-type PCS

For a pull-type PCS, the notation follows the literature [224] where the term A_s^h is the production trigger for stage *s* in period *h.* $\mathrm{D^h}$ represents the demand in period *h*, and *SS* refers to the safety stock of the final product as presented in Equations (4-13)(4-14). The SS term originally explored in [224] was excluded from the model designed.

Considering the dynamic of dairy bulk powder production, during peak season all manufacturers operate at maximum capacity, so any extra volume produced to cover safety stock would be absorbed by the actual demand. Therefore, D^h+ SS is well represented solely by the demand term D^h. In addition, an appropriate control for WIP levels for intermediate stages replace the necessity of safety stock levels.

Considering the stage controlled by a pull control policy, the production trigger for the stage follows the equations:

$$A_s^h = max\left[P_{s^{min}}, I_{s^{max}} - I_s^h\right] \; s = 1,2,\dots,S-1 \tag{4-13}$$

$$A_S^h = max\left[P_{S^{min}}, D^h - I_S^{(h-1)}\right] \tag{4-14}$$

As demonstrated in section **4.4.2 - Investigating Supply Distributions under Identical Volumes,** the demand fulfilment is heavily impacted by the raw material availability and consequently by seasonality. During the peak season, the system flows according to the available capacity at the main bottleneck and some level of backlog must be managed. Conversely, during medium and off-season, the flow works below its plant capacity and the demand is managed according to previous contracts and raw material availability.

Therefore, the term ($I_{s^{max,}} - I_s^{(h-1)}$) in Equations (4-15) (4-16) at stage s differs for peak and off-season. This term is defined by the Kanban or, during the peak season, $I_{s^{max}}$ is also physically limited by the silo capacity. In addition, the production objective for stage s, given period h, is restricted by the CIP schedule R_s^h according to the following equations:

$$\mathrm{PO_S^h} = \min\left[\mathrm{A_s^h}, \left\{\mathrm{B_s^{(h-1)}}\right\}, P_{s^{max}}, \max\left[0, I_{s^{max}} - I_s^{(h-1)}\right]\right] \mathrm{R_S^h} \;\; \mathrm{s} = 1,2,\dots,\mathrm{S}-1 \tag{4-15}$$

$$\mathrm{PO_S^h} = \min\left[\mathrm{A_S^h}, \{\mathrm{B_S^{(h-1)}}\}, P_{S^{max}}, \max\left[0, I_{S^{max}} - I_S^{(h-1)}\right] + \mathrm{D^h}\right] \mathrm{R_S^h} \tag{4-16}$$

The term $\left\{\mathrm{B_s^{(h-1)}}\right\}$ might restrict the flow even during the peak season due to stochastic events such as unplanned disruptions. This term is also related to the packaging and chemical components required for each stage.

The term $\max[0, I_{s^{max}} - I_s^{(h-1)}]$ guarantees only positive numbers for WIP volumes. The variability observed during the chemical transformation of products at each stage might cause negative volumes at the subsequent stages. The separation of the whole milk into fat and skimmed milk for example.

4.6.4. Kanban Control Strategy

Figure 4.12 presents the KSC system adapted from Figure 2.17 especially to reflect the stages of one of the main production processes in the dairy bulk powder manufacturing environment where the inventory is represented by silos and is limited by its capacity. The transformation process occurs in each appropriate equipment, the flow is processed and its composition, density and even the physical form is changed.

In this example, the separation process is represented by S2 (Stage2) and the dryer process is represented by S3 (Stage3). The current volume being processed is represented by p, which refers to the volume of production. The inventory buffer B3 is where the total final products are stored to fulfil specific customer demand for this production line. B1 refers to the Raw milk Silos while B2 refers to the Skim Milk Silos. The available capacity for i buffer stages are determined by the number of maximum Kanbans K, $i = \{1,..,2\}$. The customer demand triggers the production is represented by D3 and triggers the production according to the availability in the last inventory buffer, B3 in this example.

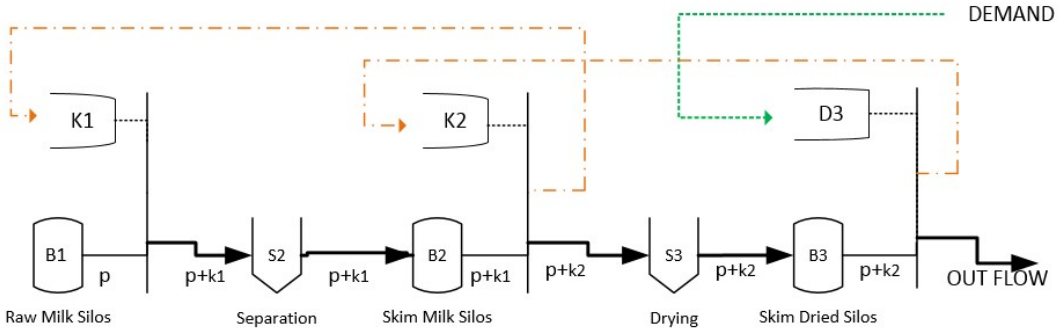

Figure 4.12 - KCS line with two stages applied to a dairy manufacturing process – Adapted [173]

For KCS, the equations were adapted to consider the CIP cycle-time for each stage through the term R_s^h, which controls the flow of material. In addition, only one term was used combining both Production Trigger and Production Objective, referred to as Production Authorisation PA_s^h where $1 \ll s \ll S-1$ is achieved from equations (4-17) and (4-18).

$$PA_s^h = min\left[max\left[0, K_s - I_s^{(h-1)}\right], \left\{B_s^{(h-1)}\right\}, P_{s^{max}}\right] R_s^h \quad (4\text{-}17)$$

$$PA_S^h = min\left[K_S - max\left[0, I_S^{(h-1)} - D^h\right], \left\{B_S^{(h-1)}\right\}, P_{s^{max}}\right] R_S^h \quad (4\text{-}18)$$

4.6.5. CONWIP Control Strategy

In this production country system, there is only one parameter to be optimised, which simplifies the implementation and maintenance. Conversely to KCS where the demand information travels from the final to the initial stage, CONWIP is instantly communicated to the initial stage and the release rate is adjusted. Figure 4.13 presents a system ruled by the CONWIP strategy adapted from Figure 2.19.

In this example, the separation process is represented by S2 (Stage2) and the dryer process is represented by S3 (Stage3). The current volume being processed is represented by p, which refers to the volume of production. The inventory buffer B3 is where the total final products are stored to fulfil specific customer demand for this production line. B1 refers to the Raw milk Silos while B2 refers to the Skim Milk Silos. The available capacity for i buffer stages is determined exclusively by the CONWIP volume (C). The customer demand triggers the production is represented by D and triggers the production according to the availability in the last inventory buffer, B3 in this example.

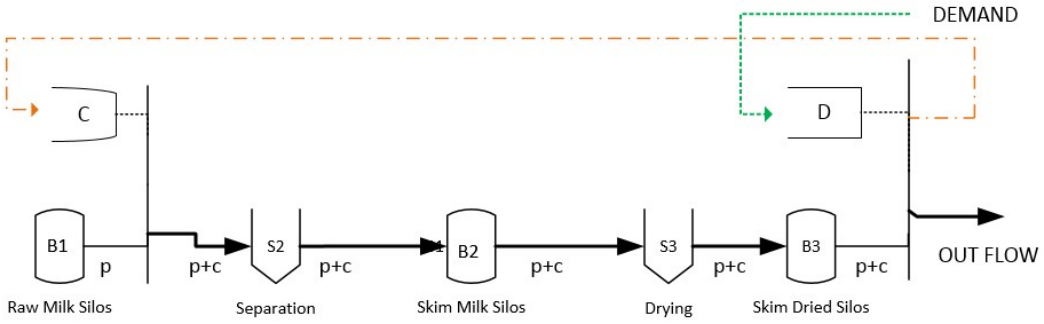

Figure 4.13 CONWIP with two stages in a dairy manufacturing process - Adapted [173]

In the CONWIP system, the initial stage receives the demand information; thus, the Production Authorisation PA_s^h for stage (s = 1) is constrained as defined by equation (4-19) . For the final stages $s = \{3, \dots, S\}$ equation (4-20) is applied to stage 3 where the restriction only relies on the raw material availability or production capacity. The term R_s^h also controls the material flow for all stages.

Two changes are required for the dairy environment: (i) negative values for zero inventory would increase CC cards. Therefore, a restriction is required. (ii) both equations were modified to consider CIP cycle time.

$$PA_s^h = min\left[CC - max\left[\left(\sum_{i=s}^{S} I_s^{(h-1)} - SI_s^{(h-1)} - D^h\right), 0\right], \left\{B_s^{(h-1)}\right\}, P_{s^{max}}\right] R_s^h \quad (4\text{-}19)$$

$$PA_S^h = min\left[\left\{B_S^{(h-1)}\right\}, P_{s^{max}}\right] R_S^h \quad (4\text{-}20)$$

4.6.6. CONWIP/KCS Control Strategy

In a hybrid system controlled by CONWIP and KCS policies, WIP is globally and individually controlled at each stage. Figure 4.14 presents a system ruled by the Hybrid CONWIP/KCS strategy adapted from Figure 2.22.

In this example, the separation process is represented by S2 (Stage2) and the dryer process is represented by S3 (Stage3). The current volume being processed is denoted by p, which refers to the volume of production. The inventory buffer B3 is where the total final products are stored to fulfil specific customer demand for this production line. B1 refers to the Raw milk Silos while B2 refers to the Skim Milk Silos. The available kanbans (or maximum capacity) for i stages are determined by *K*, $i = \{1,..,2\}$ while CONWIP (CC) denotes the maximum capacity by of raw material to be authorised in the system. The customer demand which triggers the production is represented by D3 and triggers the production at the last stage according to the availability in the last inventory buffer.

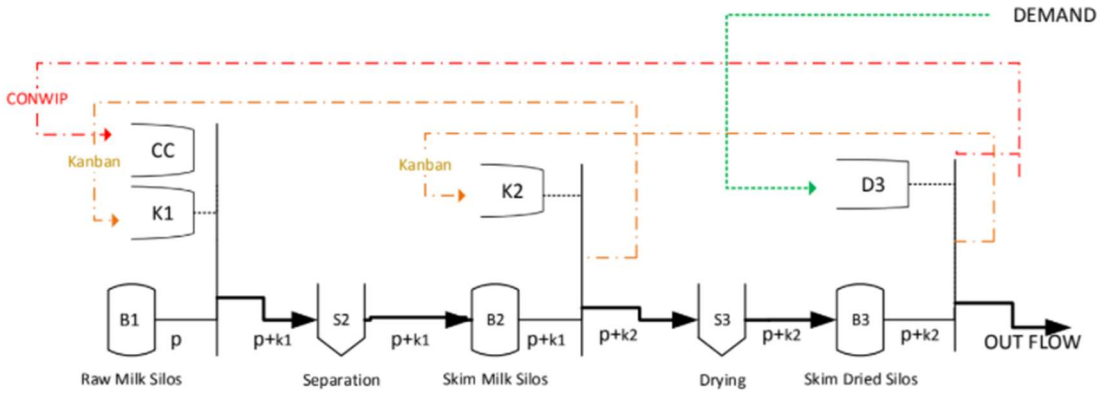

Figure 4.14 CONWIP with two stages in a dairy manufacturing process - Adapted [173]

In the CONWIP/KCS system, the equation for the initial stages $(s = 1)$ is a combination of KCS and CONWIP models as defined by equation (4-21) . For the remaining stages $(s = 2, \dots, S-1)$ the Kanban equation is applied (4-17) and for the final stage equation (4-18) is considered.

$$PA_s^h = min\left[CC - max\left[\left(\sum_{i=s}^{S} I_s^{(h-1)} - C_s^{(h-1)} - D^h\right), 0\right], max\left[0, K_s - I_s^{(h-1)}\right], \left\{B_s^{(h-1)}\right\}, P_{s\,max}\right] R_s^h \quad (4\text{-}21)$$

4.7. Optimisation Methods Applied in This Research

This section describes the optimisation methods for examining the main factors involved in dairy bulk powder manufacturing in order to optimising the responses previously described in section 4.2 as follows.

4.7.1. Pareto-Frontier

A crucial task for optimisation algorithms is to intelligently explore the search space and identify the optimum global rather than the optimum local. With respect to dairy, the optimum global is a combination of conflicting metrics such as best SLA achievable at a lower possible WIP level to distinct stages of the manufacturing process. Multiple solutions or a non-dominant set of values could be recommended, namely when multi-objective responses are sought.

An effective way to demonstrate the non-dominant set of values is efficiently performed by a Pareto Frontier graph as shown in Figure 4.15 where the optimum set is defined according to the objective criteria selected [225]. In a multi-objective optimisation problem, a set of non-dominated trade-off solutions is presented instead of a single optimal solution [226].

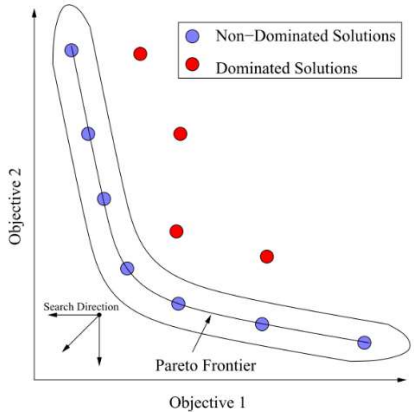

Figure 4.15 – Pareto Frontier [225]

The method for selecting the non-dominant set consists of finding the variance between the two objective criteria and calculating the Gaussian Equation (4-22) and Euclidean Distance Equation (4-23) for the first minimum point and for the least distance, respectively.

$$g(x, x') = exp - \left(\frac{(x - x')^2}{2\sigma^2}\right) \tag{4-22}$$

$$d(x, x') = \sqrt{\sum_{i=1}^{n} (x_i - x_i')^2} \tag{4-23}$$

In order to enhance the visualisation, the optimised solutions selected from the space simulated are presented in a Pareto Frontier graph developed in RStudio see **Appendix F.3 - Pareto Frontier Graph – Rstudio Algorithm**. The non-dominant set of solutions for individual periods and production strategies are plotted according to the responses selected. The objective is to provide an approximation of the most appropriate factors: the volumes of milk processed at each stage; for each optimised conflicting responses: WIP levels and SLA.

4.7.2. Response Surface Methodology

According to Montogmery and Runger [202], [230], Response Surface Methodology (RSM) is a collection of statistical techniques for modelling and analysis of problems influenced by several variables or inputs (factors) where the objective is to optimise the response according to the significant factors. Equation (4-24) represents the relationship for the first order or linear model, where the term x_i is the number of independent variables and the term ε is the statistical error or residuals of the model.

$$y = f(x_1, x_2, \dots, x_k) + \varepsilon \tag{4-24}$$

A second-order polynomial model is represented in equation (4-25) where β_o is the intercept, $\beta_i x_i$ are the linear terms, $\beta_{ii} x_{ii}^2$ are the quadratic terms, $\beta_{ij} x_i x_j$, the interaction terms.The error or residuals is represented by ε and it assumes to follow a normal distribution.

$$y = \beta_0 + \sum_{i=1}^{k} \beta_i \, x_i + \sum_{i=1}^{k} \beta_{ii} \, x_{ii}^2 + \sum_{\substack{i,j=1 \\ i \neq j}} \beta_{ij} \, x_i x_j + \varepsilon, \quad \varepsilon \sim \text{NID}\,(0, \sigma^2) \tag{4-25}$$

In RSM problems, due to the unknown relationship between the response and the independent variable, an approximation by a second-order polynomial model is more appropriate. Some models are more significant than others [230] and it is essential to explore the following considerations in order to obtain an optimised approximation for the model design:

i. A Full Factorial is recommended to identify linear models and their interactions.
ii. Fractional Factorial options (Res III, IV and V) are suitable for screening experiments but have limited support for quadratic models.
iii. RSM supports quadratic effects and it is widely explored for optimisation designs and Central Composite Design (CCD) models, which require fewer running experiments.

A Box-Wilson Central Composite Design or CCD contains a fractional factorial design with augmented star points allowing curvature assessment. The main advantage of using CCD is the reduction of the number of experiments when compared to a full factorial design model. The model previously presented in Equation (4-25 contains $1 + 2k + k\,(k-1)/2$ parameters. Thus, for all the experiments designed, this number of

distinct points or extra runs is required. In addition, at least three levels for each selected independent variable are required [202], [230].

The star points represent new limit values (low and high) for each factor in the model designed. There are three types of CCD defined as follows [230]:

i. Circumscribed or CCC: In a CCC model, the star points distance from the design points is defined based on the number of factors and levels in the design. Extra high and low limit levels are required for all factors. By augmenting a factorial or resolution V fractional, the same design can be achieved.
ii. Face Centred CCF: In this design, the star points rely on the centre of each face of the factorial model space. This design requires 3 levels for each factor. Similar to CCC, by augmenting a factorial or resolution V fractional the same design can be achieved.
iii. Inscribed CCI: in this design, the lower and higher limits are defined as a star point. Thus, the CCI is reduced to a CCC design. This design requires 5 levels for each factor.

In any strategy of experimentation [230], it is essential to understand the impact of changing certain input factors and the cause-and-effect relationships in a system. This process is known as conducting experiments on the system and each experimental run is a test. An experiment is defined as a test or series of runs in which changes are made to the input variables in order to observe the change in the output responses.

In order to identify the optimum authorisation volume according to each PCS for individual stages the method consists of the following steps:

I. Simulating a combination of lower and upper limits for each factor according to each pull-type PCS.
II. Performing Design of Experiments (DOE) based on the results simulated. Thus, the first step in the experiment is to find an appropriate approximation for the main relationship between responses and the factors simulated.
III. Analysing the fitness of the data and the statistical metrics namely *Predicted* R^2 *and Adjusted* $R^{2.}$
IV. Defining the criteria for optimising the responses such as maximising, minimising and targeting values.
V. Comparing the RSM optimum factors against the factors suggested by the non-dominant pareto frontier algorithm.
VI. After the model has been characterized and the important factors identified, the next objective is to identify the most appropriate and optimised strategy for each season.
VII. All Input Factors and Responses tables for both seasons are entirely presented in **Appendix G - Input Factors and Responses.**

Many response surface problems involve the analysis of several responses. Based on the experiments conducted, an optimum authorisation lot size for each stage is required and in order to align the objectives

of minimizing WIP at each stage and increase the total yield measured by the SLA percentage, a multi-objective optimisation problem called Multi-Response Optimization (MRO) is essential. The most common approach relies on finding the Desirability Function (DF) index as described in section **4.7.3 - Desirability Function.**

For the model assessment, the coefficient of determination and *F* values for ANOVA tables for each response is examined. *F* values are the criteria to consider when selecting the main effect for each response. From the ANOVA table some responses are impacted by the factor curvature in which the quadratic model is more appropriate than linear models [202], [230].

The coefficient of determination [202] measures how much the variability identified in the response can be explained by the selected independent variable. However, *Adjusted* R^2 measures how significant the factors selected are to each response and it will decrease when unnecessary terms are added. Both indicators *Adjusted* R^2 and R^2 were evaluated simultaneously in order to identify if a non-significant term was included in the model.

Another indicator is PRESS which stands for "prediction error sum of squares" firstly proposed by [231] where no new runs are required. The method consists of applying cross-validation criterion by eliminating one experimental run and then recalculating based on the remaining runs. A large difference between the residual sum of squares and PRESS indicates the model is unsuitable for predictions. For these cases, *Predicted* R^2 provides an indication of the amount of variation in predicting new observations by the fitted model.

An appropriate rule to guarantee the quality of the model is by comparing the difference between *Predicted* R^2 and Adjusted R^2 any difference less than 0.20 demonstrates a strong indication of reasonable consistency [202], [230].

4.7.3. Desirability Function

Desirability Function is a simultaneous optimisation of a multiple-responses technique popularized by Derringer and Suich [232] where each response is defined as an objective function and can be defined in the Design-Expert statistical package *Stat-Ease Inc* as:

- Target value: define which input factors should be changed to reach the objective target.
- Maximise or Minimise: define which factors should be changed to result in a maximised or minimised response.

The desirability index is calculated according to each response returning individual Desirability Function d_i that varies over the range $(0 < di < 1)$. The objective is to achieve the optimum d_i [230]. Then the design variables are chosen to maximize the overall desirability as defined by the equation (4-26)

$$D = [d_1 * d_2 * \ldots * d_m]^{1/m} \quad (4\text{-}26)$$

The objective or target *T* for the response can assume distinct equations. For *y* as a maximum value, the desirability function is determined according to Equation (4-27). The coefficient r is the weight to emphasize the individual desirability for each response. For $r = 1$, the desirability function became a linear function, when $r > 1$ the result should be close to the target value and by choosing $r < 1$ it makes the individual d_i inferior. When the response y is a minimum value di is calculated according to Equation (4-28). The two-sided desirability function assumes that the target is located between the Lower (L) and Upper (U) limits according to Equation (4-29) [202], [230] in Equation (4-27) is applied. For uniquely minimising one response, such as WIP Equation (4-28) is applied. Finally, in multi-objective optimisation problems such as maximising SLA and minimising WIP, Equation (4-29) the most appropriated.

Table 4.17, therefore, for experiments related to maximise SLA for example, Equation (4-27) is applied. For uniquely minimising one response, such as WIP Equation (4-28) is applied. Finally, in multi-objective optimisation problems such as maximising SLA and minimising WIP, Equation (4-29) the most appropriated.

Table 4.17 – Desirability Function Equations

Equation (4-27) [230] Maximum value	Equation (4-28) [230] Minimum Value	Equation (4-29) [230] Two-sided desirability function
$d = \begin{cases} 0 & y < L \\ \left(\frac{y-L}{T-L}\right)^r & L \le y \le T \\ 1 & y > T \end{cases}$	$d = \begin{cases} 1 & y < T \\ \left(\frac{U-y}{U-T}\right)^r & T \le y \le U \\ 0 & y > U \end{cases}$	$d = \begin{cases} 0 & y < L \\ \left(\frac{y-L}{T-L}\right)^{r_1} & L \le y \le T \\ \left(\frac{U-y}{U-T}\right)^{r_2} & T \le y \le U \\ 0 & y > U \end{cases}$

The number of responses is represented by *m* and *t*he overall desirability will be zero if any of the individual responses are undesirable. The individual desirability functions are graphically structured as presented in Figure 4.16.

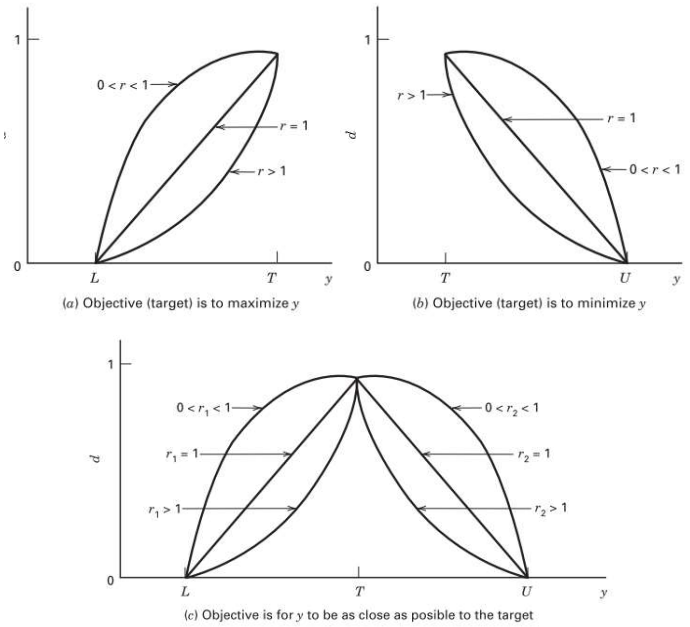

Figure 4.16 – Desirability Function for simultaneous optimisation [230]

4.8. Defining all Factors for the Optimised Responses for each PCS

During the design of the experiment, the full and fractional factorial models' designs were initially performed for the pull-type PCS examined. The working range of the selected input factors represents the volumes authorised by each stage. The input factors define the search space from lower to higher limits in order to detect the optimised response. In an optimisation process, it is common to have more than only one criterion to be achieved and sometimes conflicts among responses are inevitable [230].

In order to optimise the volume authorised for each stage, a Design of Experiments (DOE) was performed combining minimum and maximum limits at each stage defined for each PCS. The factors for authorising volumes at individual stages applied in this research are described in Table 4.18. For peak season, the term high volumes are adopted interchangeably in this section.

Table 4.18 – Factors for Each Stage - Legend

Factor	Stage	PCS	Description
Supply	0	CONWIP, KCS, CONWIP/KCS	The volume supplied into the system
CC	1	CONWIP, CONWIP/KCS	The volume authorised for the entire system
K1	1	KCS, CONWIP/KCS	The volume authorised at stage 1
K2	2	KCS, CONWIP/KCS	The volume authorised at stage 2
K3	3/4	KCS, CONWIP/KCS	The volume authorised at stages 3 and 4

The total number of hours for each pull-type optimised is defined according to the number of scenarios and replicated for 3 distinct periods of 120 hours. The region of operability is defined for each PCS as follows.

4.8.1. Kanban Control Strategy – Scenarios

In this strategy, the material flow is controlled by the customer demand and the flow for each stage is determined by the number of authorisations or lot-size volumes. For the KCS strategy equation (4-17) for initial stages and equation (4-18) for the last stage are simulated.

With respect to DOE design, the region of operability and the region of experimentation for each independent variable is identical to the working ranges with four input variables (*k=4*). In this design each variable will have only three levels: low, middle and high coded as (-1,0,+1) notation. The number of experimental runs of all scenarios according to this design is [2k(k-1) = 24] augmented with 6 replicated centre points coded (0,0,0). The total number of experimental results is 30.

For KCS, four factors or independent variables representing (Supply-Stage0, K1-Stage1, K2-Stage2 and K3-Stage3) in the production flow are considered. For each period, 735 scenarios were simulated, resulting in 88,200 hours according to the volume limits as shown in Table 4.19.

Table 4.19 – KCS - Ranges for High Season

Factors		***A -Supply Stage 0***	***B - K1 Stage 1***	***C – K2 Stage 2***	***D – K3 Stage 3***
	Min	57.14	7.14	7.14	1.07
	Max	71.43	17.86	17.86	3.21
	Steps	3.57	1.79	1.79	1.07
Total	**735**	**5**	**7**	**7**	**3**
Hours Simulated	**88,200**				

For Medium seasons, 441 KCS scenarios were run for each period according to the volume limits shown in Table 4.20.

Table 4.20 – KCS - Ranges for Medium Volume

Factors		***A -Supply Stage 0***	***B - K1 Stage***	***C – K2 Stage 2***	***D – K3 Stage 3***
	Min	46.43	7.14	7.14	1.07
	Max	53.57	17.86	17.86	3.21
	Steps	3.57	1.79	1.79	1.07
Total	**441**	**3**	**7**	**7**	**3**
Hours Simulated	**158,760**				

4.8.2. CONWIP - Scenarios

For CONWIP pull-type shown in equation (4-19), the factors are: **A-Supply** and **B-CC**. Thus, the number of CONWIP authorisation volumes controlled by factor **B-CC** will dictate the material flow in the entire system. The ranges for each factor during the high season are shown in Table 4.21.

For DOE design, the face-centred-CCD (FCD) model was considered as the axial points take place at the centre of the cube faces. The experiment consists of two-level full factorial points $(2^k = 4)$ coded (+/-1, +/-1), augmented with $(2k = 4)$ axial points coded as (+/- 1,0), (0,+/-1), and 5 extra centre points coded as (0,0,0). Therefore, each season requires 13 experimental runs.

Table 4.21 – CONWIP - Ranges for High Volumes

Factors		***A – Supply Stage 0***	***B – CC Stage 1***
	Min	57.14	7.14
	Max	71.43	57.14
	Steps	3.57	1.79
Total	**145**	**5**	**29**
Hours Simulated	**52,200**		

For Medium seasons, 87 CONWIP scenarios were run for each period according to the volume limits shown in Table 4.22.

Table 4.22 – CONWIP - Ranges for Medium Volume

Medium Factors		***A – Supply Stage 0***	***B – CC Stage 1***
	Min	46.43	7.14
	Max	53.57	57.14
	Steps	3.57	1.79
Total	**87**	**3**	**29**
Hours Simulated	**31,320**		

4.8.3. Hybrid CONWIP/KCS or HKCS – Scenarios

For the Hybrid approach, both equations CONWIP and KCS are combined. CONWIP equation (4-21) for the first stage, KCS equation (4-17) for subsequent stages, and equation (4-18) for the last stage.

Regarding DOE design, the region or operability and the region of experimentation for each independent variable is equal to the working ranges with five input variables (*k=5*) which is exactly the same BBD model considered to KCS. The total number of experimental runs of all scenarios according to this design is 46 due to the additional factor (CC); [2k(k-1) = 40] augmented with 6 replicated centre points coded as (0, 0, 0).

For CONWIP/KCS five factors were defined for each period according to the volume limits and 8,100 scenarios as shown in Table 4.23.

Table 4.23 – CONWIP-KCS – Ranges for High Volumes

Factors		*A – Supply Stage 0*	*B – K1 Stage 1*	*C – K2 Stage 2*	*D – K3 Stage 3*	*E - CC Stage 1*
	Min	57.14	8.93	8.93	1.07	7.14
	Max	71.43	17.86	17.86	3.21	54.17
	Steps	3.57	1.79	1.79	1.07	3.57
Total	**8100**	**5**	**6**	**6**	**3**	**15**
Hours Simulated	**2,916,000**					

For Medium seasons, 2,646 CONWIP/KCS scenarios were run for each period according to the volume limits shown in Table 4.24.

Table 4.24 – CONWIP-KCS – Ranges for Medium Volumes

Factors		*A – Supply Stage 0*	*B – K1 Stage 1*	*C – K2 Stage 2*	*D – K3 Stage 3*	*E - CC Stage 1*
	Min	46.43	7.14	7.14	1.07	7.14
	Max	53.57	17.86	17.86	3.21	25.00
	Steps	3.57	1.79	1.79	1.07	3.57
Total	**2646**	**3**	**7**	**7**	**3**	**6**
Hours Simulated	**1,312,560**					

4.9. Responses Optimisation Methods

Seven responses were selected and examined for each PCS under the Pareto-Frontier graph and RSM as follows.

- **StageB1_Mean**% and **StageB2_Mean**%: Equation (4-4): refers to the average WIP at both stages.
- **StageB1_Max**% and **StageB2_Max**%: Equation (4-3) refers to the maximum WIP volumes at both stages.
- **RespSupply Accuracy**: Equation (4-6) is the ratio of the raw material authorised in the system and the raw material planned.
- **SLA**: Equation (4-7) refers to the ratio of the total produced and demand required.
- **Utilisation at Stage 2**: Equation (4-9) refers to the ratio between the total processed and total capacity at stage 2.

4.10. Adaptive Pull-Type Approach

As explored in section 2.8.8 - Dynamic and Adaptive pull-type PCS, much of the research and improvements have been conducted for the discrete manufacturing environment and adaptive methods to dynamically control the material flow. In the dairy sector, opportunities for applying pull-type PCS are evident and this

section is dedicated to designing an adaptive pull-type to improve the production flow for the dairy powder manufacturing environment.

The objective is to manage the variability identified in this environment, considering all the benefits and drawbacks of the main traditional pull-type PCS modelled. As observed, two distinct seasonality must be examined since it has a significant impact on defining the best strategy to guarantee improved results.

For high volumes, it is observed that the capacity restricts the production flow, the volumes must be managed in order to avoid overburdening the system and reducing waste of raw material caused by excess WIP. Conversely, during medium and off-seasons the main objective relies on optimising the current resources due to the limited raw material that restricts the production flow as demonstrated in equations (4-17) to (4-21). The manufacturing system requires to be rearranged to guarantee an efficient process.

Therefore, the first step consists of identifying the seasonality volume. Since the manufacturing environment is data-driven controlled, the plant design (flows and storage capacities) combined with the operational process information are crucial in determining the amount of WIP in the system since the CIP schedule has a significant impact on SLA performance as previously demonstrated in section **4.5 - Exploring push and pull systems in dairy manufacturing.**

4.10.1. The Manufacturing Environment Design

The method consists of simulating the manufacturing plant designed according to the structure described in **Chapter 3 –** section **3.4.5 - Dairy Manufacturing Stages in the ePMPS Framework.** Flows and silos capacity is primarily defined through the Manufacturing Design (MD) plant files while the daily operation through Process Flow (PF) files as detailed in **Appendices E.2 to E.10.** Therefore, since the operational environment is defined two main adaptive solutions are available as described as follows.

4.10.2. Controlling the Material Flow for Peak Seasons

The necessity to control the volume of raw material during the peak season is evident since the decisions regarding accepting extra raw milk cause several implications, as previously explored. Therefore, Figure 4.17 demonstrates the proposed processing flow for the dairy bulk powder manufacturing environment during peak seasons based on a dynamic KCS. After designing the manufacturing plant, capacity and process flow are determined by the parameters provided, the simulation of the current process is performed and the metrics defined in section **4.2 - Performance metrics.**

The algorithm was developed in RStudio and the main advantage of choosing RStudio is the ability to support several vector operations rather than operating individual elements in a dataset through a loop structure. This process is called vectorisation and a single instruction is applied to multiple data (SIMD) [233]. In addition, RStudio provides powerful libraries to support data visualisation.

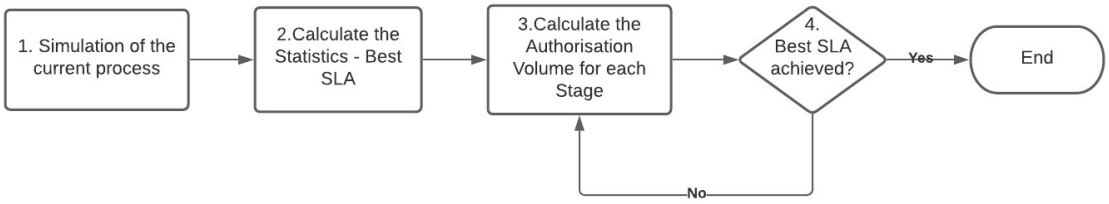

Figure 4.17 – Adaptive pull-type PCS for Dairy Powder Manufacturing Environment - Flow

For peak seasons, the plant must operate at the maximum capacity and control WIP volumes at certain levels in order to avoid the current push system and ; therefore, reduce the risk of perishability and all implications previously described. The process of identifying the optimised level of the inventory consists of the following steps:

1. The first interaction will simulate the production plant according to the original data defined
2. All metrics are calculated and stored in a dataset entitled *statistics* for the first interaction.
3. The subsequent interactions consist of progressively calculating the authorisation volume at each stage according to equation (4-30) and comparing the results to the metrics calculated for the push system.

$$KCS_s = Lot_s + CIP_{(s+1)} \tag{4-30}$$

4. This process is repeated, the metrics are calculated and stored in the *statistics* dataset as the authorisation volumes are being calculated and the WIP levels are reduced.
5. As the desired SLA is achieved, the loop stops and the volume authorised at each stage is suggested.

Therefore, rather than define the optimum autorisation based on the number of lots for each stages, the algorithm consists of identifying the optimum level to cover the CIP cycle time for the $s + 1$ stage and to avoid shortage, as presented in section **4.5 - Exploring push and pull systems in dairy manufacturing.**

Figure 4.18 demonstrates the number of interactions simulated to achieve the improved SLA. Taking lot 57.14 as an example, less than 10 interactions are required to find the optimum WIP level that fulfils the SLA for all three periods analysed due to the limited supply volumes. By increasing the volume more interactions are needed since each interaction increases the volume of WIP at stage 2. Each lot supplied requires distinct interactions due to the variability as shown in periods 1, 2 and 3. As observed for period 3, 14 to 15 interactions were performed to reach the maximum SLA for volumes higher than 67.86 lots.

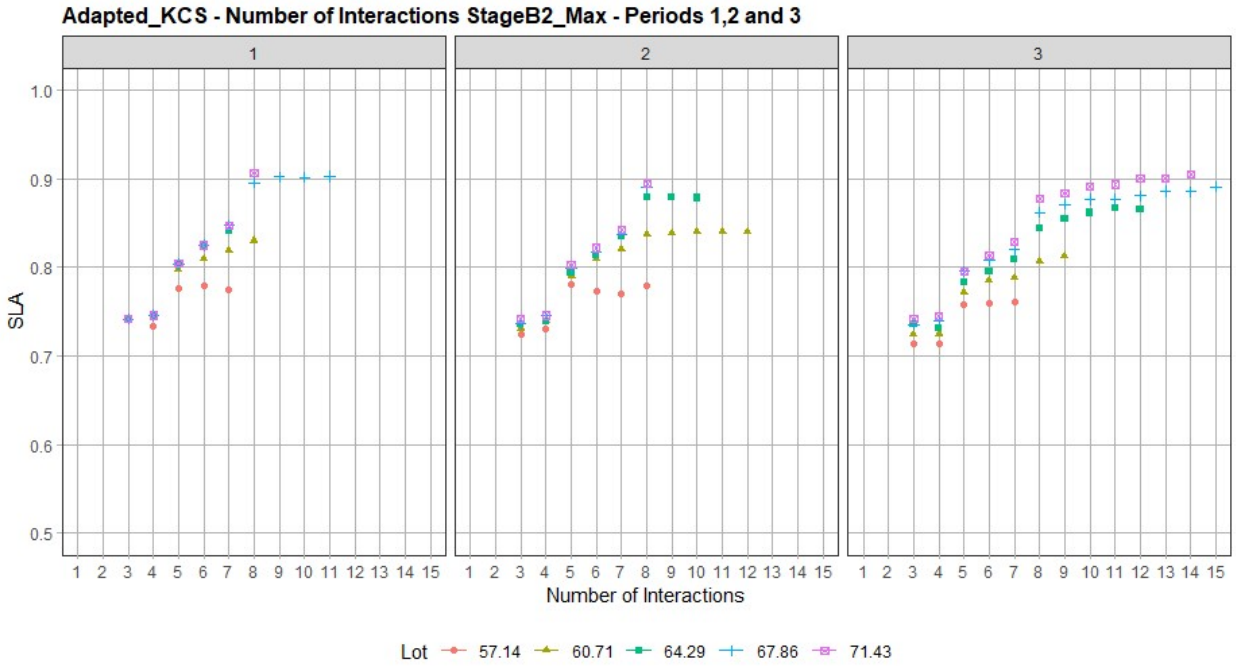

Figure 4.18 – Adaptive pull-type PCS for Dairy Powder Manufacturing Environment - Interactions

4.10.3. Controlling the Material Flow for Medium and Off-Seasons

For medium seasons the plant must operate at a specific capacity avoiding waste generated by poor equipment utilisation, energy and water for example. Therefore the following steps consist of:

a. Define the equipment set as described in section 4.10.4
b. Define the search space by restricting the minimum and maximum running hours for each piece of equipment and simulating the schedules described in section 4.10.5
c. Choose the scheduling plan according to the recommended pareto optimum-set according to the criteria selected.

4.10.4. Equipment Set

The decision variables defined in the model considers the equipment set for each stage such as: $Rmax_{s_e}$, $Rmin_{s_e}$, $Cmin_{s_e}$, $Cmax_{s_e}$, $StCip_{s_e}$. The equipment set is created according to a binary variable (0,1). In addition, an extra combination for all pieces of equipment run is added as shown in equation (4-31).

$$Cequip(e,r) = \left(\frac{e!}{r!\,(e-r)!}\right) + 1 \tag{4-31}$$

According to the equation (4-31), an example of four pieces of equipment combined 2 by 2 is shown in Table 4.25. The last set refers to the total pieces of equipment running at full capacity.

Table 4.25 – Example - Equipment Set - 2 by 2

Equipment Set	Eq1	Eq2	Eq3	Eq4
1	0	0	1	1
2	0	1	0	1
3	0	1	1	0
4	1	0	0	1
5	1	1	0	0
6	1	0	1	0
7	1	1	1	1

4.10.5. Search Space and Planning Schedules

In order to overcome the drawbacks in the dairy bulk powder commodity environment, the algorithm proposed was developed to define the population or search space dynamically by combining all equipment sets and the range of decision variables, rather than the proposed by Evolutionary Algorithms are described in section **4.11.2 - Evolutionary Algorithms (EA)** or Genetic Algorithms (GA). The notation referred to variables and indices formulated is presented in Table 4.26.

Table 4.26 - Notation in MDP model adapted to the scheduling algorithm

Notation	Description
e, E	Piece of equipment where *1 ≤ e≤ E*
s, S	Production stage where 1 ≤ s ≤ S
s_e, S_E	Piece of equipment at *s* stage
P_{s_e}	Production centre at *s* stage s and *e* equipment
$PA_{s_e}^h$	Production Authorisation for *e* equipment at stage *s* in period *h*
$Cmin_{s_e}$	Minimum cycle-time for CIP *e* equipment at *s* stage
$Cmax_{s_e}$	Maximum cycle-time for CIP *e* equipment at *s* stage
Cip_{s_e}	CIP running for *e* equipment at *s* stage, where $Cmin_{s_e} \leq Cip_{s_e} \leq Cmax_{s_e}$
$Rmin_{s_e}$	Minimum running time *e* equipment at *s* stage
$Rmax_{s_e}$	Maximum running time *e* equipment at *s* stage
Run_{s_e}	Running time *e* equipment at *s* stage, where $Rmin_{s_e} \leq Run_{s_e} \leq Rmax_{s_e}$
$StCip_{s_e}$	Start CIP cycle-time for *e* equipment at *s* stage, where $\{StCipx_{s_e} = 1, StCipx_{s_e} = Run_{s_e} + 1\}$
$R_{s_e}^h =$	$\begin{cases} 1, & \sum_{h=1}^{H} R_{s_e}^h \geq Cip_{s_e} \\ 0, & \sum_{h=1}^{H} R_{s_e}^h < Cip_{s_e} \end{cases}$
$R_{s_e}^h =$	$\begin{cases} 1, & \sum_{h=1}^{H} R_{s_e}^h < Run_{s_e} \\ 0, & \sum_{h=1}^{H} R_{s_e}^h \geq Run_{s_e} \end{cases}$
$R_{s_e}^h =$	$\begin{cases} 1, & \sum_{h=1}^{H} R_{s_e}^h \geq StCip_{s_e} \\ 0, & \sum_{h=1}^{H} R_{s_e}^h < StCip_{s_e} \end{cases}$

The range is defined by $Rmax_{s_e}$, $Rmin_{s_e}$, $Cmin_{s_e}$, $Cmax_{s_e}$, $StCip_{s_e}$ input parameters to limit high and low levels rather than applying probabilistic methods. The space is defined according to equation (4-32). Where the equipment sets, the CIP vectors calculated according to the min-max ranges generate the scheduling plans. The combination according to the equipment sets $Cequip(e,r)$, the start CIP cycle-times $StCipx_{s_e}$, the range of running hours $((Rmax_{s_e} - Rmin_{s_e}) + 1)$ and the range of cip hours $\left(Cmax_{s_e} - Cmin_{s_e}\right) + 1)$ are then used as a limit to calculate the total Schedules.

$$TSch = \left(Cequip(e,r) * StCipx_{s_e} * ((Rmax_{s_e} - Rmin_{s_e}) + 1) * \left(\left(Cmax_{s_e} - Cmin_{s_e}\right) + 1\right)\right) \quad (4\text{-}32)$$

Thus, all the possibilities are defined, and no further generations are required, especially owing to the fact that the optimisation criteria are indefinite. The extension of the schedule H ,is an input parameter and it defines the total data points according to equation (4-33).

$$DataPoints = (TSch * H) \quad (4\text{-}33)$$

4.10.6. Evaluating the Algorithm Performance

Due to the large amount of data generated, the performance evaluation is a vital step in identifying the effectiveness of the proposed algorithm by running the worst-case scenario or the most significant range possible combinations, as shown in Table 4.27.

The number of simulations generated in the *Dataset Summary Observations* (f) column represents the total plans created for the input parameters: Number of Equipment Set (a) {1,..,7} combinations, Max CIP/OFF (b) and Min CIP/OFF(c), Max Running Hours(d) and Min Running Hours (e). By reducing the input parameters range (maximum and minimum), the range becomes more restrictive and the Dataset Number of Schedules (f) followed by the Time in Seconds (g) columns are both reduced. The time in seconds (column g) was extracted from the Profile option available in the RStudio package.

Table 4.27 – Performance Evaluation

Number of Equipment Set (a)	Max Cip/OFF (b)	Min Cip/OFF (c)	Max Running Hours (d)	Min Running Hours (e)	Number of Schedules (f)	Time in seconds (g)
7	14	2	8	4	**910**	**21.48**
7	14	2	8	5	**728**	**16.64**
7	14	2	8	6	**546**	**13.69**
7	14	2	8	7	**364**	**11.97**
..	…	..	..	..	**…**	**…**
7	8	3	8	6	**252**	**11.11**

The performance evaluation was replicated by restarting the environment for each run; therefore, no previous updated variable impacts the results for the next execution. The total processing time required to create all the schedule plans and define the best schedule through the Pareto Frontier was 22 seconds while the function ***CalculateSchedule*** required less than 6 seconds to generate 21,840 data points.

4.11. Optimisation Approaches Explored

In this section two initial approaches considered and explored during this research are described. However, their applications were replaced by a more appropriate method of optimisation for dairy manufacturing requirements.

4.11.1. Machine Learning and Artificial Intelligence (ML/AI)

Artificial Intelligence and Machine Learning are areas of research ever-growing of industrial applications and academic research. The models developed are heavily based on processing historical data and are divided into four main groups as follows [227]:

i. Supervised learning: It relies on identifying which predictors or independent variables predict the target or dependent variable, it is widely applied for forecasting solutions.

ii. Unsupervised learning: it relies on clustering the population or the distance among the data points, widely applied for classification problems.

iii. Reinforcement Learning: It is based on trial and error, the algorithm learns from past experience and tries to capture the best possible knowledge to make accurate decisions. Artificial Neural Networks (ANN) for image recognition is an example of application.

iv. Evolutionary learning: it relies on biological evolution and its mechanisms to adapt survival rates by having offspring to their environment. Evolutionary Algorithms or Genetic Algorithms are examples of algorithms.

Initial experiments and algorithm prototypes were developed in order to evaluate the applicability of such models to solve the optimisation problems for research in order to optimise the desired responses. However, the first two types were discarded since it requires a high volume of historical data. In addition, after diving into the production strategy required for dairy manufacturing, optimisation problems are more appropriate rather than classification or prediction problems proposed by supervised and unsupervised models.

In addition, a prototype of Artificial Neural Network (ANN) was developed using the Google open-source libraries TensorFlow. TensorFlow is a collection of machine learning and artificial intelligence models and frameworks available for developers which facilitates the development of neural layers, training and testing ANN models [228]. However, the results failed in providing an optimum response since rules such as stopping CIP for a minimum of running hours or interrupting after a maximum of running hours were violated. Finally, the evolutionary type widely used for optimisation problems was also explored as demonstrated in section **4.11.2 - Evolutionary Algorithms (EA)** or Genetic Algorithms (GA)**.**

4.11.2. Evolutionary Algorithms (EA) or Genetic Algorithms (GA)

Genetic Algorithms (GA) is usually combined with Pareto-frontier for selecting the optimum is widely applied in Multi-objective Algorithms (MOA) [229]. GA is an optimisation algorithm inspired by Darwinian Evolutionary Theory. A simplified diagram is shown in Figure 4.19. The search starts based on an initial population (1) which is evaluated through predefined criteria (2). The selected individuals at (3) are then reproduced through Crossover (4) and Mutation (5) processes. The mutation process is usually performed by probabilistic methods and this cycle is repeated through successive interactions towards the optimum solution.

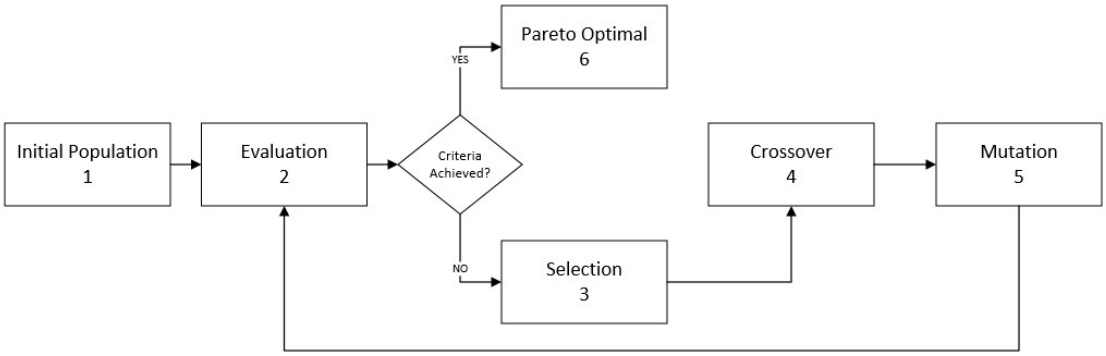

Figure 4.19 – Genetic Algorithms

Even though GA, is commonly considered in optimising multi-response problems, the following drawback was identified during the initial attempt to optimise the responses defined for this research:

I. The initial schedule or Initial Population (1) was created considering all equipment available and then the number of pieces of equipment in each interaction was reduced. According to the initial population combined with the variability in the supply deliveries, the time required to find the optimal set increases dramatically.
II. The evaluation (2) is performed according to a predefined Criteria; thus, an initial criterion or objective function must be defined in anticipation.
III. The time required to perform the Selection (3), Crossover (4) and Mutation (5) processes is heavily impacted by the mutation rate.
IV. After providing the scheduling plans, it was identified that the objective function (minimising WIP and maximising SLA), was achieved; however, vital requirements for dairy manufacturing such as maximum running hours and minimum to perform CIP were violated.

4.12. Conclusion and Contribution to the Research

In this chapter, three pull-type PCSs: KCS, CONWIP and CONWIP/KCS, were modelled and adapted to improve the key performance metrics in the bulk powder dairy manufacturing environment. In optimisation problems based on the pull-type PCS researched, reducing the overall WIP average in the system is one of the criteria traditionally sought. However, the perishability pattern increases significantly after passing through the separation process [10]. In addition the average as a KPI might hide potential bottlenecks when the capacity is limited. An adaptive pull-type based on KCS was designed to define the optimum level of inventory for individual stages based on the raw material supplied.

The metrics were defined considering individual manufacturing stages. Distinct volumes supplied and supply distributions were defined in order to evaluate the impact of the variability on the demand fulfilment.

Decisions regarding when the cleaning process starts are related to supply deliveries during the day and influence the overall results in adapting dairy manufacturing in a pure pull-system.

In the Dairy environment, the raw material destination must be planned in order to avoid disrupting the production flow. This scenario is aggravated due to high WIP levels remaining longer in the silos thus, increasing the risk of perishability. Consequently, supply and demand must be efficiently balanced in order to optimise the entire system and satisfy customer service levels.

Initially, the results under no policy were analysed and compared with the original manufacturing processes provided by the Industrial Partners. The next step consisted of progressively increasing the supply volume and examining the impact on the key performance defined. In order to explore the efficiency of WIP levels on controlling the variability in the system, distinct periods of 5 days each were initially considered and compared. The metrics defined were correlated and the essential relationship between the standard deviation and maximum storage utilisation results were highlighted, providing significant insights regarding the impact of variability in the current process. The initial experiments suggest that increasing the volume in the system does not contributed to in a desired SLA as observed in section **4.4.2 - Investigating Supply Distributions under Identical Volumes**, but how the raw material is received and the internal process is prepared to mitigate the variability within the manufacturing process.

A transition from the current push system to traditional pull-type PCSs was designed in order to investigate the best alternative for the dairy manufacturing environment. In addition, the particularities highlighted for this sector were embedded into an adaptive pull-type model. Therefore, the results provided by the experiments designed in this chapter will be demonstrated in the following chapter.

CHAPTER 5
EXPERIMENTAL CHAPTER – PULLING THE DAIRY PRODUCTION SYSTEM THROUGH PRODUCTION CONTROL STRATEGIES

5.1. Introduction

In the previous chapter, three distinct 5-day periods were randomly selected from the industrial partner 3 and defined as the control group to create the search space and identify the optimum factors for individual stages in the manufacturing system as described in section **4.4 - Simulating and Analysing the Current Production System**. The bulk-powder dairy manufacturing environment was modelled considering the three main PCS pull-types: CONWIP, KCS and hybrid CONWIP/KCS as described in section **4.6 - Modelling pull-type PCS for Dairy Manufacturing**. In addition, an adaptive pull-type was designed to define the optimum level of inventory for individual stages based on the raw material supplied as described in section **4.10 - Adaptive Pull-Type Approach.**

The objective of this chapter is to demonstrate the results of running dairy manufacturing stages under the three pull-type PCSs modelled: CONWIP, KCS and Hybrid CONWIP/KCS within the simulation framework developed. As previously verified in section **4.5 - Exploring push and pull systems in dairy manufacturing**, the supply variability combined with CIP times require an appropriate level of WIP to guarantee the demand fulfilment and therefore, an improved SLA.

The proposed framework utilises the simulation model and architecture developed as described in **Chapter 3** and modelled for dairy manufacturing according to **Chapter 4**. The simulated results are explored in two distinct approaches: (i) By evaluating the simulated non-dominant selection set in a Pareto Frontier graph which demonstrates potential best factors to achieve optimum multi-responses. (ii) By the RSM optimisation in order to identify the responses and main factors to be optimised. Ultimately, the results obtained from the experiments conducted under the adaptive pull-type are also compared to the PCS for the two distinct seasons explored in this research.

5.2. Experimental Results under Production Control Strategies

In order to evaluate the results provided by each PCS designed for the dairy environment, individual pull-type CONWIP, KCS and CONWIP/KCS were examined under identical conditions. Authorisation volumes are released according to the defined lot size. High volumes represent the peak season while medium volumes represent the intermediate seasonality concentrated between high and off-season. The data simulated for each experiment is presented in **Appendix G – Input Factors and Responses**. The resulting RSM models in terms of actual significant variables for each selected response studied in this research are presented in **Appendix H – Anova and Final Equation – Actual Factors**.

The results achieved by implementing the KCS pull-type system for the dairy sector are entirely explored and presented as follows, while the results provided by CONWIP and HKCS policies are demonstrated in **Appendices I – CONWIP** and **J – HKCS – Hybrid CONWIP/KCS.**

The improved outcomes for both optimisation methods RSM and Pareto-Frontier are compared for each pull-type investigated to achieve the three main objectives in this research:

1) To identify the optimum factors for each manufacturing stage suitable for distinct periods that efficiently mitigate the variability caused by this manufacturing environment.
2) To identify the optimum volume to be authorised for the conflicting trade-off: maximise customer satisfaction through the SLA response and reduce the waste caused by excessive WIP levels.
3) To reduce the risk of perishability caused by the extra WIP levels at Stage B2 – The Skimmed milk process after the separation process.

The best desirability function solution suggested for each period was selected by defining simultaneously the trade-off: maximising/minimising the responses evaluated as described in section **4.7.3 - Desirability Function**. Solutions with insignificant factors for each pull type as suggested by the Design Expert software were discarded**.**

5.2.1. Kanban Control Strategy - High season

The DOE summary is presented in Table 5.1. The first part of the table refers to the limits used for the optimisation experiment space definition as defined in section **4.8.1 - Kanban Control Strategy – Scenarios**, more precisely in Table 4.19 for Kanban High season factors. The second part refers to the responses evaluated according to each period examined.

Table 5.1 - KCS – Summary - High Season Raw Material – Supply Periods 1, 2 and 3

Factor	*Name*	*Units*	*Type*	*Minimum*	*Maximum*	*Coded*	*Values*	*Mean*	*Std. Dev.*
A	Supply – Stage 0	Lots	Numeric	57.14	71.43	-1.000=57.14	1.000=71.43	64.29	4.60
B	K1 – Stage 1	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.30
C	K2 – Stage 2	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.30
D	K3 – Stage 3	Lots	Numeric	1.07	3.21	*-1.000=1.07*	*1.000=3.21*	*2.14*	*0.69*
Response	*Name*	*Units*	*Obs*	*Minimum*	*Maximum*	*Mean*	*Std. Dev.*	*Ratio*	*Period*
R4	StageB1_Mean	%	30	7.21	40.89	18.88	8.76	5.67	
R6	StageB1_Max	%	30	43.74	100.00	76.00	14.52	2.42	
R7	StageB2_Mean	%	30	10.06	33.92	19.33	5.66	2.29	
R9	StageB2_Max	%	30	32.23	53.46	39.65	5.60	1.66	1
R10	SupplyAccuracy		30	0.78	1.00	0.93	0.06	2.01	
R11	SLA		30	0.67	0.90	0.83	0.08	1.66	
R13	Stage2 Utilisation		30	0.54	0.63	0.59	0.03	1.29	
R4	StageB1_Mean	%	30	5.69	40.04	18.34	9.14	7.04	
R6	StageB1_Max	%	30	45.82	100.00	78.01	16.38	2.73	
R7	StageB2_Mean	%	30	9.79	31.12	18.08	5.46	2.18	
R9	StageB2_Max	%	30	27.12	53.47	38.64	6.08	1.97	2
R10	SupplyAccuracy		30	0.78	1.00	0.92	0.06	1.83	
R11	SLA		30	0.66	0.88	0.82	0.08	1.97	
R13	Stage2 Utilisation		30	0.53	0.62	0.59	0.03	1.29	
R4	StageB1_Mean	%	30	7.07	31.20	17.29	6.78	4.42	
R6	StageB1_Max	%	30	71.75	100.00	85.19	8.76	2.06	
R7	StageB2_Mean	%	30	8.44	27.94	15.47	5.09	1.39	
R9	StageB2_Max	%	30	25.17	53.46	37.93	6.51	2.12	3
R10	SupplyAccuracy		30	0.78	0.97	0.88	0.06	1.86	
R11	SLA		30	0.62	0.88	0.76	0.08	2.12	
R13	Stage2 Utilisation		30	0.50	0.61	0.55	0.03	1.25	

As observed in Table 5.1 each response returned similar Maximum values for periods 1 and 2, namely for **StageB2** and **SLA** responses. The optimisation was initially performed according to the key metrics that dominate the literature in this space, namely **average WIP** and **SLA**:

- StageB2_Mean%: (Minimise) the objective function is to minimise WIP average at stage 2 with importance (+++).
- SLA: (Maximise) the objective function is to maximise the demand fulfilment controlled by SLA performance with importance (+++).

Each factor represents each manufacturing stage: A:Supply, B:K1, C:K2 and D:K3 and the optimum solutions according to the selected criteria are suggested as shown in Table 5.2. The optimisation criteria defined in the RSM experiment are highlighted in the table.

Table 5.2 - KCS – RSM Optimisation (SLA - StageB2) – High Season

is in range	is in range	is in range	is in range	None	minimize	none	none	maximize		
A:Supply	B:K1	C:K2	D:K3	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Per
71.43	9.58	8.93	2.67	77.77	11.83	27.76	0.86	0.90	0.96	1
71.43	10.99	8.93	2.72	83.36	9.79	29.57	0.86	0.88	1.00	2
71.43	16.07	8.93	2.64	101.06	10.25	34.08	0.85	0.88	0.96	3

The traditional trade-off suggested an optimised solution by accepting extra raw material within the system as observed by factor A: Supply. However, as previously explained in section **4.2 Performance metrics**, the **Supply Accuracy** metric below 1 as shown in the table indicates the raw material planned was not entirely processed. Even though the lot-sizes volumes for each factor: **A:Supply, C:K2** and **D:K3** propose a consistent volume and the optimising criteria is fully achieved, this solution causes an undesired extra level of raw material to be accepted. In addition, the average is already stable as observed in Table 5.1; therefore, no improvement is observed by selecting this trade-off.

Since the WIP levels are already controlled by $max\ [0, K_s - I_s^{(h-1)}]$ volumes, as demonstrated in equations (4-17) and (4-18) in section **4.6.4 - Kanban Control Strategy**, the desirable optimisation criteria are observed by connecting the supply and demand responses according to the following responses:

- Supply Accuracy: (Maximise) to achieve an accurate volume of raw material for the system.
- SLA: (Maximise) the objective function is to maximise the demand fulfilment.

The results are presented in Table 5.3 with overall improvements for the responses selected. The supply volumes for each period are suggested according to the capacity of the system and reasonable volumes for WIP are observed at Stage B2.

Table 5.3 - KCS – RSM Optimisation (SLA – Supply Accuracy) – High Season

is in range	is in range	is in range	is in range	None	none	none	maximize	maximize		
A:Supply	**B:K1**	**C:K2**	**D:K3**	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Per
63.85	**14.61**	**14.95**	**2.66**	79.39	21.55	44.41	0.98	0.90	0.96	1
60.34	**14.40**	**14.67**	**2.72**	74.79	18.20	38.72	1.00	0.89	1.00	2
62.45	**15.94**	**16.04**	**2.72**	85.87	20.86	44.89	0.97	0.88	1.00	3

The entire system has demonstrated a significant improvement in controlling the excess of raw material under KCS. In this optimisation, WIP is not considered as an operating parameter but it is improved by the volumes authorised in the system. The fluctuation observed for all three periods observed in **StageB2_Max%** column is justified due to the variations in the supply volumes and frequencies. In addition, an ideal supply volume is suggested for all three observed periods.

This analysis provides significant evidence that the variability in the supplied raw material impacts all the responses evaluated. However, this fluctuation can be mitigated through an appropriate pull-type PCS and similar authorisation volumes for each stage. The RSM graphs corresponding to each desirability index for periods 1, 2 and 3 are illustrated in Figure 5.1, Figure 5.2 and Figure 5.3 respectively.

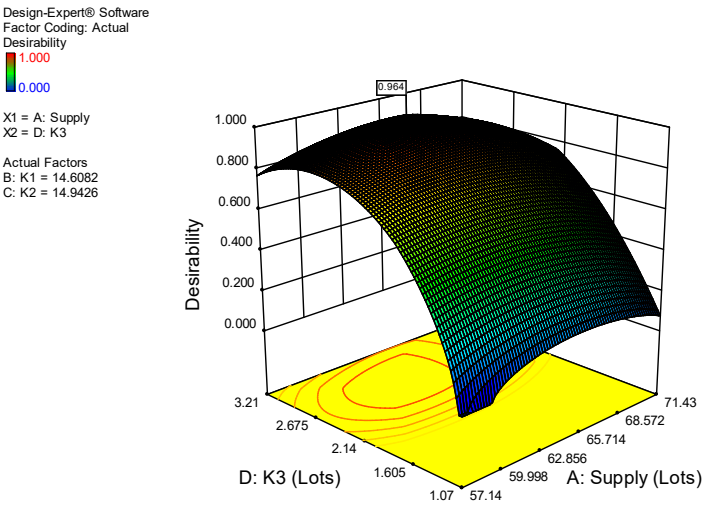

Figure 5.1 – Desirability Function RSM – KCS - High Season – Period 1

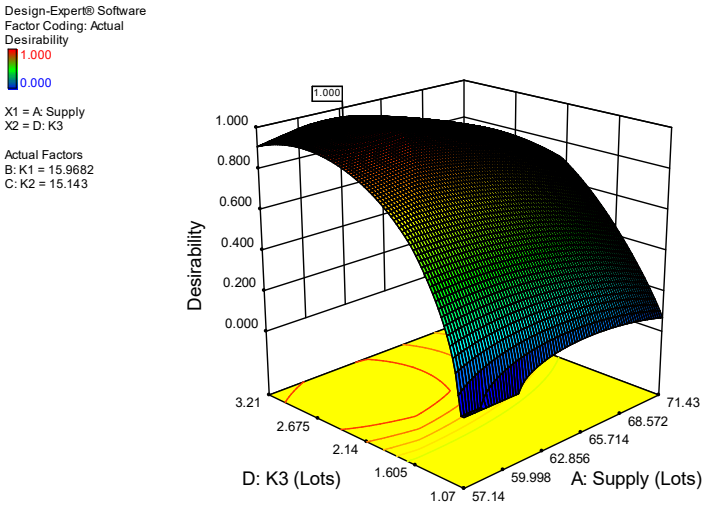

Figure 5.2 – Desirability Function RSM – KCS - High Season – Period 2

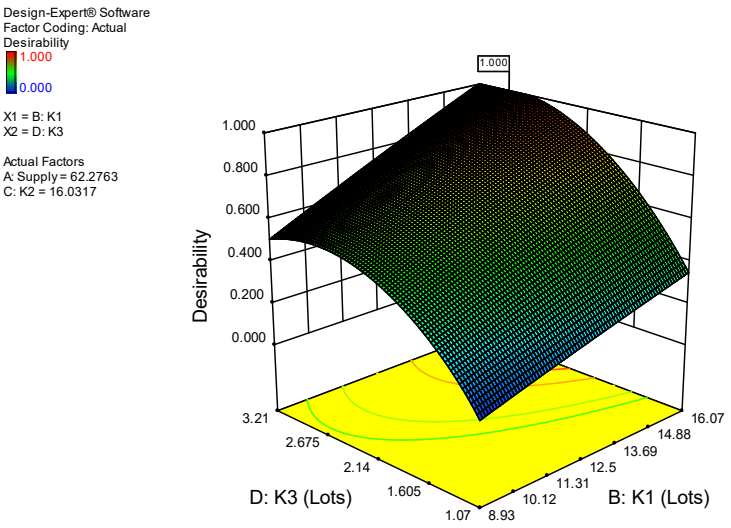

Figure 5.3 – Desirability Function RSM – KCS - High Season – Period 3

The resulting simulation under KCS policy is also demonstrated through non-dominant Pareto-Frontier graphs. The non-dominant datapoints or optimum responses attainable Figure 5.4 were selected according to the algorithm described in section **4.7.1 - Pareto-Frontier.** All the simulated scenarios compose the defined space; however, only the optimum data points that satisfy the multi-objective criteria in this case SLA and WIP reduction are highlighted. Therefore, with respect to dairy, the optimum global is a combination of conflicting metrics such as best SLA achievable at a lower possible WIP level in the manufacturing environment process. An example of the non-dominant selection presented for **StageB2 – Max%** is illustrated in Figure 5.4. All data points represent the simulated scenarios and the non-dominant sets are highlighted for each supplied period. The grey area represents all performed simulations and its respective feasible solutions; however, without achieving the optimum criteria. The variance observed by each supply period refers to the variability of how the raw material is supplied throughout the day since the number of simulations and volumes supplied are identical for all three periods. A high variability is observed in period 3, and despite periods 1 and 2 present a similar variation, period 1 converges faster with the lowest level of WIP to the desirable SLA.

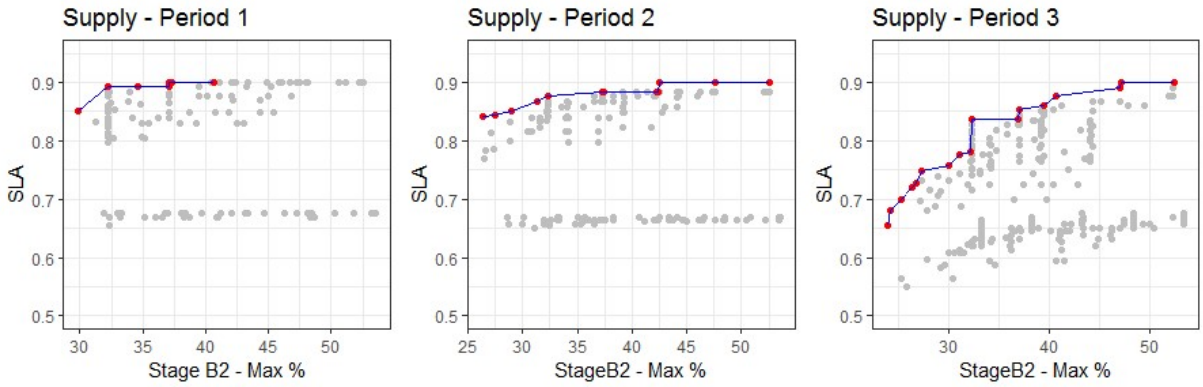

Figure 5.4 – Pareto Frontier – Non-dominant results for KCS – Supply Periods 1, 2 and 3

According to the Pareto Frontier algorithm, the trade-offs: Maximising **SLA** and minimising **WIP** levels for the following metrics: **StageB1_Mean, StageB2_Mean, StageB1_Max** and **StageB2_Max** are shown in Figure 5.5. It is observed that the level of WIP at distinct stages, namely at StageB2, has significantly reduced under the KCS policy when compared to the push-type system as presented in section **4.5 - Exploring push and pull systems in dairy manufacturing,** suggesting that the flow is being controlled and the WIP is gradually being authorised throughout the system.

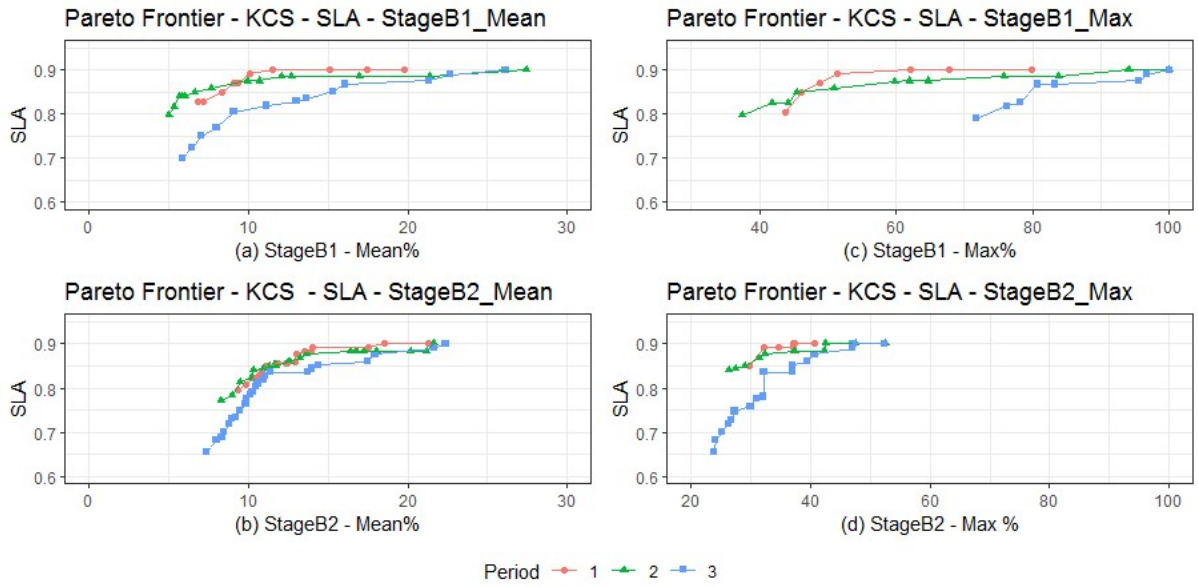

Figure 5.5 – Pareto Frontier – Non-dominant results for KCS – High Season

In the graphs, **StageB1 – Mean%** and **StageB2 – Mean%** present an analogous performance as investigated for push systems in section **4.4.4. - Simulating 3 Periods - Examining the impact of CIP variability on downstream processes.** By measuring the system through averages, some inconsistencies are observed: both levels are below 30% of buffer utilisation and the excess of WIP in the system is not observable.

Despite the supply variability on StageB1, namely for period 3, WIP levels progressively increase the SLA response under KCS strategy. In addition, **StageB2 – Max%** presents the results of controlling the flow under KCS where a higher SLA performance is reached for levels lower than 60% of capacity utilisation.

In both stages, the control proposed by KCS provides an inadequate SLA when a lower level of authorisation restricts the flow of raw material in the system, this behaviour is expected as defined in equations (4-17) and (4-18) in section **4.6.4 - Kanban Control Strategy**. As the number of authorisations increases, the volume authorised starts enhancing the SLA response.

The impact of distinct volumes supplied for responses **StageB1_Max, StageB2 Max** is also explored in Figure 5.6. The simulated dataset is divided into identical lot-sizes defined for factor **A:Supply** in section **4.8.1 - Kanban Control Strategy – Scenarios** , presenting volumes from 57.14 to 71.43, individually. An enhanced

visualisation by the volumes and the impact on the SLA performance previously confirmed by the desirability index calculation is therefore provided where it is possible to observe:

1. Although KCS controls WIP at stages B1 and B2, the variability observed in all three periods still impacts SLA performance, namely when supply volume is below 60.71 lot-sizes.
2. Period 3 presents a slow conversion towards the optimum **SLA** performance when compared to periods 1 and 2 as observed for all supply volume presented in the graph.

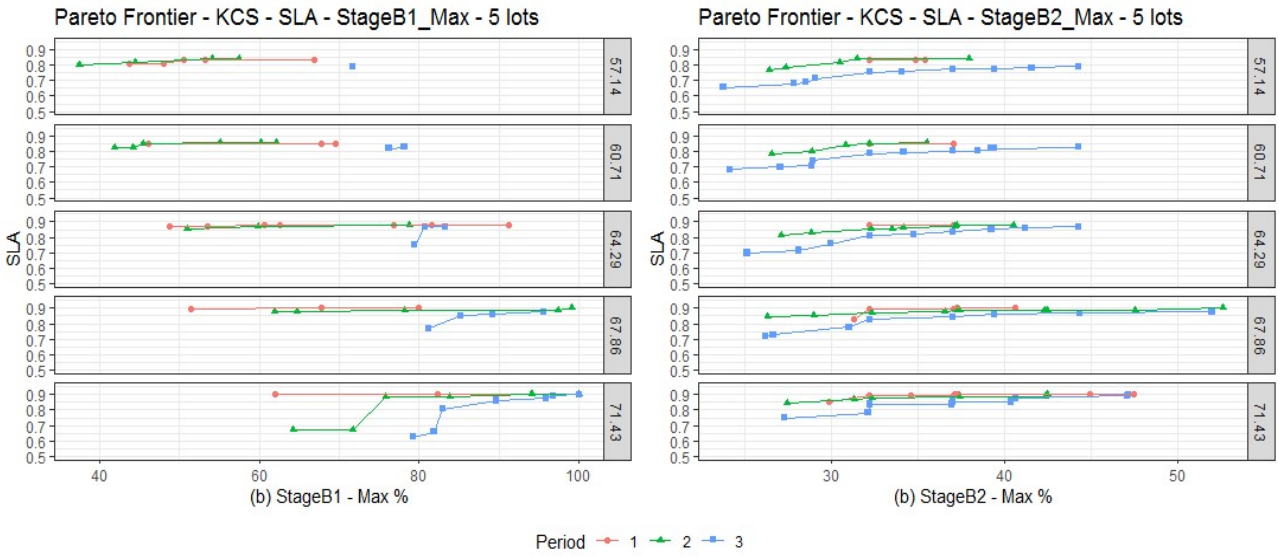

Figure 5.6 – Pareto Frontier – Non-dominant set results for KCS – High Season – 5 Lot-sizes

The results optimised by the RSM returned more precise volumes as expected due to the fitted model for each selected response, whereas pareto-frontier provides an approximation since the results are based on the simulated intervals. The results simulated under KCS provide significant insights for supporting decision-makers in balancing the production flow during the high season period according to the WIP levels in the system.

5.2.2. Kanban Control Strategy – Medium Season

The same steps in defining the optimum volumes for each factor are conducted for medium seasons as defined in section **4.8.1 - Kanban Control Strategy – Scenarios**, more precisely in Table 4.20, for Kanban Medium season factors. The responses also are considering three levels of supply as shown in Table 5.4.

Table 5.4 - KCS – Summary - Medium Season Raw Material – Supply Periods 1,2 and 3

Factor	Name	Units	Type	Minimum	Maximum	*Coded*	*Values*	*Mean*	*Std. Dev.*
A	Supply – Stage 0	Lots	Numeric	46.43	53.57	-1.000=46.43	1.000=53.57	50.00	2.30
B	K1 – Stage 1	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.30
C	K2 – Stage 2	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.30
D	K3 – Stage 3	Lots	Numeric	1.07	3.21	*-1.000=1.07*	*1.000=3.21*	*2.14*	*0.69*

Response	Name	Units	Obs	Minimum	Maximum	Mean	Std. Dev.	Ratio	Period
R4	StageB1_Mean	%	30	4.13	11.10	5.71	1.82	2.69	
R6	StageB1_Max	%	30	35.24	63.14	42.53	9.27	1.95	
R7	StageB2_Mean	%	30	4.80	17.99	8.71	3.68	1.79	
R9	StageB2_Max	%	30	24.94	39.77	29.63	3.86	1.59	1
R10	SupplyAccuracy		30	0.98	1.00	1.00	0.00	2.14	
R11	SLA		30	0.59	0.78	0.69	0.06	1.59	
R13	Stage2 Utilisation		30	4.13	11.10	5.71	1.82	2.69	
R4	StageB1_Mean	%	30	3.49	11.04	4.86	1.70	3.17	
R6	StageB1_Max	%	30	31.95	68.58	44.75	7.59	2.21	
R7	StageB2_Mean	%	30	4.63	18.34	7.71	3.12	2.15	
R9	StageB2_Max	%	30	21.89	36.06	28.34	3.75	1.65	2
R10	SupplyAccuracy		30	0.98	1.00	1.00	0.00	1.81	
R11	SLA		30	0.57	0.76	0.67	0.05	1.65	
R13	Stage2 Utilisation		30	0.46	0.54	0.50	0.02	1.02	
R4	StageB1_Mean	%	30	4.63	13.87	8.39	2.75	3.00	
R6	StageB1_Max	%	30	58.30	79.98	63.70	4.63	1.98	
R7	StageB2_Mean	%	30	6.13	16.31	9.67	2.68	1.37	
R9	StageB2_Max	%	30	23.76	46.33	34.82	4.42	1.95	3
R10	SupplyAccuracy		30	0.91	1.00	0.97	0.03	1.81	
R11	SLA		30	0.55	0.74	0.65	0.05	1.95	
R13	Stage2 Utilisation		30	0.43	0.53	0.48	0.02	1.10	

The results suggested in Table 5.4 demonstrate that minimising WIP at StageB2 is not required since the values are already controlled by KCS. Therefore, the RMS model considered only the performance with respect to SLA for all three periods. The unique analysis for optimising **SLA** response as shown in Table 5.5 was completed according to the following response:

- SLA: (Maximise) the objective function is to maximise the demand fulfilment.

Table 5.5 - KCS – RSM Optimisation: the objective function is to maximise the demand fulfilment (Maximise - SLA) – Medium Season

is in range	is in range	is in range	is in range	None	none	none	None	maximize		
A:Supply	B:K1	C:K2	D:K3	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Per
53.57	10.12	12.50	2.14	48.89	11.53	33.09	1.00	0.78	1.00	1
53.40	13.36	15.69	2.85	50.96	7.77	32.52	1.00	0.76	1.00	2
52.68	15.44	10.14	2.83	66.57	9.45	35.18	0.98	0.74	1.00	3

The results suggest the highest value for factor **A:Supply.** The **Supply Accuracy** response confirms that the volume was entirely processed. WIP levels are concentrated on StageB1 and the variation relies on the authorised volumes for individual stages. The desirability function suggested several insignificant solutions for factors **A:Supply, B:K1, C:K2** and **D:K3**. Thus, the first solution for each period was considered as an optimised outcome as shown in Table 5.5.

By adding extra criteria such as Minimizing **StageB2_Max** or Maximising **Supply Accuracy**, a lower desirability function index followed by a lower SLA performance is achieved since extra constraints are also added. This behaviour is expected as defined by equation (4-26) in section **4.7.3 - Desirability Function,** since each element of the equation $(d_{response1} * d_{response2} * \dots * d_{responsem})$ might reduce the overall geometric mean for nom optimum responses.

The simulated results for KCS medium season defined in Table 4.20 were processed by the same algorithm that extracts the optimum solution as demonstrated in Figure 5.4. However, only the optimum solutions are presented in a four Pareto-Frontier graphs illustrating the equivalent non-dominant trade-offs: maximising SLA and minimising WIP levels (StageB1_Mean, StageB2_Mean, StageB1_Max, StageB2_Max) as observed in Figure 5.7.

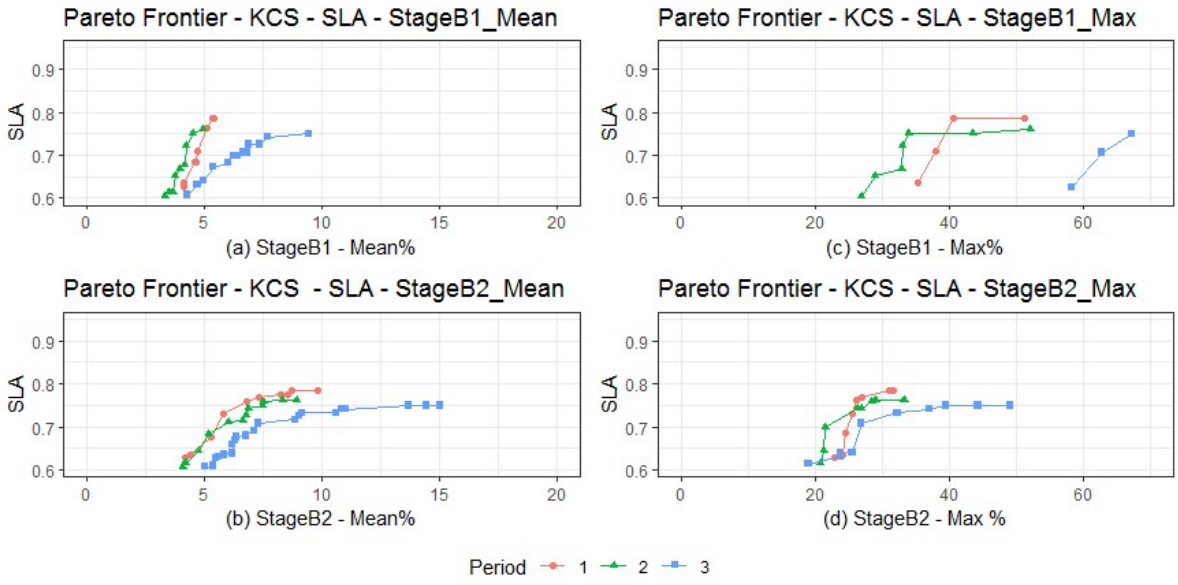

Figure 5.7 – Pareto Frontier – Non-dominant results for KCS – Medium Season

In Figure 5.7, graphs **StageB1 – Mean%** and **StageB2 – Mean%** illustrate the level of WIP to achieve a desirable SLA is below 15% average for all three periods whereas **StageB1 Max%** illustrates how heavily WIP at StageB1 is affected by the supply variability in the system. Stage B2 volumes converge to stable levels for all periods as shown by **StageB2 – Max%** levels. The volumes for medium seasons are also demonstrated in Figure 5.8. The system has extra capacity and the supplied volumes are clearly the main restriction to the flow as demonstrated by $\left\{B_S^{(h-1)}\right\}$ as defined in equations (4-17) and (4-18) in section **4.6.4 - Kanban Control Strategy**.

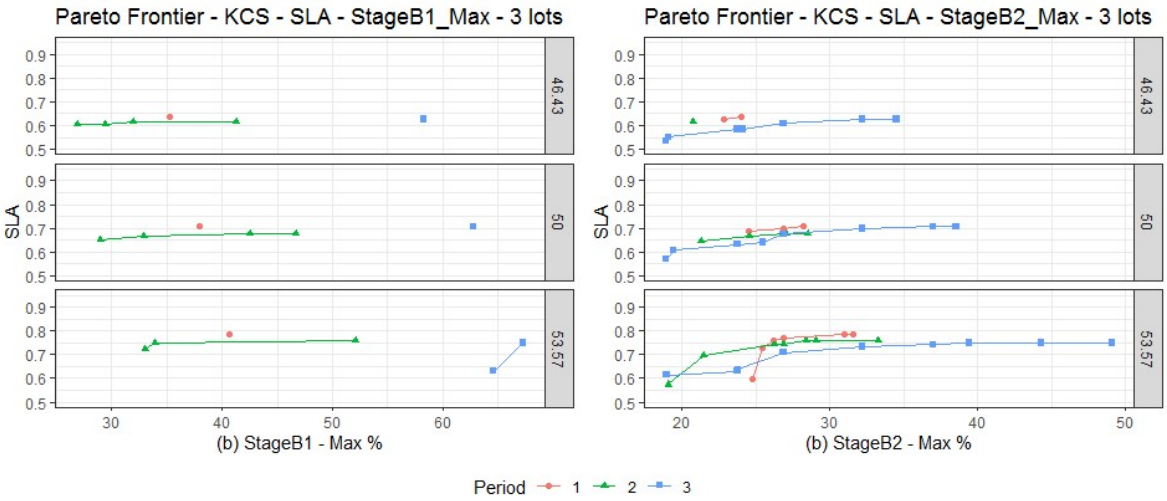

Figure 5.8 – Pareto Frontier – Non-dominant results for KCS – Medium Volumes – 3 Lot-sizes

5.2.3. Conclusions for Kanban Control System

The results presented have proven that KCS contributes to an advanced control over WIP between stages converting the current push system into a stable production flow. Several contributions were observed in enhancing the dairy manufacturing environment through the pull-type KCS in contrast to the push-type production flow as follows:

1. WIP levels confirmed to be consistently controlled by KCS.
2. By restricting the raw material in the system, namely during high seasons, improvements for supply management are evident, supporting decision-makers in defining the appropriate level of raw material reducing extra volumes, queue, risk of perishability and all the consequences inherited by an overburdened system.
3. Evidence was shown that **StageB2,** when wisely controlled, maintains the SLA performance.

Based on the results demonstrated by KCS simulation responses, the system improves the internal operations since StageB1 absorbs the variability from the supply deliveries. Supply Accuracy optimised supports the decision-makers through the volume to be supplied to the system, especially during high season when the process is more likely to be overburden. In addition, a systematic volume authorisation for each stage improves the balance between supply and demand reducing mura, muri and muda as defined by lean principles in section **2.7- Lean Thinking**.

In conclusion, all three definitions of pull-type PCS explored in section **4.5 - Exploring push and pull systems in dairy manufacturing** are achieved under KCS policy during high season as previously investigated in. WIP is managed by stages and each stage stores reasonable volumes; SLA performances are feasible and supply volumes are suggested according to the restrictions found in the system.

For medium seasons, despite appropriate levels of WIP at individual stages, the drawback observed is the excess of control when the processing capacity is evident higher.

5.2.4. CONWIP

The results of controlling dairy manufacturing stages under CONWIP are demonstrated in this section according to the modelling section **4.6.6 - CONWIP/KCS Control Strategy** and scenarios simulated in **4.8.2 - CONWIP - Scenarios.** The DOE factors and responses are presented in **Appendix I – CONWIP**. For High and Medium season is presented in **Appendix I.1 - CONWIP – Summary - High Season Raw Material – Supply Periods 1,2 and 3.**

The optimisation for CONWIP also considered the criteria performed by the literature studied where the **WIP average** and **SLA** are selected. The solutions suggested by the RSM desirability functions are presented in **Appendix I.2- CONWIP – RSM Optimisation (SLA - StageB2_Mean) – High Season** and suggested a higher supply volume as observed in factor **A:Supply** for all three periods.

The response **StageB1_Max**% was increased for period 3 as a consequence of higher lot-sizes authorised by factor **B:CC** – **CONWIP authorisation volumes** which represents the total WIP in the system, but evidently not entirely accepted by **Stage 2**.

A distinct approach for optimising the system under CONWIP is demonstrated in Table 5.6 by limiting **StageB2_Max%** utilisation and maximising both responses **SLA** and **Supply Accuracy** as follows:

- StageB2_Max%: (Target = 60, 70 and 80%) to restrict WIP according to maximum levels.
- SLA: (Maximise) for maximising the demand fulfilment controlled by SLA performance with importance (+++).
- Supply Accuracy: (Maximise) for maximising the accuracy of the total raw material planned with importance (+++).

Table 5.6 - CONWIP – RSM Optimisation – StageB2_Max%, SLA and Supply Accuracy – High Season

is in range	is in range	None	Minimize	Target	maximize	maximize		
A:Supply	B:CC	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Period
61.24	27.09	43.62	25.21	60.00	0.99	0.87	0.86	1
65.04	28.57	45.37	34.26	70.00	0.97	0.88	0.88	1
69.32	28.57	48.23	45.02	80.00	0.94	0.90	0.85	1
62.00	27.40	67.88	28.48	60.00	1.00	0.87	0.95	2
64.45	28.57	71.03	35.20	70.00	0.98	0.87	0.94	2
67.58	28.57	76.39	42.80	80.00	0.96	0.88	0.90	2
60.92	22.55	80.76	22.54	60.00	0.96	0.83	0.83	3
62.06	26.53	81.33	26.59	70.00	0.97	0.85	0.89	3
67.82	28.57	88.36	35.58	80.00	0.94	0.89	0.90	3

The main advantage of this strategy is the consistent level of WIP independent of supply uncertainty. Thus, only the level of silos at stage B2 would be controlled. However, the main drawback observed is the high

level reached of WIP at **StageB2** in contrast to **StageB1** this behaviour was previously observed in the current push-system.

A final investigation for CONWIP high season is performed similarly to KCS as shown in **Appendix I.3-**

CONWIP – RSM Optimisation – SLA and Supply Accuracy – High Season. The criteria consist of simply maximising both responses **SLA** and **Supply Accuracy**. The same effect is observed where the volumes fluctuate as observed at StageB2 levels, which is justified by the variability in the supply deliveries.

The RSM graphs corresponding to each desirability index for periods 1, 2 and 3 are illustrated **Appendices I.4, I.5 and I.6** respectively. In addition, the results simulated for CONWIP high season were also investigated under the non-dominant set depicted in the Pareto Frontier graphs as presented in **Appendix I.7** and divided by lot-sizes in **Appendix I.8**.

Similar steps in defining the optimum volumes for each factor are conducted for medium season considering three levels of supply as shown in **Appendix I.9.** The results suggest that no requirements for minimising the WIP at Stage 2 are needed since the WIP is exclusively controlled by CONWIP factor **B:CC.** As previously observed for KCS, under CONWIP policy the unique criterion for optimisation relies on maximising the **SLA** response as shown in **Appendix I.10 - CONWIP – RSM Optimisation (SLA) – Medium Season**.

The results suggest consistent volumes for CONWIP, and a slight variability is observed at Stage B2. In addition, StageB2 remains lower than StageB1 satisfying the objective functions of minimising WIP at stage 2 and maximising SLA.

Similar advantages in controlling medium season production flow under KCS are observed also for the CONWIP policy. WIP levels at StageB2 remain low in contrast to StageB1 and all the additional requirements for a pull-type system are reached. The supply is entirely accepted in the system, WIP is controlled and the SLA achieves desired levels according to the maximum volumes for this season.

The non-dominant set are demonstrated in Pareto-Frontier graphs for identical responses (StageB1_Mean, StageB2_Mean, StageB1_Max, StageB2_Max) as shown in **Appendix I.11 - CONWIP –Pareto Frontier – Simulated results – Medium Seasons.**

A higher level of factor **B:CC** authorisations were initially allowed to guarantee sufficient volume of raw material since the system has extra processing capacity during medium seasons. The non-dominant set by lot-sizes is shown in **Appendix I.12 - CONWIP –Pareto Frontier – Simulated results – Medium Seasons – Lot Sizes** which also demonstrate the supplied volumes are clearly the main restriction to the flow in performing a desirable SLA response.

5.2.4.1. Conclusions for CONWIP

Similar contributions as observed in KCS system are also identified in CONWIP policy as follows:

1. WIP levels were controlled for both medium and high seasons.
2. By restricting the raw material in the system, improvements for supply management are observed.

However, unbalanced WIP levels are evident. The dairy bulk powder environment requires distinct levels of WIP for distinct stages concluding that CONWIP is not an appropriate strategy to control WIP levels at individual stages. In addition, it behaves similarly as a push-system during high seasons.

5.2.5. KCS/CONWIP - Control Strategy

As previously explored in the literature, HKCS or Hybrid CONWIP/KCS is a pull-type strategy where individual stages are controlled by KCS mechanisms and the overall inventory is also controlled by CONWIP authorisation. This PCS is explored in this section as modelling according to section **4.6.6 - CONWIP/KCS Control Strategy** and simulated according to scenarios defined in section **4.8.3 - Hybrid CONWIP/KCS or HKCS – Scenarios.**

The results of controlling dairy manufacturing stages under HKCS high season are presented **Appendix J.1 - CONWIP/KCS – Summary - High Season Raw Material – Supply Periods 1,2 and 3.**

The traditional criteria examined **WIP average** and **SLA** solutions suggested are shown in **Appendix J.2 - CONWIP/KCS – RSM Optimisation (SLA – StageB2_Mean) – High Season**. For KCS/CONWIP strategy, it was observed that the RSM model returned similar volumes when compared to KCS optimised solutions where higher volumes for factor **E:CC** are suggested.

The optimised solutions follow the same pattern as identified in CONWIP and KCS. A higher supplied volume is observed in factor **A:Supply** for all three periods. Even though the lot-sizes for factors: **A:Supply, C:K2, D:K3 and E:CC** propose a consistent volume and the criteria are fully achieved, this solution causes an undesired level of raw material to be accepted.

The criteria of maximising both responses **SLA** and **Supply Accuracy** is presented in **Appendix - J.3 - CONWIP/KCS – RSM Optimisation (SLA – Supply Accuracy) – High Season.** The SLA performance is slightly improved for period 3 and the maximum levels for **StageB2** are lower. Period 3 presented distinct levels of authorised volumes.

The desirability index calculated under this criteria for periods 1, 2 and 3 are illustrated in **Appendices** - **J.4, J.5** and **J.6** respectively. In addition, the simulated results for KCS/CONWIP high season were also investigated under the non-dominant set depicted in the Pareto Frontier graphs as presented in **Appendix J.7** and divided by lot-sizes in **Appendix J.8.**

In conclusion, all three definitions of pull-type PCS are achieved under KCS/CONWIP strategy during high seasons. However, despite increasing the complexity in controlling the production flow, no extra improvements in the performance responses are observed under KCS/CONWIP when compared to KCS strategy.

For medium seasons consider three levels of supply as shown in **Appendix - J.9.** For KCS/CONWIP the results follow an identical pattern where no requirements for minimising the WIP at Stage 2 are needed and the unique criterion for optimisation relies on maximise the **SLA** response as shown in **Appendix J.10 - CONWIP/KCS – RSM Optimisation – SLA – Medium Season.**

By controlling the system through KCS/CONWIP policy, WIP levels at StageB2 remain low in contrast to StageB1 and all the additional requirements for a pull-type system are reached. The supply is entirely accepted in the system, WIP is controlled and the SLA achieves desired levels according to the maximum volumes for this season.

The non-dominant set are demonstrated in Pareto-Frontier graphs for identical responses (StageB1_Mean, StageB2_Mean, StageB1_Max, StageB2_Max) as shown in **Appendix - J.11 - CONWIP/KCS - Pareto Frontier – Non-dominant results for CONWIP/KCS – Medium Season.**

The non-dominant set by lot-sizes as shown in **Appendix - J.12 - CONWIP/KCS - Pareto Frontier – Non-dominant results for CONWIP/KCS – Medium Season – 3 Lot-sizes** which also demonstrate the supplied volumes are clearly the main restriction to the flow in performing a desirable SLA response.

The advantage of CONWIP/KCS pull-type for medium season over push-system is the guarantee of controlling appropriate levels of WIP at different stages. The drawback observed is the complexity in controlling the production flow during medium seasons especially when a simplified model such as CONWIP could be adopted.

5.2.5.1. Conclusions for CONWIP/KCS

Similar results as observed for KCS policy were demonstrated in the dairy environment under the CONWIP/KCS system. However, the search space defined for CONWIP/KCS is higher for both high and medium seasons as shown in Table 4.23 and Table 4.24, respectively. For the high season, the simulation consisted of 8,100 combinations while for the medium season 2,646 were generated. Therefore, the extended search space combining KCS and CONWIP factors have not improved the responses as expected while similar results are reachable by KCS strategy. In addition, the complexity of the system is increased by adding an extra factor.

5.3. Production Control Strategy Comparison

After individually demonstrating the results under each pull-type CONWIP, KCS and CONWIP/KCS. A comparison of the non-dominant set is presented in Figure 5.9 . All non-dominant or best factors sets are shown for individual PCS highlighting the individual performance for periods 1,2 and 3.

The graphs illustrate the impact of both conflicting responses: the WIP levels at **StageB2** and the **SLA** performance for all 5-day periods simulated. Through these graphs, it is evident that despite the inevitable variability presented for each period, KCS and CONWIP/KCS perform similarly and outperform CONWIP. By adopting CONWIP within the manufacturing environment an extra restriction in the system is observed since the SLA converges slowly to the maximum performance, namely for period 3 with higher variability. In addition, as previously demonstrated in section **5.2.4 - CONWIP**, as the supply volumes increase, the SLA performance also increases. However, the results suggests that CONWIP for this manufacturing environment behaves similarly to a push-system allowing extra material in the storage silos.

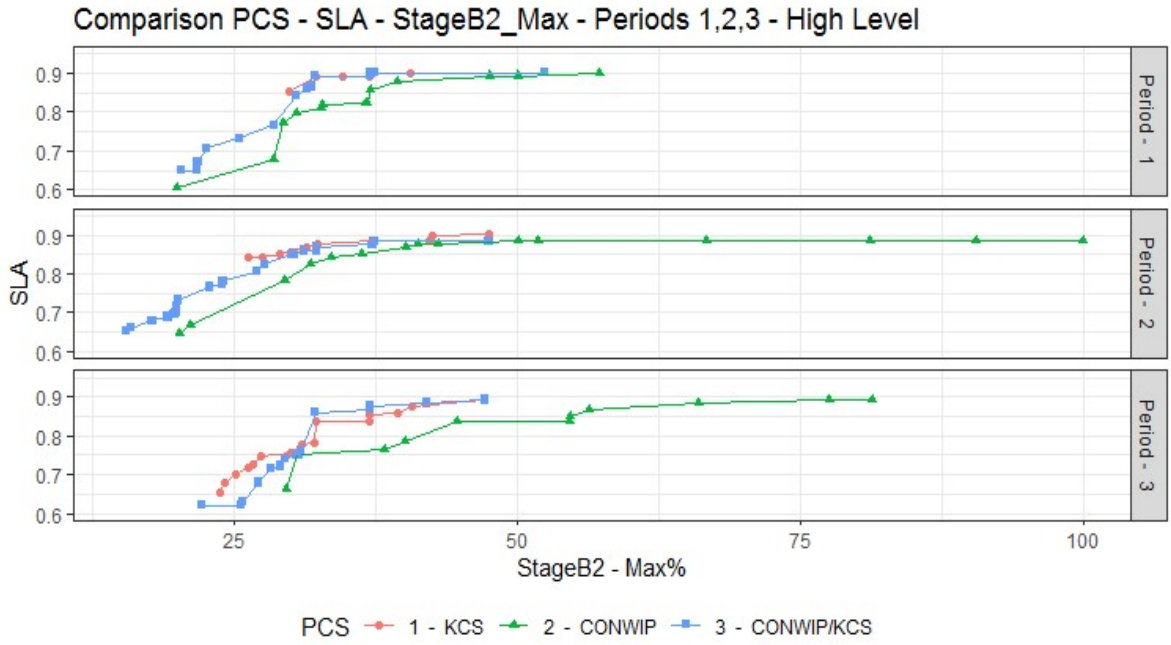

Figure 5.9 – Comparison PCS – SLA – Stage B2 Max – High Season

In Figure 5.10 the simulated dataset is divided into lot-sizes where an enhanced visualisation by volumes is provided. Through the graphs, it is possible to conclude:

1. KCS and CONWIP/KCS outperform CONWIP for all three periods and supply volumes for high seasons.
2. Even though KCS and CONWIP/KCS results are similar, the extra control required by CONWIP/KCS heavily impacts SLA levels and must be well defined which increases the complexity of the system.
3. SLA is heavily impacted by supply variability under the CONWIP strategy since the authorisation is controlled at the initial stage. As observed in Period 3 a higher level of WIP is required to reach a desired SLA.

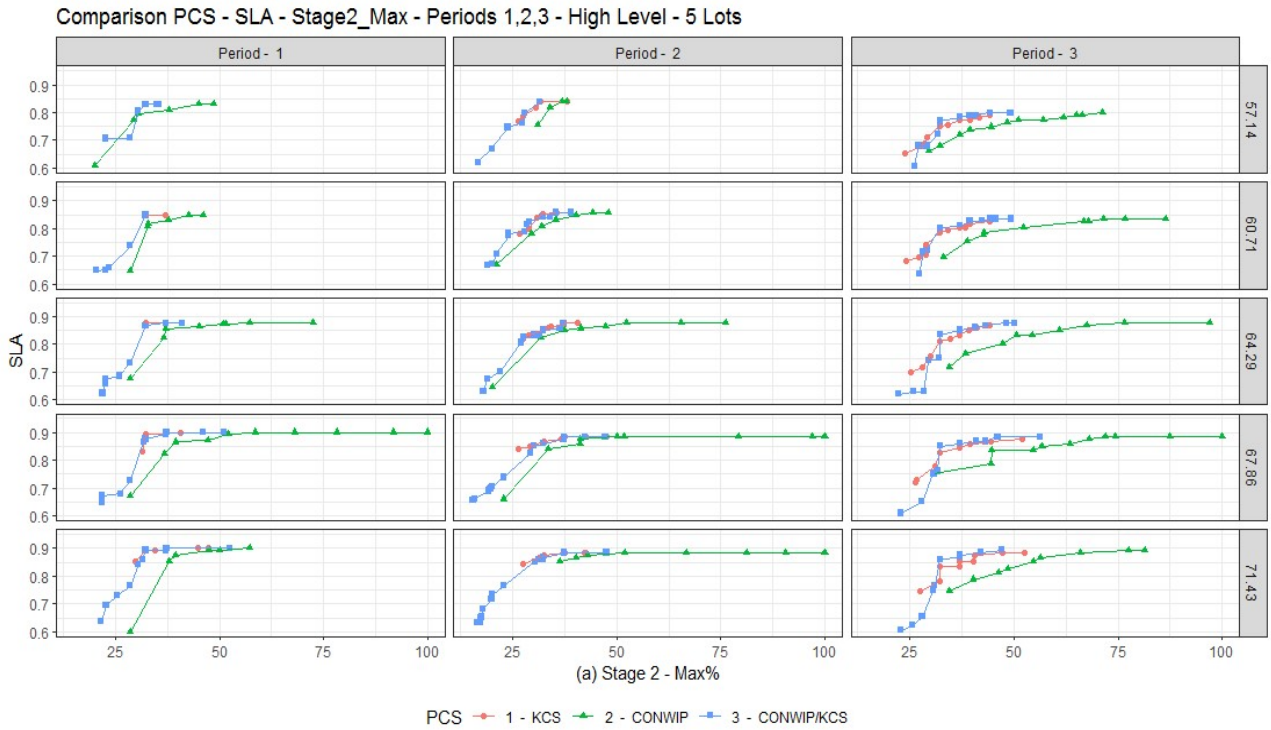

Figure 5.10 – Comparison PCS – SLA – Stage B2 Max – High Supply Volumes – 5 Lot-sizes

CONWIP, KCS and CONWIP/KCS are also analysed for medium seasons. The trade-off **SLA** and **Stage B2 Max%** is presented in Figure 5.11 illustrating that KCS and CONWIP/KCS reach similar performance for periods. However, as previously stated, each PCS is heavily affected by the supply variability.

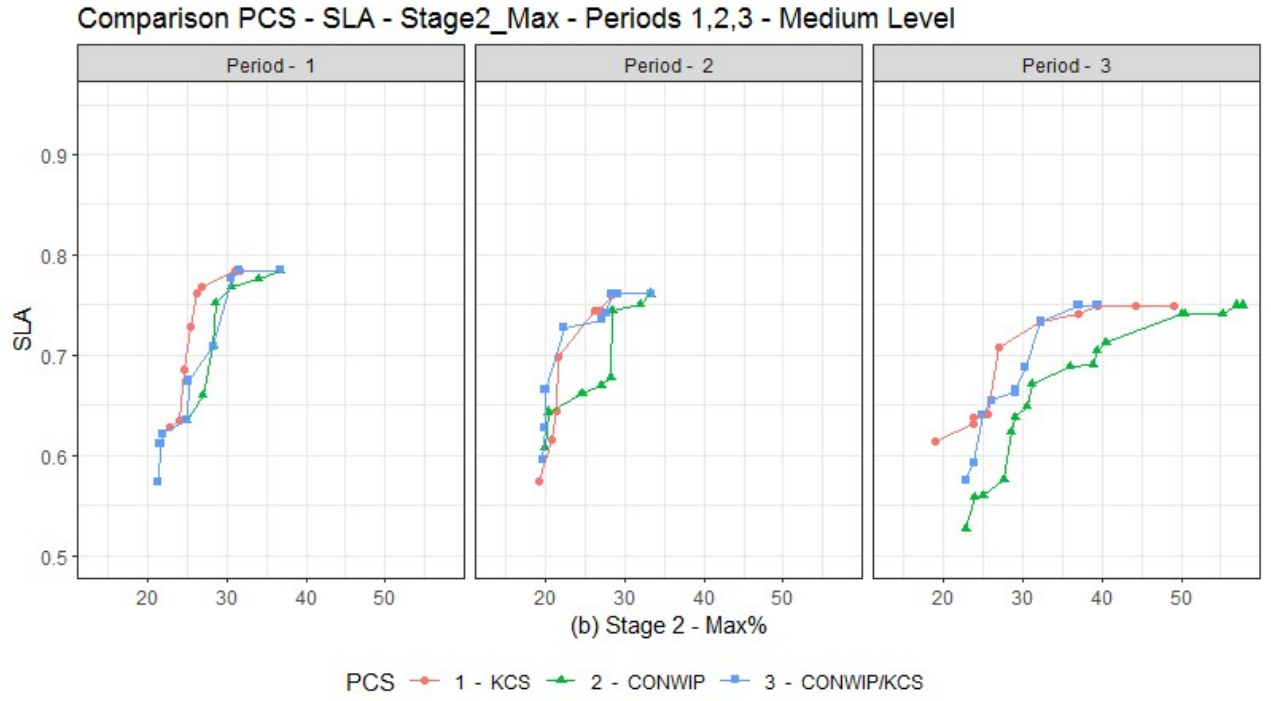

Figure 5.11 – Comparison PCS – SLA – Stage B2 Max – Medium Supply Volumes

In Figure 5.12 the same dataset simulated is presented in three lot-sizes to enhance the visualisation by supply volumes. Through the graphs, it is possible to conclude:

1. All three policies provided similar results for medium seasons as observed in periods 1 and 2 while in period 3 KCS and CONWIP/KCS outperform CONWIP.
2. CONWIP is heavily impacted by supply variability as observed in Period 3, which requires a superior level of WIP to reach the desired SLA as observed for lot-sizes 50 and 53.57.

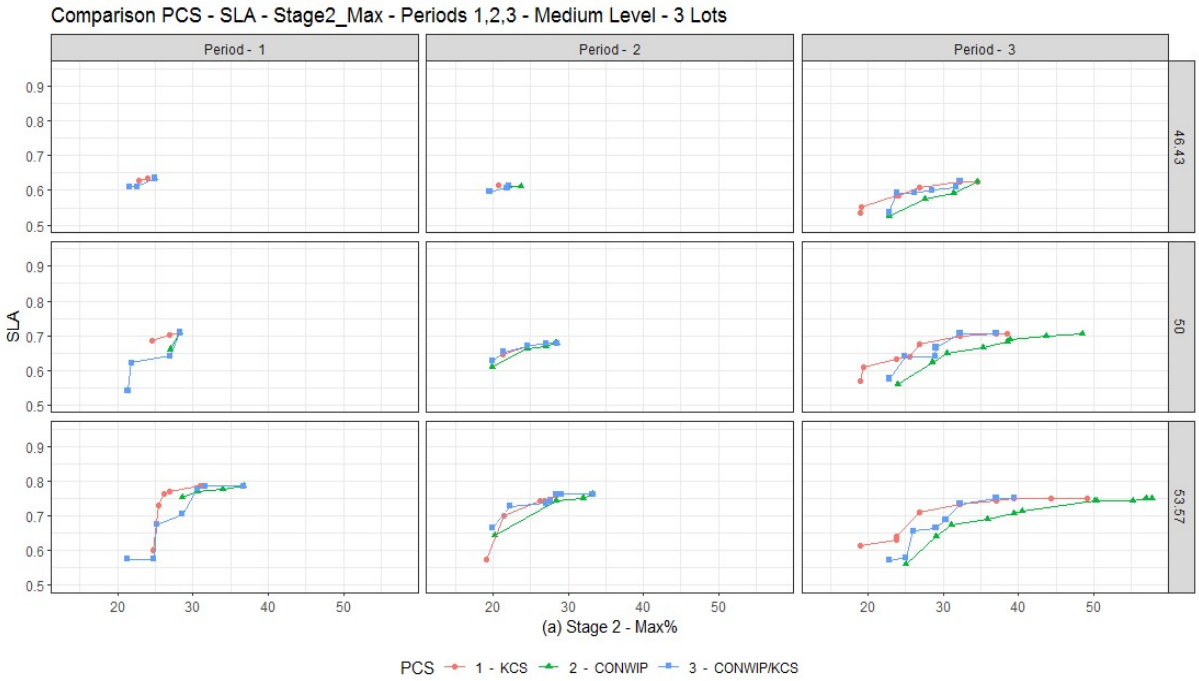

Figure 5.12 – Comparison PCS – SLA – Stage B2 Max – Medium Season – 3 Lot-sizes

5.4. Evaluating KCS Performance for Additional Periods

According to the results previously presented, KCS is the most appropriate pull-type PCS to control the excess of WIP between stages achieving the desired SLA for high seasons for the dairy bulk-powder environment. The objective is to highlight the contribution to the system under KCS pull-type where the WIP level is well controlled reducing the risk of perishability based on the optimised factors investigated in section **5.2.1 - Kanban Control Strategy - High season**. Therefore, in order to evaluate the contribution of KCS optimised factors for distinct periods, additional simulations were performed considering the factors suggested by the RSM as presented in Table 5.3. All the high season periods (from 1 to 12, including periods 1,2 and 3) were simulated for one unique supply volume (Supply Lot 67.86) and compared between the current push system and the KCS results as shown in Figure 5.14.

Both stages Stage B1 and Stage B2 under the current push system are heavily impacted by the variability of the supply, by accepting extra raw material and pushing the excess from Stage B1 to Stage B2 whereas under KCS the system identified a balanced and optimum volume between the stages mitigating the variability for Stage B2 but maintaining the SLA at the desired level.

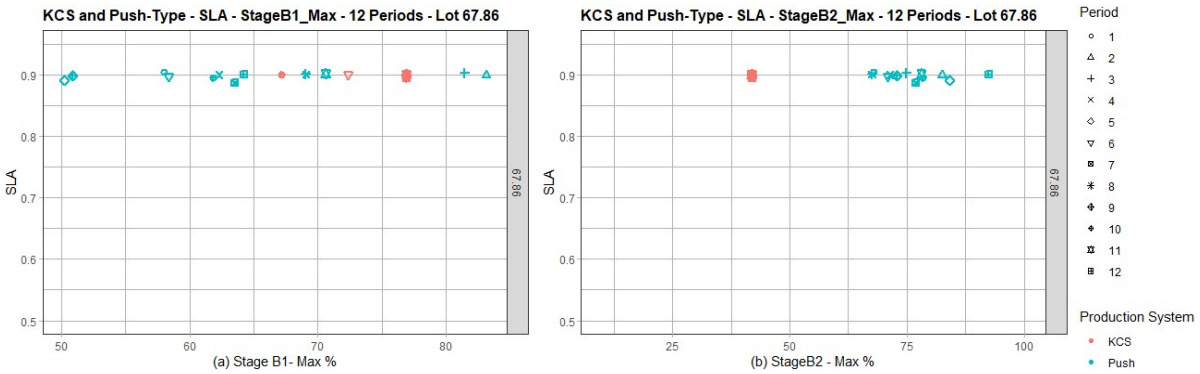

Figure 5.13 –KCS and Push-Type – Extended to 12 periods – Lot 67.86 - Stages B1,B2 and SLA

In Figure 5.14, all the five volumes defined as factor **A:Supply** in section **4.8.1 - Kanban Control Strategy – Scenarios** , presenting volumes from 57.14 to 71.43, individually are demonstrated. Once more, under the current push system, the volumes planned are accepted and pushed throughout the system, volumes higher than 64 lot-sizes increase the WIP levels while the SLA metric remains identical as observed for 12 simulated periods. Thus, overproduction is evident under push-system whereas under KCS the volumes are limited to an optimised WIP volume to achieve the desired SLA for all periods simulated.

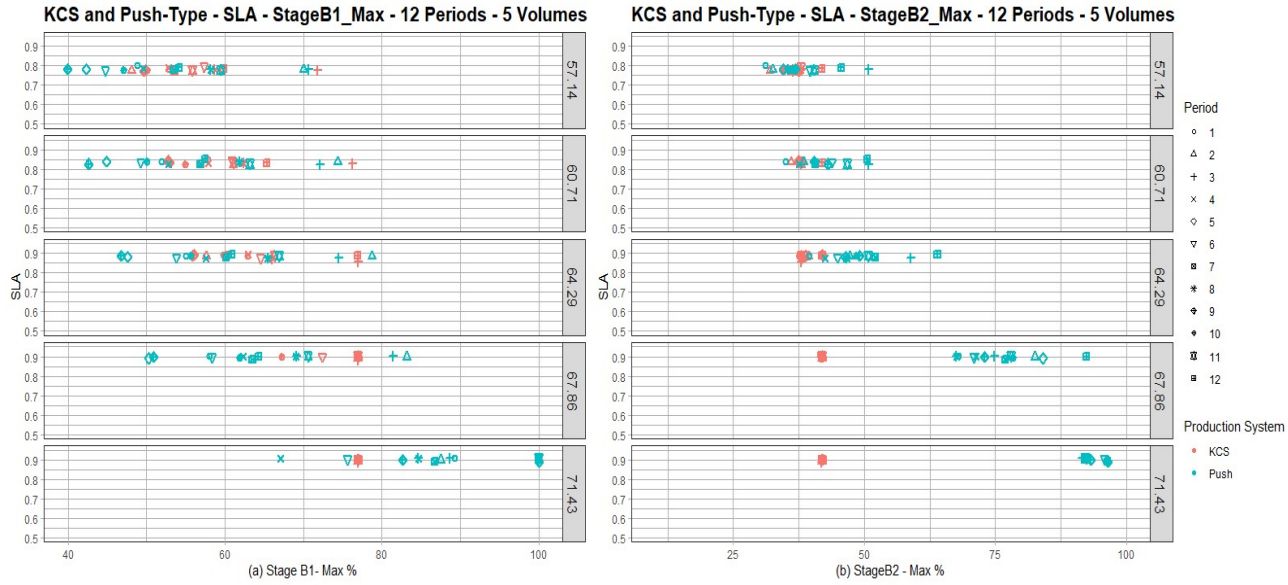

Figure 5.14 – KCS and Push-Type – Extended to 12 periods – 5 Volumes - Stages B1,B2 and SLA

It is possible to observe that volumes supplied lower than 60 lots are heavily impacted by the supply variability, namely at stage B1. The WIP levels are controlled for both stages especially when the supply volumes are gradually increased, supporting operation decisions in accepting extra material in the system.

An additional comparison for metrics **SLA** and **Stage 2 Process Utilisation** for all identical simulated periods is presented in Figure 5.15. In this graph, the utilisation is reduced for periods lower than 64 lot-sizes for

both push and KCS strategies, suggesting that the processing capacity could be managed for medium seasons.

Volumes higher than 64 lot-sizes indicate that the current push production increases the utilisation at stage 2 by separating extra raw material as expected. However, such extra processing remains in WIP silos as previously explored. Owing to the production control under KCS, the volumes are controlled; thus, the utilisation is reduced since no extra volumes are authorised in the system.

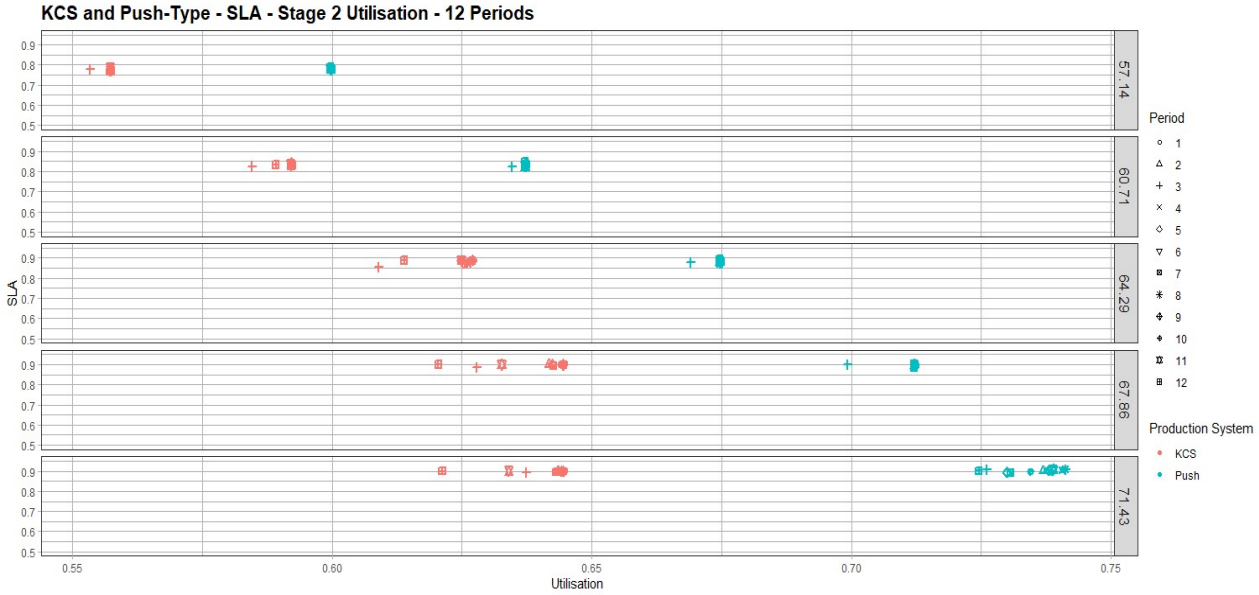

Figure 5.15 – KCS and Push-Type – Extended to 12 periods – Utilisation and SLA

An additional analysis compares **SLA** and **SupplyAccuracy** for push and KCS production systems as shown in Figure 5.16. Once more, volumes under 60 lot-sizes behave similarly, indicating the total raw material planned was processed by the system. Under KCS policy the flow is well controlled avoiding extra raw material. Therefore, the Supply Accuracy metric performed poorly as the volumes are being gradually increased.

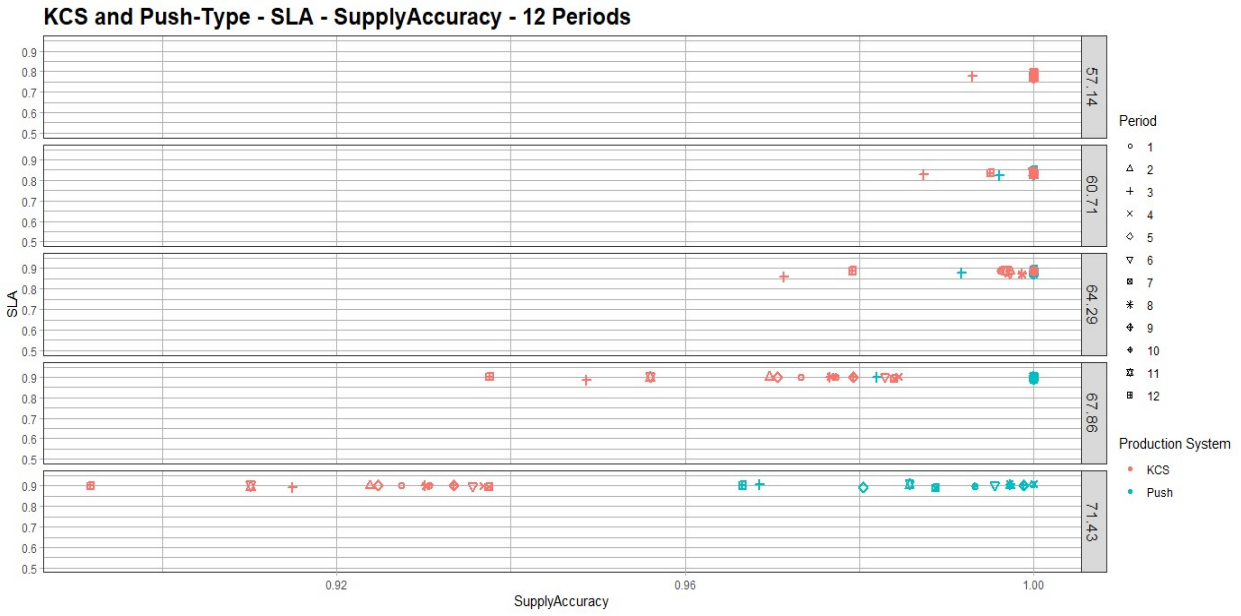

Figure 5.16 – KCS and Push-Type – Extended to 12 periods – Supply Accuracy and SLA

Ultimately, a comparison between the traditional trade-off conducted by previous research for Discrete Event Manufacturing as proposed by [168], [184], [216]–[218] is illustrated in Figure 5.17. The overall WIP average was calculated considering both stages B1 and B2 levels. Under push and KCS pull-type, the results suggest a similar behaviour, suppressing potential improvements in this environment.

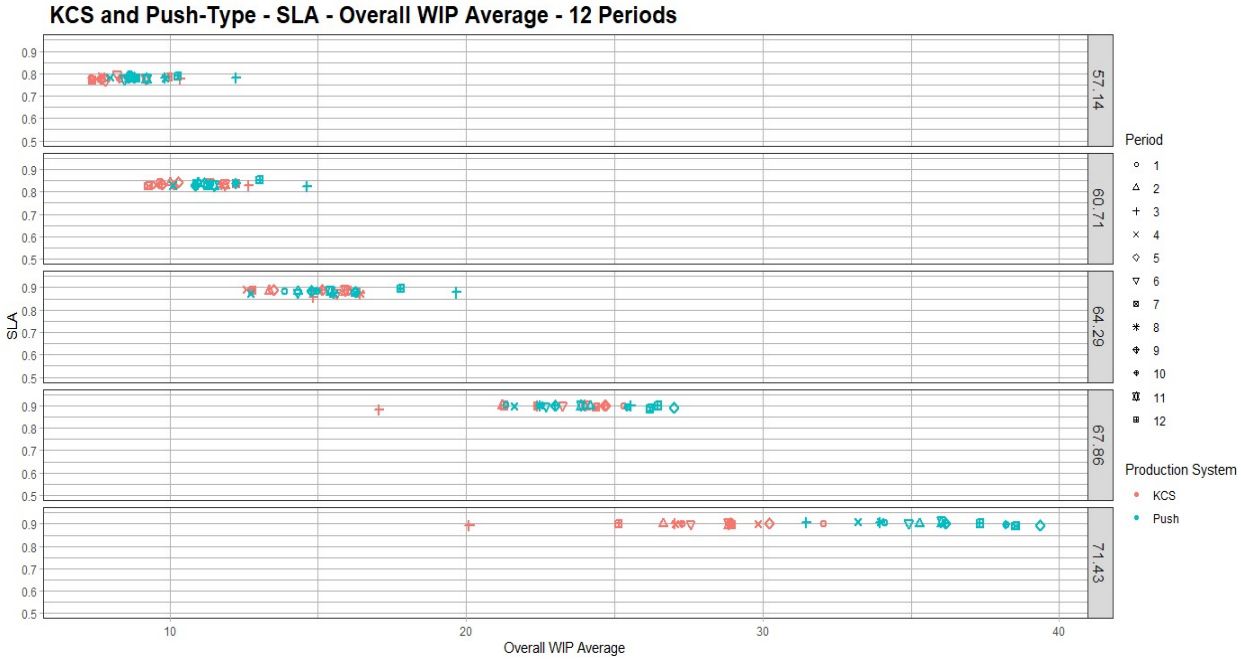

Figure 5.17 – KCS and Push-Type – Extended to 12 periods – Traditional Approach Overall WIP Average and SLA

For volumes below 71 lot-sizes the graph presents insignificant improvements. However, it has previously proven that for volumes higher than 67 lot-sizes, no contribution to the SLA is achieved. Therefore, the traditional trade-off for optimisation usually sought is not applicable to the dairy bulk powder manufacturing environment since average conceals critical challenges identified in this sector.

As stated in section **2.4.3 - Separation,** the milk spoilage pattern changes significantly after passing through the separation process , therefore, measuring WIP levels independently at individual stages and maximum WIP levels are considered conversely to the overall WIP average conventionally adopted. The metrics selected in this research are proved to be more effective since by measuring the overall WIP, the variability is smoothed, and the limited storage capacity which restricts the system is disregarded.

5.5. Adaptive Pull-Type for Dairy Manufacturing

In the previous section, all results of designing the PCS focused on Dairy Manufacturing were demonstrated and the metrics for optimising the current operations were compared between KCS and Push-type systems. The importance of controlling WIP levels at different stages was proven to be an efficient method to manage intermediate inventory and achieve improved SLA metrics for the dairy environment.

KCS is the most appropriate PCS to be considered in dairy manufacturing due to the individual control by stages. The last step in pulling the dairy manufacturing production flow is dynamically selecting the levels according to the variability explored in the system.

To identify the optimum volume for each stage, a sequence of simulations were performed and the responses optimised according to the factors defined in section **4.8.1 - Kanban Control Strategy – Scenarios** , presenting volumes from 57.14 to 71.43, . In order to two prevent these limitations observed in the pull-type PCS examined, this section demonstrates the benefits of identifying the optimum volumes dynamically according to the volumes supplied and the intermediate inventory. Therefore, the results obtained by the optimisation method described in section **4.10 Adaptive Pull-Type Approach** are presented for a manufacturing environment operating during high season. In addition, during medium and off-seasons, the next step in improving the dairy operation is to guarantee that CIP times are scheduled without compromising the three main assumptions for a pull system: achieving the demand fulfilment, authorising supply volumes according to demand and controlling WIP levels.

5.5.1. Results Adaptive Pull-Type under High Seasons

The results obtained by simulating the identical periods and compared between KCS and push system as explored in section **5.4 Evaluating KCS Performance for Additional Periods** are presented in this section. However, the comparison between KCS and the adaptive pull-type system developed according to the rules

defined in section **4.10 Adaptive Pull-Type Approach.** The optimised results were applied to all 12 periods previously evaluated and compared to the KCS.

By analysing one particular volume as presented in Figure 5.18, it is possible to observe that for all periods, the adaptive KCS pull-type behaves similarly to the KCS optimum factors restricting the WIP in the system for both stages: Stage B1 and Stage B2. In the adaptive KCS pull-type there are some variations since the authorisation levels are dynamic select conversely to the fixed optimum factor suggested by the RMS model.

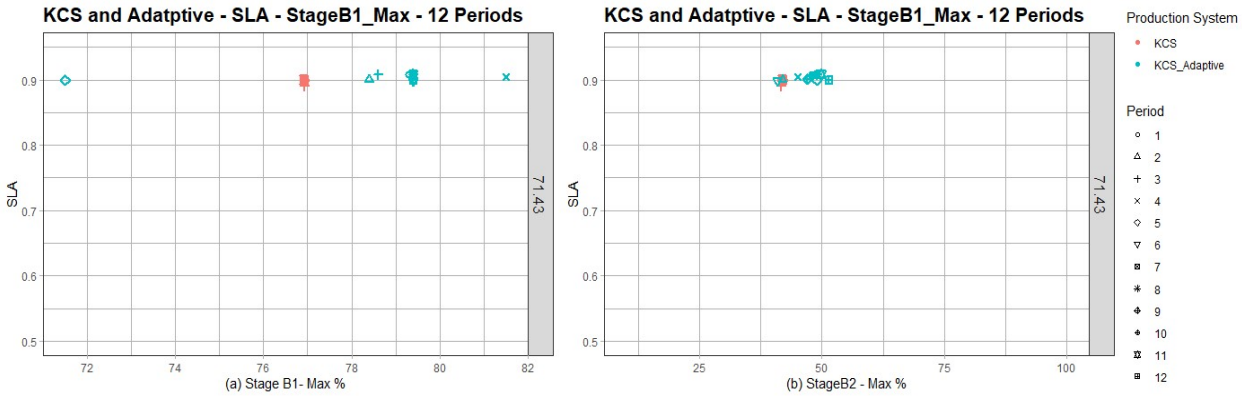

Figure 5.18 –KCS and Adaptive Pull-Type – Stages B1 and B2 Max% and SLA – Periods 1 and 12 – Lot 71.43

Figure 5.19 replicates the same visualisation for all volumes analysed. It is possible to observe that for all periods, the adaptive KCS pull-type behaves similarly to the KCS optimum factors restricting the WIP in the system for both stages: Stage B1 and Stage B2. In the adaptive KCS pull-type all volumes present variations since the authorisation levels are dynamic select conversely to the fixed optimum factor suggested by the RMS model. The system simplifies the WIP control since it is dynamically calculated according to the volume supplied, cip schedules and manufacturing design as explored in section **3.4.5 - Dairy Manufacturing Stages in the ePMPS Framework.**

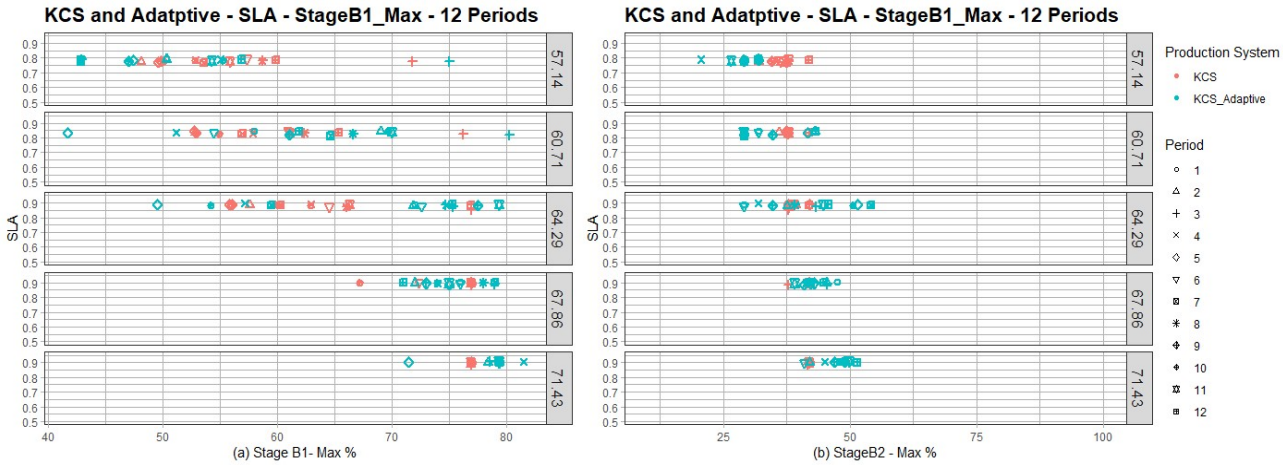

Figure 5.19 –KCS and Adaptive Pull-Type – Stages B1 and B2 Max% and SLA – Periods 1 and 12

The main advantage of the Adaptive pull-type over KCS is that the algorithm will dynamically determine the level of authorisation for each stage. Figure 5.20 presents the cumulative curve of all 12 periods and five distinct volumes simulated. It is possible to observe that the Adaptive performs slightly better, but the difference is not significant since some differences are lower than 0.01. However, given the results presented for SLA and maximum WIP at stages B1 and B2 the method is an alternative to identify the best volume to be authorised for each stage in the researched manufacturing environment. The data simulated is entirely demonstrated in **Appendices K.1 - KCS - Results Simulated – SLA Cumulative Curve** and **K.2 - Adaptive Pull-Type - Results Simulated – SLA Cumulative Curve.**

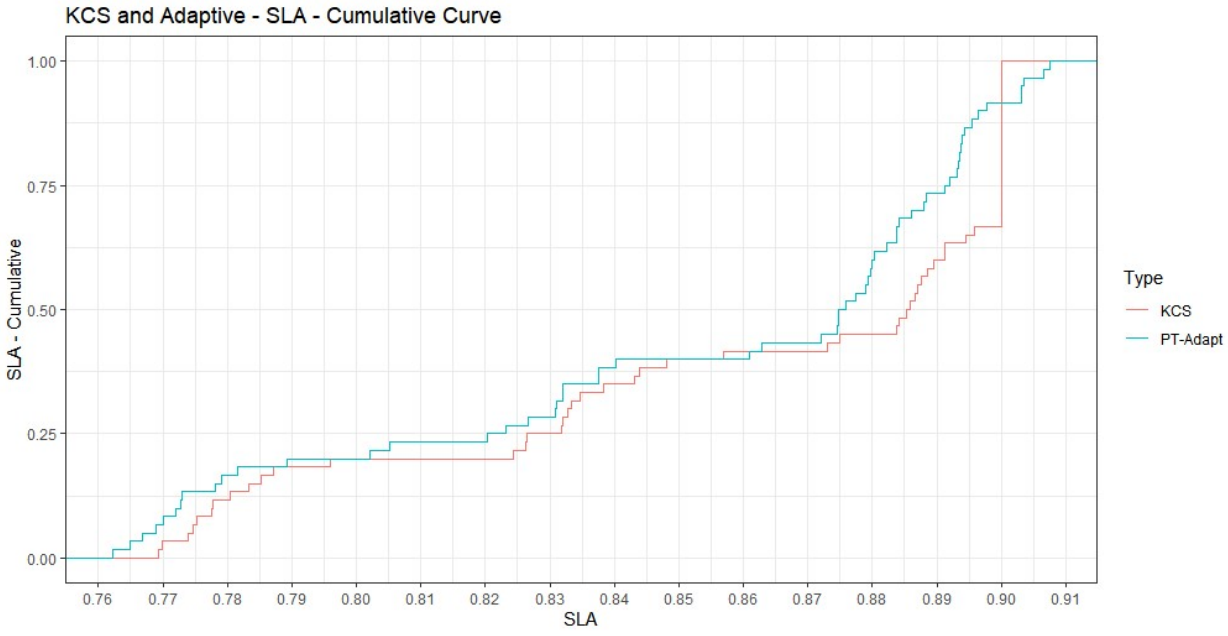

Figure 5.20 – KCS and Adaptive Pull-Type – Cumulative Curve for SLA

5.5.2. Results under Medium Seasons

Under medium seasons, the manufacturing environment must consider not only the WIP levels but also to optimise the internal resources achieving the best SLA and reducing potential sources of waste. The risk of perishability is reduced since the supplied volumes are limited. Therefore, according to the PCSs explored and the results demonstrated in section **5.2.2 Kanban Control Strategy – Medium Season** a distinct strategy is required for this specific period of the year. The results obtained by the recommendation schedule were published by Eccher and Geraghty in [234], expanding the algorithm to extra conflicting criteria such as energy consumption.

For medium and low volumes, the objective for optimisation might change since the dairies have sufficient capacity to process the restricted raw material supplied. However, in this section, the results follow the same criteria previously explored such as SLA and WIP at Stage B2, considering the best set of equipment. The equivalent three lot sizes for all three 5-day periods were replicated. The algorithm input parameters were defined according to the ranges described in Table 5.7.

Table 5.7 – Parameter for comparison

Parameters	Min	Max
Equipment Set	2	4
Running Hours	5	8
CIP/OFF (equipment availability)	2	8
Schedule Hours	120	120

The Recommendation Algorithm for medium seasons initially created 392 plans for each period and each lot-size volume supplied as described in Table 5.8 according to the range defined.

Table 5.8 – Scheduling Planning

Parameters	Set	Assumptions
Equipment Combinations	{{1},{2},{3},{4},{5},{6},{7}}	For Set = 1 {0,0,1,1} {Equipment 3 and 4} Table 4.25
CIP/OFF Cycle Time (Hours)	{2,3,4,5,6,7,8}	Hours the equipment is unavailable
Running (Hours)	{5,6,7,8}	Hours Equipment Running
Start CIP cycle time	{{1,6},{1,7},{1,8} {1,9}}	RunSet5 = Start at 1 or at 6 (starting at 5 it would conflict to the minimum running hours)
Total Scheduling Plans	392	Applying Equations (4-31) and (4-32)
Total Data points	47040	Considering 120 hours per each schedule (5 days)

According to the total scheduling plans created, the Scheduling Plans that best fit the objectives criteria defined by the user are selected according to the Pareto Frontier Graph. The response equations previously evaluated are compared for the medium season.

The algorithm structure results are presented in **Appendix K.3 - Example of the Structured Scheduling Algorithm** for Medium Season with Maximum Running hours 8 and Minimum CIP hour 2 as the range defined.

A function called ***ScheduleStage*** see **Appendix K.5 - Function ScheduleStage** receives three parameters: the stage, the number of pieces of equipment and the number of combinations allowed for each schedule. A second function called ***CalculateSchedule*** see **Appendix K.6 - Function CalculateSchedule** accesses vectors *EquipmentSet*, and the *CIPVector.* The supply volumes are imported and calculated according to each schedule defined. In addition, each schedule plan is linked to a summary dataset covering the indicators available for the final user to define the most appropriate objective function and further visualise it in a Pareto Frontier Graph.

Maximising SLA and minimising WIP at StageB2 are the initial criteria defined to compare the performance results from PCS. Figure 5.21 illustrates an example of the schedules simulated for period 3 for volumes corresponding to medium season. The graph highlights the non-dominant Pareto-Frontier solution. The non-dominant datapoints or optimum responses attainable in the figure were exactly selected according to the algorithm described in section **4.7.1 - Pareto-Frontier.** All the simulated scenarios compose the defined space; however, only the optimum data points that satisfy the multi-objective criteria in this case SLA and WIP reduction are selected.

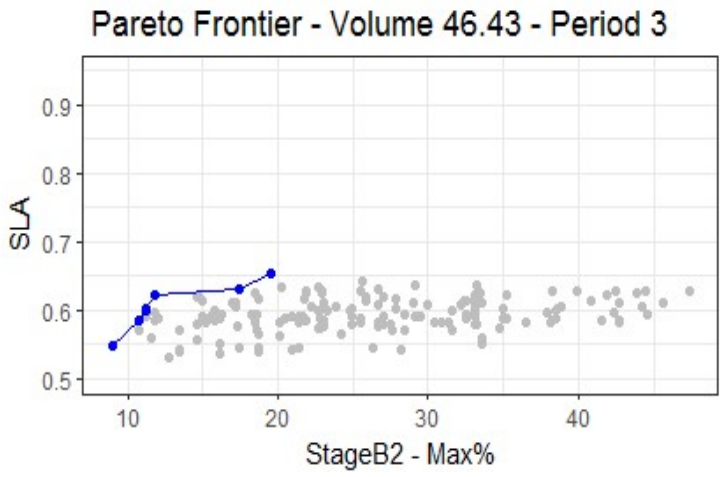

Figure 5.21 – Optimum Scheduling Plans – StageB2 Max% and SLA – Volume 46.43 – Period 3

All periods and volumes simulated are demonstrated in **Appendix K.7 - Pareto Frontier Medium Season – 3 Periods.** Three main vital information is observed in these graphs:

I. Despite the performed schedules highlighted by the Pareto optimum set, distinct results for each period are presented.

II. The equipment schedules defined during medium seasons heavily impact the key performance metrics (SLA and WIP levels), since the equipment set will authorise the material flow within the system.

Through the graphs, it is evident that an optimum scheduling plan for medium seasons is the most appropriate strategy combining a desirable SLA level, managing WIP levels and additionally controlling the equipment utilisation through an efficient scheduling plan. The equipment utilisation is a strong criterion for optimisation considering the extra capacity during medium and low volumes, as previously shown in **Figure 4.11 – SLA and Stage 2 Utilisation**. The non-dominant solutions selected are presented in Figure 5.22. The best Pareto Optimum set provides similar results for all three periods reducing the supply variability influence on SLA and Stages B1 and B2 WIP metrics.

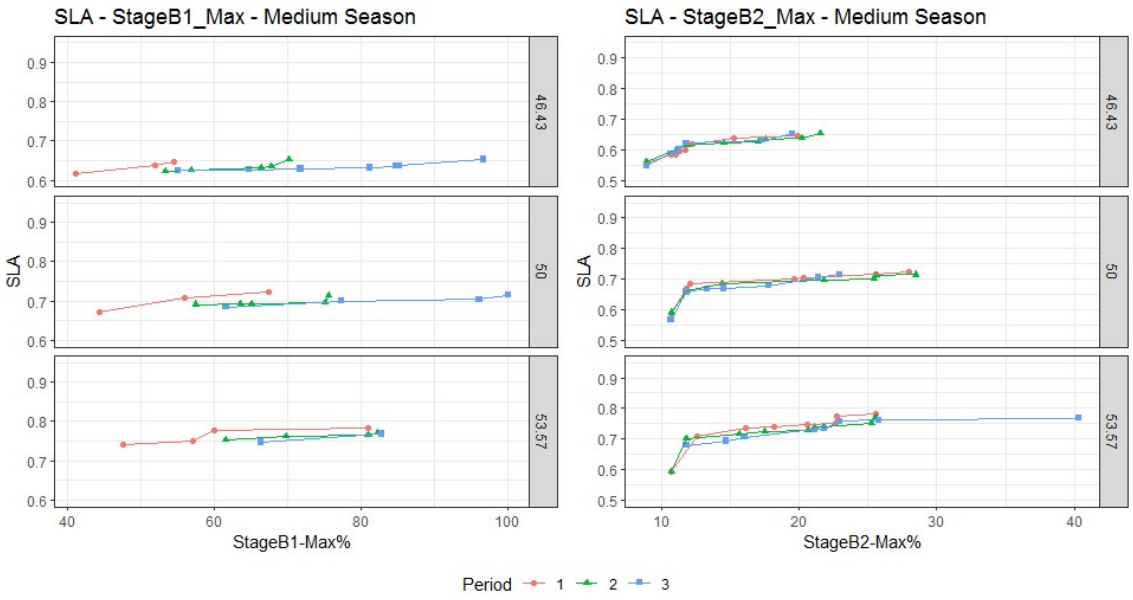

Figure 5.22 – Optimum Scheduling Plans – StageB1 Max% - StageB2 Max% and SLA

The supply variability heavily influences the initial storage stages Stage B1, while StageB2 indicates that the defined schedules can be easily adapted to reduce the variability for further stages.

Table 5.9 demonstrates the optimum trade-off for maximising SLA and minimising Stage2_Max for all three periods shown in the Period column. Through the Total Best Schedules Column, it is possible to observe the non-dominant recommended total schedules. However, only one equipment set is demonstrated in the Equipment Set Column to simplify the visualisation. An example of a simulated scheduling plan is presented in **Appendix K.8 - Example ePMPS Best Scheduling Period 1 – Medium Season.**

Table 5.9 – Medium Volumes – SLA and StageB2

Period	Lot Size	Total Best Schedules	Equipment Set 1st	CIP/OFF	Running Hours	Start CIP	Stage1WIPMeanPerc	Stage1WIPMaxPerc	Stage2WIPMeanPerc	Stage2WIPMaxPerc	SupplyAccuracy	SLA	Utilisation
1	46.43	26	1	7	5	1	22.07	54.54	2.64	19.92	1.00	0.65	0.84
1	50.00	22	2	7	5	1	28.05	67.41	3.89	28.00	1.00	0.72	0.91
1	53.57	21	4	3	7	8	22.98	57.01	6.44	22.69	1.00	0.75	0.77
2	46.43	17	2	7	5	1	24.75	70.15	2.69	21.57	1.00	0.65	0.84
2	50.00	22	1	8	8	1	31.21	75.55	3.66	25.58	1.00	0.71	0.91
2	53.57	21	1	8	8	1	40.46	82.25	4.39	25.58	1.00	0.77	0.96
3	46.43	18	1	2	7	8	30.71	81.15	2.15	11.25	1.00	0.60	0.83
3	50.00	18	4	7	5	1	27.90	96.11	4.98	21.40	1.00	0.70	0.72
3	53.57	20	7	7	5	1	20.06	82.77	12.18	40.29	1.00	0.77	0.52

Each lot size 46.43 and each period has an adapted equipment set recommended as the best schedule with different suggestions for the CIP/OFF and Running Hours. For period 3, the schedule suggested full capacity (equipment set = 7) with lower running hours, in order to ensure the undisruptive process.

The *Supply Accuracy* column reached the desired level; thus, all the material planned is received and no restrictions in authorising the raw material occurred. The main contribution of the schedule for Medium Seasons is an optimised utilisation equipment.

Distinct equipment sets are suggested according to the criteria selected. By minimising StageB1, for example, several optimum or non-dominant schedules are recommended as shown in Table 5.10.

Table 5.10 – Medium Volumes – SLA and StageB1

Period	Lot Size	Total Best Schedules	Equipment Set 1st	CIP/OFF	Running Hours	Start CIP	Stage1WIPMeanPerc	Stage1WIPMaxPerc	Stage2WIPMeanPerc	Stage2WIPMaxPerc	SupplyAccuracy	SLA	Utilisation
1	46.43	13	2	7	5	1	22.07	54.54	2.64	19.92	1.00	0.65	0.99
1	50.00	7	4	8	6	1	19.3	55.95	6.63	38.16	1.00	0.71	0.99
1	53.57	6	4	3	7	8	22.98	57.01	6.44	22.69	1.00	0.75	0.99
2	46.43	10	1	7	7	1	24.75	70.15	2.69	21.57	1.00	0.65	1.00
2	50.00	9	7	4	8	9	15.53	57.43	8.83	41.99	1.00	0.69	0.48
2	53.57	8	7	8	8	1	16.86	80.94	12.8	47.22	1.00	0.77	0.52
3	46.43	14	7	8	5	1	15.84	71.73	10.27	47.36	1.00	0.63	0.45
3	50.00	11	7	7	5	1	17.81	77.25	9.43	39.29	1.00	0.70	0.48
3	53.57	3	7	7	5	1	20.06	82.77	12.18	40.29	1.00	0.77	0.52

As observed, the natural strategy by minimising StageB1 is sending the product to the next stage as recommended by the schedule plans *Equipment Set 7* which refers to the maximum capacity at this stage. For this set, all the pieces of equipment are running which justifies the lower utilisation performance. However, the schedule limits the running hours to 5 and suggests a higher number of OFF hours.

The main benefits of a dynamic support scheduling plan are the flexibility to cope with the supply variability and guarantee the increase in SLA response independent of the period selected as observed. All three periods have responded similarly to the suggested schedule. For the medium season, there is no evidence of extra material in the system. The plant is able to process all the material received as observed by the Supply Accuracy response. The benefit of efficiently planning the equipment is the cost reduction during the raw material unavailability.

5.5.3. Comparing Production Control Strategies and ePMPS Recommendation for Medium Seasons

A comparison between PCS policies and the ePMPS schedule recommendation for the medium season is illustrated in Figure 5.23 for one specific period and volume supplied. As previously observed in Figure 5.21, by appropriately scheduling the equipment, the SLA converges faster to the maximum SLA expected when compared to the PCSs examined. Also more, medium seasons have a restriction of raw material supplied, so a distinct strategy is required during this specific period of the year reducing the restrictions suggested by the PCSs examined.

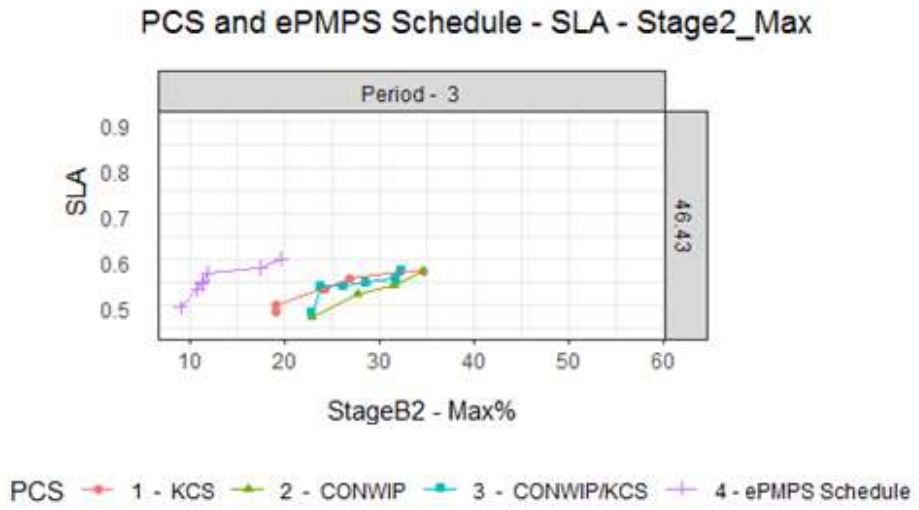

Figure 5.23 – Comparison ePMPS Recommendation Schedule and PCS

In Appendix **K.9 - Pareto Frontier - ePMPS Best Scheduling Periods 1,2,3 – Medium Season,** the same volumes examined for medium seasons as explored in section **4.8.1 - Kanban Control Strategy – Scenarios**, more precisely in Table 4.20 are presented.

The results achieved the equivalent SLA levels which is justified due to the volume supply authorised in the system. The main benefit observed is the reduced volume of WIP to achieve a desirable SLA level. As observed in period 3, which is the most impacted by the supply variability, both objectives have improved.

The scheduling plan must comply with the tactical directions and a variety of restrictions at the operational level. By evaluating the graphs and the Pareto-optimal set area, it is possible to conclude that more than one schedule could be selected. Furthermore, the ability to dynamically select the optimum criteria provides

more insights into choosing a suitable scheduling plan. By authorising WIP levels according to the equipment capacity, an enhanced system is achieved for medium seasons in comparison to the PCS investigated.

5.6. KCS and Scheduling Plan on the Cloud-Based Framework ePMPS

The optimisation strategies for distinct seasons such as Peak and Medium to control the material flow for the dairy bulk powder manufacturing environment are available for the ePMPS framework described in **Chapter 3.** Distinct scenarios can be simulated on the cloud-based framework as described as follows.

5.6.1. ePMPS for Peak Seasons – High Volumes Supplied

For peak/high seasons where the supplied volumes are higher, Figure 5.24 presents a comparison between the current state and the proposed KCS for this specific production environment. The CIP cycle time was uploaded without any variation in order to guarantee the same production flow for the two simulated scenarios. The **Current** scenario reflects the current manufacturing condition for case study detailed in section **3.2.1 - Industrial Partner Case Study 1 – Exploring M&S for bottleneck evaluation** explored in **Chapter 3.** The **Future-KCS** scenario suggests individual authorisation for all three stages simulated.

Metric	Current	Future-KCS	Variation
Total Supplied (L)	10,160,270	9,371,261	-7.766%
Total Separated (L)	9,855,119	9,331,494	-5.313%
Total Skim (L)	4,360,000	4,360,000	0%
Total Cream (L)	492,756	466,575	-5.313%
Total Process2 (L)	4,130,000	4,130,000	0%
Total Utilisation Separators %	70.798%	67.037%	-5.313%
Total Utilisation Dryers %	98.198%	98.198%	0%
Total CIP Separators (Hours)	317	317	0%
Total Average WIP Stage 1	0.752%	0.439%	-41.589%
Total Average WIP Stage 2	0.831%	0.338%	-59.374%
Total Waste	0	0	0%

Figure 5.24 – Comparison Dashboard – ePMPS - Current Push-system and KCS

In the **Comparison** dashboard the SLA, which is composed of the Total of Skimmed Milk and Process2 produced, remained exactly the same as highlighted in Figure 5.24. The bottleneck in this manufacturing

environment is represented by the Dryer utilisation, which also remained the same. Intermediate WIP levels are reduced, as shown for both stages, and the raw material required to fulfil the current demand is also reduced. For this specific simulated scenario, the volume reduced in the system represents approximately 25 extra trucks during peak seasons for the exactly same 5-day period simulated throughout this research.

Figure 5.25 demonstrates the behaviour of each silo for both stages: Stage B1 and B2 represented by Whole and Skimmed milk silos, respectively. The evidence of the manufacturing environment running under KCS is observed by comparing the *Current Stage* and the *Future State – KCS* graphs depicted in Figure 5.25. A stable process for all 5 days simulated when compared to the current production process. The x-axis demonstrates the daily volume stored. The volume stored demonstrated in the y-axis represents the maximum utilisation for Stage B1 which is less than 80% while for Stage B2 under 50%, as previously proved in section **5.2.1 - Kanban Control Strategy - High season.**

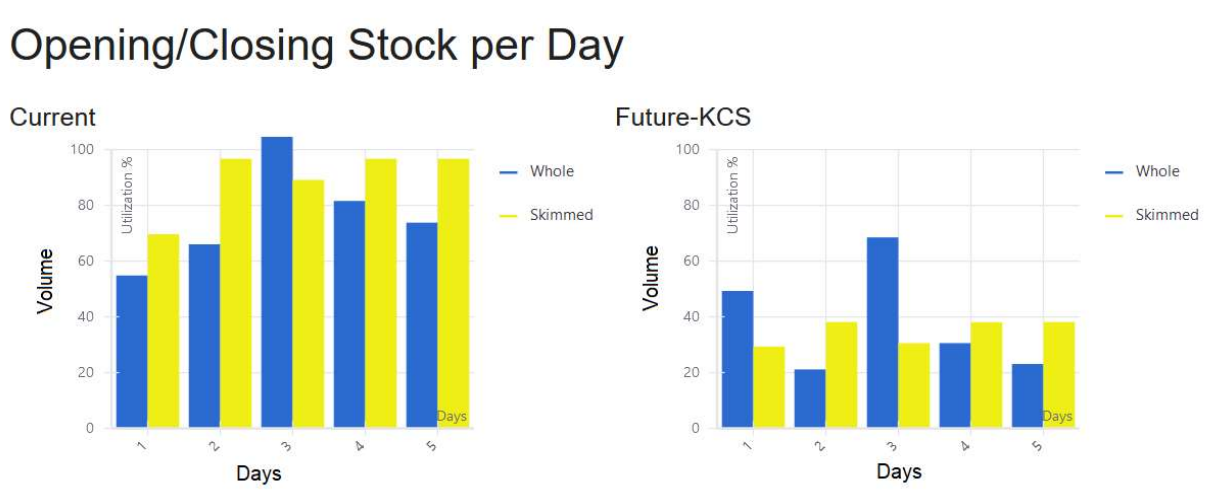

Figure 5.25 – Summary Dashboard ePMPS - the Current Push-system and KCS

5.6.2. ePMPS for Medium Seasons

As described in section **4.10.3 - Controlling the Material Flow for Medium and Off-Seasons**, for medium seasons, the plant must operate at a specific capacity avoiding waste generated by poor equipment utilisation, energy and water, for example. Therefore, the recommendation algorithm that suggests an optimum scheduling plan based on a Pareto-optimal is also part of the ePMPS framework.

Through the *Recommendation* options, the decision-maker has the option to choose multi-objective criteria by Maximising/Minimising the desired objective functions. The schedule is calculated according to the simulation available on the cloud-based framework. One example is illustrated in Figure 5.26 where SLA and Stage 2 WIP Max level were selected as an objective to be optimised.

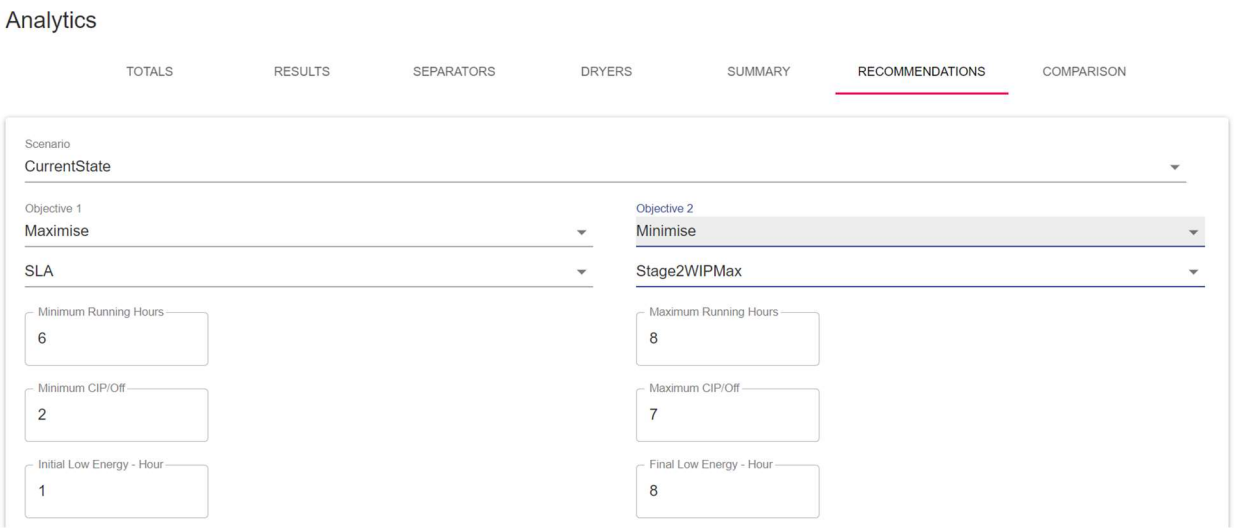

Figure 5.26 – ePMPS Recommendation – Defining the criteria for optimisation

The Pareto-optimal set is then presented in an interactive graph as shown in Figure 5.27. The algorithm developed is the same described through this research developed in RStudio see **Appendix F.3 - Pareto Frontier Graph – Rstudio Algorithm.** It was also widely applied to extract the optimum set from all the simulations performed as were described in section **4.7.1 - Pareto-Frontier.** The algorithm is accessed through the ePMPS framework according to the parameters defined in Figure 5.26. In this example, this simulation suggests a limited SLA since there is a restriction in raw material supplied. This graph is interactive; therefore, by directly selecting the best optimised scenario in the datapoint, the suggested **Plans** are presented as observed at the bottom of the page as shown in Figure 5.28.

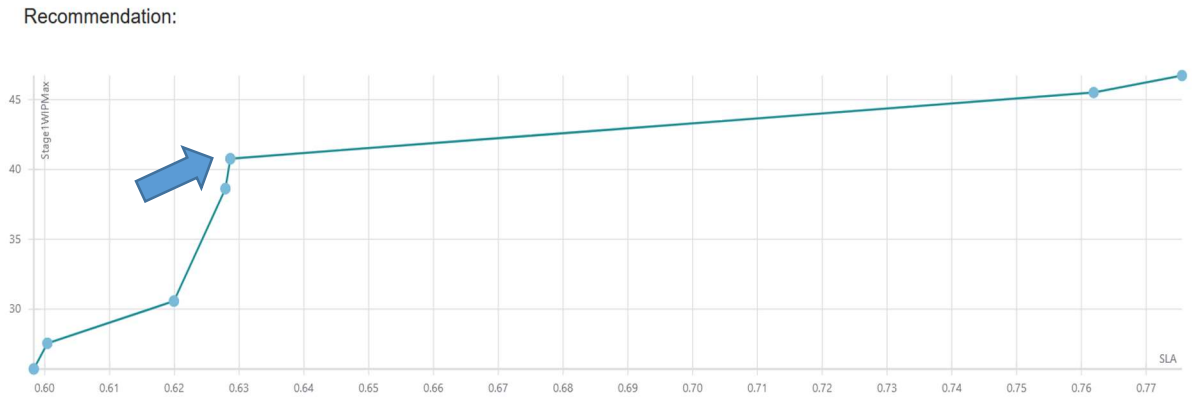

Figure 5.27 – ePMPS Recommendation – Pareto Optimal Set

Figure 5.28 presents all the metrics defined in section **4.2 - Performance metrics** for the simulated schedules. In addition, the combination pieces of equipment, number of hours running, the recommendation of when to start the CIP process in order to achieve the optimised scenario.

Figure 5.28 – Partial Example of ePMPS Recommendation Plans for Scheduling

5.7. Conclusion and Contribution to the Research

The contributions by implementing pull-type PCS: CONWIP, KCS and CONWIP/KCS were demonstrated in this Chapter. The MDP model previously modelled in Chapter 4 was simulated according to distinct supply volumes and frequencies. The main objective of these experiments is to evaluate which PCS guarantees an optimised condition balancing supply and demand and effectively controlling WIP levels under supply variability conditions.

The uncertainty observed during the raw material supply is also a concern regarding production-planning processes. During the analysis, different supply distributions were explored showing clear evidence that the stochastic behaviour in volume and frequency of raw milk supplied fluctuates daily which increases the instability in the system. In addition, each potential source of variability was examined in order to identify similar problems for distinct dairy manufacturers.

By examining trade-offs between conflicting objectives of maximising SLA and minimising WIP levels, it is possible to observe that this sector requires distinct WIP levels at individual stages. An evaluation of the overall average of WIP, as proposed by several previous studies, is insufficient to ensure higher performance metrics since WIP average mitigates the peak level silo utilisation.

A systematic volume authorisation for each stage improves the balance between supply and demand, as demonstrated in both policies: KCS and CONWIP/KCS. However, KCS has two main advantages over CONWIP/KCS:

1. Individual control mechanisms for each stage, while CONWIP/KCS requires the extra CONWIP volume control.
2. The extra control required by CONWIP/KCS causes restrictions in SLA achievement when it is inappropriately defined.

3. The main advantage of CONWIP and CONWIP/KCS in communicating the changes in allowing the release rate to be paced to the actual demand rate is insignificant for the powder bulk commodity production which is strongly dependent on contracts.

The provided results by each policy are fundamental inputs for distinct levels in the decision-making process:

1. At the strategic level, decisions regarding capital investment in storage and processing capacity design are affected by the appropriate PCS results produced. Distinct outcomes are achievable according to the PCS adopted.
2. At the tactical level, decisions regarding raw material supply are improved in agreement with the volumes planned. In addition, the effects caused by variability are mitigated under appropriate WIP levels at individual stages as proposed by KCS.
3. At the operational level, decisions regarding equipment utilisation are improved according to the volume to be processed and therefore the capacity required is defined through the CIP scheduling plan combined with the PCS adopted specially during off and medium-seasons where the raw material is restricted.

The results demonstrated KCS was the most appropriate system owing to the ability to control individual stages as required for the dairy sector as presented in Figure 5.9. The optimum volumes were identified through the RSM for each PCS where KCS provided satisfactory WIP control and SLA achievement. The results were also expanded to distinct periods in order to cover similar performance for the entire high season.

In addition, the adaptive algorithm to support pull-type decision-making processes does not require the solution space definition based on the previous simulation and provides similar results as examined for KCS as shown in Figure 5.19. It is possible to observe that for all volumes, the adaptive pull-type behaves similarly to the KCS optimum factors designed by Design Expert and no extra levels of WIP are required. For high seasons, the first interaction is performed in order to identify the best SLA achieved in a push-system environment; then the system gradually reduces the WIP levels suggesting the precise raw material to be authorised. As presented in section 5.6.1 - ePMPS for Peak Seasons, extra volumes represent a significant number of extra trucks to be managed and the potential risk of perishability caused by excessive WIP levels.

For medium seasons, it is performed by equipment scheduling since the capacity is higher than the raw material supplied as shown in Figure 5.11 illustrating that KCS and CONWIP/KCS reach similar performance for periods. However, each PCS is heavily affected by the supply of raw material restriction. Therefore, a comparison between PCS policies and the ePMPS schedule recommendation for the medium season is illustrated in Figure 5.23 where it is possible to observe that the SLA converges faster to the maximum SLA expected when compared to the PCSs. In addition the ePMPS schedule recommendation algorithm was expanded to consider sustainability metrics. The results were published to the **Manufacturing and System journal** entitled **“Incorporating sustainable criteria in a dynamic multi-objective recommendation planning tool for a continuous manufacturing process : A dairy case study " (see Appendix L.4).**

CHAPTER 6
DISCUSSIONS AND LIMITATIONS OF THIS RESEARCH

6.1. Discussions and Outcomes

The Dairy Sector, in particular the bulk powder manufacturing environment investigated in this research, is heavily impacted by external and internal factors: Seasonality, variability of the raw material supply, high volatility of market prices, risk of perishability, limited stored capacities and CIP interruptions. All these factors contribute to increasing the complexity of the production plan.

Constant interruptions caused by CIP cycles are observed in dairy bulk powder manufacturing and it heavily compromises the system processing capacity. CIP cycle times cannot be ignored since it must comply with governmental regulations and seriously impacts the product quality. Therefore, in order to create a reliable process, all these challenges identified in this sector must be mutually investigated to reproduce the events observed in the dairy bulk powder environment.

Much of the research investigated and explored in section **2.3 - The Dairy Supply Chain** is focused on fresh dairy finished goods for end-consumers within the dairy supply chain. Consequently, in order to fill the current gap, this research is focused on the bulk powder environment which supplies several other sectors and differs from fresh dairy products manufactured for end-customers.

As studied in the literature, the first challenge faced by the dairy environment is the raw material seasonality which is explained by the lactation curve described in [34]. The supply delivery increments the randomness in the system influencing the level of raw material in the internal storage silos. Therefore, distinct seasons require distinct approaches and strategies since it is one of the main sources of variability considered during the investigation phase, as described in section **2.3.1 Milk Seasonality.**

The initial activities within Dairy Supply Chains are similar across dairy manufacturers, the raw material must be stored at a low temperature and the short shelf-life requires a fast processing flow in order to reduce the risk of perishability. However, according to the product to be processed, the production flow is designed to separate the raw material into several end-products according to its composition as demonstrated (see **Appendices A1** and **A2**). In addition, since it refers to a commodity, the strategy for market prices must rely on contracts to protect their operations against price volatility as studied in section **2.3.2 - Dairy Market Prices**.

As explored in section **2.5 - Comparing Dairy Supply Activities Across Similar Sectors**, by comparing Dairy Supply Chain activities with other sectors, challenges identified in dairy cannot be similarly addressed, especially regarding the nature of the raw material supplied. In the pharmaceutical sector, namely solid dosage forms, when the API is imported, strategies to incorporate the supply lead time into the production planning process must be considered [70] as opposed to the dairy bulk powder commodity where the raw

material is constantly supplied and also follows a cyclical pattern. In addition, a comparison between the Dairy and the Food and Beverage sector indicates that similar WIP volumes to those observed in dairy bulk powder manufacturing are required in order to process large volumes of products. In addition, issues regarding perishability occur due to the pH levels. However, once more, the raw material supplied to this sector is largely dependent on water and High Fructose Corn Syrup (HFCS) producers [68] and the issues and the impacts caused by the frequency of the fragmented supply are not observed.

Simulation models to improve dairy manufacturing operations are focused on specific stages in the production process as explored in section **2.6.7 - Simulation to Support Dairy Supply Chain Activities.** It is observed that M&S applied to balance supply and demand, supply assessment, LCA for specific products and production scheduling is the main field in the literature investigated. However, mature production control strategies already validated in mass production and globally adopted by manufacturing industries were waiting to be investigated under the restrictions observed in the dairy sector.

Other sectors have been applied M&S to improve specific processes as observed in the literature, for example as described in [194] where review of simulations for pharmaceutical processes are investigated. However, as explained in section **2.5.1 - Supply Chain Activities - Summary and Positioning of this Research** the bulk powder manufacturing environment faces several challenges not observed in other sectors explored despite their similarities in the equipment utilisation such as drying processes and limited storage capacity [64] presented in Table 2.1. In addition the mature process developed by Toyota and investigated in **2.8 - Production Control Strategies**, are mature mechanisms originated in mass production applied to optimise the production flow. By adopting an appropriate pull-type Production Control Strategies (PCSs) as an alternative to control the material in the system the manufacturing flow is optimised. Several types of PCS were designed to manage the authorisation of products. However, as explored, the dairy bulk-powder manufacturing requires pull-type PCS able to simultaneously cope with seasonal volumes of raw material, stochastic supply deliveries, constant interruptions due to the CIP cycle times, and variability of downstream processes, increasing or reducing the flow according to these criteria.

The contribution to the academia and industry sectors in mature manufacturing processes developed for the discrete parts manufacturing environments and the current gap in innovation faced by the dairy sector is evident. The simulation platform developed for discrete parts manufacturing entitled DREAM as described in section **2.6.4 Integration and Interoperability between Models** is one example of investment for the purpose of emulating the production process for decision-making processes as explored in [115]. Through CMD files, several practical applications for simulation and data integration for manufacturing, as observed in [119] were highlighted in this research. However, the drawback of the method developed is the necessity of internal algorithms to generate the required files which require technical skills for decision-makers. In addition, appropriate interfaces for accessing the XML files and analysing simulated results restrict the utilisation to technical resources.

The industrial partners directly involved in this project provided significant contributions since the phenomenon explored in the literature was also fully explored and demonstrated using real-world data from the case studies presented in section **3.2 - DPTC Dairy Industrial Partners – Case** Studies. The case studies described in this research were of paramount importance for understanding the real issues faced by the dairy sector and identifying the gaps in this field. However, the aim of this research is not limited to the case studies presented but in generalising the initial stages of the dairy bulk powder manufacturing environment for modelling, simulation and optimisation purposes. In addition, the uncertainty observed in the raw material supply is also a concern for the production-planning processes. In this research, especially section **3.3- Initial stages in Dairy Manufacturing - Generalisation,** it is evident that the stochastic behaviour in volume and frequency of supply fluctuates daily which increases the instability in the system. Each potential source of variability was studied for distinct manufacturing stages in order to identify similar problems for distinct dairy manufacturers.

Therefore, a cloud-based simulation was designed considering the generalisation of a three-stage manufacturing flow to enable the importation of excel files and demonstrate the results in a dashboard accessible from distinct devices as described in section **3.4 - ePilot Manufacturing Plant Simulation Framework for Dairy Industry**.

As described in section **3.4.2 - User Interface and Security** , each dairy manufacturer has one individual user with distinct privileges to access the framework and perform the simulation. As stated, the ePMPS architecture relies on a cloud computing provider by Google Inc. The use of Google as a Cloud Service Providers (CSPs) minimises the requirement for security tools and manual configuration as observed in local applications. CSPs are responsible for the guarantee infrastructure and software security and accessibility, whereas businesses are focused on the data performed simulation access.

After collecting data from Industrial Partners, evaluating the main consequences on dairy operations generalising the initial manufacturing stages, modelling in a cloud-based environment it was evident that an investigation of the potential transition from the current push-system to a pull-system strategy was vital to complete this research. As stated by Womack and Jones in [63], the flow is not sufficient to guarantee an efficient process as any organisation can introduce flow in any activity. Therefore, investigations on the most appropriate pull system for the dairy environment were required.

The main difference between the cloud-based simulation ePMPS and the DREAM project results from the effortless structure for decision-makers in designing their manufacturing environment, performing their simulation through the operational plans and visualising the results on the dashboard interface in multi-devices. The platform is useful for continuous improvement projects where the suggested changes for future states are easily investigated through simulated scenarios as demonstrated in section **3.5 - A Preliminary Experimental Analysis – Case Study 3 under ePMPS Framework**. Similar projects or approaches focused on the dairy sector were waiting to be addressed especially for the fact that the initial stages in the production process share similar challenges among dairies.

In addition, the manufacturing process explored in **3.2.2 - Industrial Partner Case Study 2 – By-Product Processing Analysis** demonstrates deficiency in digital transformation projects. As part of the DPTC project, the proposed framework is available for companies in similar conditions since the input data can be provided manually through spreadsheets and visualised in a webpage.

The main contributions of **Chapter 3** were achieved: (i) model the dairy sector into similar manufacturing stages (ii) provide insightful comprehension of the significant stochastic events at each production stage (iii) design a robust framework compatible with the real process and real challenges faced by Dairy Manufacturing (iv) visualise current and future state scenarios for continuous process improvement projects whereas **Chapter 4** consisted of identifying the most appropriate pull-type system for this environment and incorporate into the framework developed.

Important contributions to the field are observed in this research. First, all three definitions of pull-type were achieved under the three main PCS investigated as explored in section **4.5 - Exploring push and pull systems in dairy manufacturing**. SLA is feasible and WIP volumes are manageable by setting maximum levels to fulfil the demand. Filling the current gap and practical contribution in applying lean principles, more precisely pull-type systems, in the dairy sector. Supply Accuracy shows a connection between the raw material planning supporting decision-makers in suggesting an appropriate volume to be supplied in the system during peak/high seasons.

The main pull-type strategies: KCS, CONWIP and CONWIP/KCS were modelled and adapted in a Markov Decision Process (MDP) to improve the key performance metrics in the dairy bulk powder manufacturing environment. Markov model requires an interaction between the agent and the environment in a sequence of discrete-time steps such as hours:$h = \{1,2,3,\ldots H\}$ as fully described in section **4.6 - Modelling pull-type PCS for Dairy Manufacturing.** For this main reason, the framework and the experiments were modelled using discrete time steps. Therefore, at each time step, the model decides according to the elements defined for each PCS designed the specific volume of WIP to be authorised throughout the manufacturing stages.

During the initial phase of the optimisation process, several other algorithms were considered to achieve the desired responses as described in section **4.11 - Optimisation Approaches Explored .** As described, supervised and unsupervised learning algorithms obtainable in ML/AI methods are not appropriate to the problem investigated since classification problems or predictions are not the objectives of this research. In addition, initial experiments building an ANN were developed using TensorFlow open-source models. Still, it failed to provide optimum responses for the real-world challenges identified in the dairy sector. Rules such as stopping CIP for a minimum of running hours or interrupting after a maximum of running hours were violated. The evolutionary type as described in section **4.11.2 - Evolutionary Algorithms (EA) or Genetic Algorithms (GA)** was also initially considered during this research project and the main drawback identified was the time required to processes is heavily impacted by the mutation rate and vital requirements for dairy manufacturing such as maximum running hours and minimum to perform CIP were once more violated.

The PCSs modelled were investigated and tested were subjected to the CIP interruptions and the stochastic events observed in this sector as described in **4.8 - Defining all Factors for the Optimised Responses for each PCS**. Similar benefits observed in discrete manufacturing were expected since the flow of material requires similar authorisation mechanisms.

In order to evaluate the results provided by each PCS designed, individual pull-type CONWIP, KCS and CONWIP/KCS were modelled and assessed under identical conditions: identical volumes and identical 5-day periods. The factors was adapted according to the factors defined for each PCS; therefore, KCS for example required 4 factors: (A) Supply – Stage 0, (B) K1 – Stage 1, (C) K2 – Stage 2 and (D) K3 – Stage 3 and all of these factors were initially included for all the responses analysed (see **4.8 - Defining all Factors for the Optimised Responses for each PCS)**. By analysing **Response 9 – StageB2_Max** for KCS during peak season, for example (see **H.9 - ANOVA AND MODEL EQUATION – RESPONSES 9, 10 - HS – KCS – Period 1**), not only the referred factors are individually significant **(p-value <0.05)** but also the interaction between these factors.

It is also possible to observe that factor C – K2 – which refers to the separation process has a significant contribution to the model, followed by factor A – K0 and B – K1 whereas for the same volumes but distinct variability (see **H.11 - ANOVA AND MODEL EQUATION – RESPONSES 9, 10 - HS – KCS – Period 2**) the importance of the factors changes. Factor C – K2 has the main contribution followed by A – K0 and D – K3 which refers to the bottleneck of the manufacturing process. Finally, for period 3 (see **H.12 - ANOVA AND MODEL EQUATION – RESPONSES 7, 11, 9 - HS – KCS – Period 3**) despite factor C – K2 is the most significant factor, it is followed by B – K1, D – K3 and A – K0. Therefore, by analysing all periods individually the assessment of the significant factor according to each period was attainable.

The objective of the discussed design is to focus the experiment with similar conditions but distinct variability, as a categorical variable, in order to observe the current experimental region and confirm the impact of distinct periods in the manufacturing performance. Similar approach was observed in [188] and [218] where three levels of variability defined by SD = 1, SD = 3 and SD = 8 are applied to observe the robustness of the experiments conducted but analysed separately. However, in this research the 5-day periods evaluated represent the distinct variability since it refers to real data provided by the industrial partners.

By analysing the results provided by the CONWIP system, a reduced WIP level was expected while achieving customer fulfilment due to its simplicity in controlling the inventory through one unique mechanism. Despite the CONWIP contribution to other sectors through the simplicity in controlling WIP by only one parameter and the instant communication between demand and the internal production flow, as a pull alternative to avoid an excess of inventory, undesired levels at StageB2 were observed for high seasons. As stated by [176], CONWIP is a pull strategy alternative for the exploration of the benefits of a pull system applied to a variety of manufacturing environments. As observed, the advantage of this strategy is a unique and consistent authorisation for one unique factor, referred as **B:CC,** which simplifies the system. However, despite the

optimisation criteria being achieved, the system behaves similarly to a push system when higher levels of supply are likely to be authorised.

CONWIP results were not satisfactory since the volumes were pushed to the final stages as compared to the results in section **5.3 - Production Control Strategy Comparison.** In addition, unbalanced WIP levels are demonstrated. Dairy processing requires distinct levels of WIP according to each stage and CONWIP demonstrated poor performance in controlling WIP levels at individual stages.

CONWIP/KCS has been proven by [179] and [180] to be an efficient mechanism since WIP is controlled globally by CONWIP and locally at individual stages by KCS. In a discrete manufacturing environment, this extra communication guarantees a reliable system allowing the release rate to be paced to the actual demand rate. However, for dairy bulk powder commodities, contracts are established in anticipation which reduces the variability at the demand side regarding volumes. Consequently, limited improvements were observed by adding extra authorisations as required in the CONWIP/KCS system.

As described in section **5.7 - Conclusion and Contribution to the Research**, conversely to the literature explored that CONWIP outperforms KCS, the results confirmed that the KCS system is the most appropriate mechanism owing to the ability to control individual stages as required for the bulk powder dairy sector. The optimum volumes were identified through the RSM and Pareto-Frontier graph for each PCS where KCS provided satisfactory WIP control and SLA achievement as shown in section **5.3 - Production Control Strategy Comparison** for each PCS**.** The results were also extended to distinct periods in order to evaluate similar performance for the entire high season and the benefits of adopting KCS over the current push system is evident.

By examining the trade-offs between conflicting objectives of maximising SLA and minimising WIP levels it is possible to observe that this sector requires distinct WIP levels at individual stages. An evaluation of the overall average of WIP, as proposed by several previous studies for discrete parts manufacturing [168], [184], [216]–[218] is insufficient to ensure higher performance metrics since WIP average mitigates peak level silo utilisation.

In addition, the results provided by the adaptive algorithm to support decision-making processes according to the seasonality provided similar results are observed for KCS. However, the main advantage of using the adaptive algorithm is the fact that the volumes are authorised according to the level of silos rather than the optimum factors defined through the Design Expert as shown in section **5.4 - Evaluating KCS Performance for Additional** Periods. For high seasons, the system must reduce the WIP levels suggesting the precise raw material to be authorised as opposed to the current push-type system. On the other hand, for medium seasons, an optimisation of internal resources is more appropriate.

For medium seasons, the strategy must consider the most optimised set of resources as presented in section **5.6 - KCS and Scheduling Plan on the Cloud-Based Framework ePMPS**. By evaluating the Pareto-optimal set area and the range of optimum schedule plans recommended, it is possible to conclude that more than one schedule could be selected. Furthermore, the ability to dynamically select the optimum criteria provides more insights into choosing a suitable scheduling plan for decision-makers. The performance results demonstrated an efficient method to recommend different scheduling plans according to the defined optimal criteria with a reduced processing time, as demonstrated in section **5.5.3 - Conclusions for Kanban Control System.** This shift in strategies for different seasons was elucidated in this research and might also influence decisions regarding disabling equipment and in some cases, the entire production plant for periods of time. The results obtained by the recommendation schedule were published by Eccher and Geraghty in a high impact factor journal [234] expanding the algorithm to sustainable conflicting criteria such as energy consumption. The algorithm developed was then incorporated into the ePMPS framework developed in Chapter 3 and as described in section **5.6 - KCS and Scheduling Plan on the Cloud-Based Framework ePMPS.**

The adoption of the recommendations suggested by the ePMPS depends on the level of automation available in the manufacturing plant. In a total manual process, the schedules and volumes recommended must be manually changed. However, even a manual operation would benefit from visualising the results simulated in anticipation and compared to the current process and the impact of such decisions. In a manufacturing environment where the PLC is integrated to an MES, the adoption of the optimum conditions is smoothed since the changes are made by integrated systems. In a full-automated environment as the prototype described in [201] **(see Appendix L.3),** a dynamic authorisation supply would be self-controlled since there is a direct communication flow between each piece of equipment and the system as shown in Figure 3.8.

6.2. Limitations of this Research

This research is based on the generalisation of a three-stage production line considering the raw material supply and storage in the dairy bulk powder environment. Hence, as demonstrated the model generalisations, method, inferences, findings and contributions can be easily extended to similar production processes structures. An extension to other manufacturing plants such as fresh dairy and its by-products would provide distinct sources of variability not observed in the current process.

In addition, the ePMPS framework was designed considering characteristics observable in the case studies and focused on the dairy bulk powder commodity environment, mainly Skim Milk Powder, Milk Powder and Casein. Extension to other products such as fresh dairies requires a distinct approach by mapping product processes and changes in the internal simulation model structure developed. In addition, other commodities such as butter and buttermilk are limited in the structure defined. The current model is capable of simulating any dairy powder-bulk manufacturing environment limited to the configuration presented in **Appendix E – ePMPS File Structure**.

Regarding the scalability of the current structure focused on bulk-powder, the framework is currently running in a limited individual account in Google Console and extension to other dairies plants and users on a continuous basis would require an upgrade in the current account in order to utilise the available resources. In addition, the current ePMPS is running under a unique virtual machine (VM) and additional users would require an increase in the demand for simulation. Therefore, the migration to a professional account with a more robust and unlimited structure is required.

This research is focused on the Irish dairy sector where redistribution of raw material between dairies is a potential practice. Therefore, the excess of WIP observed could be managed through a collaborative approach among dairies increasing even more the competitiveness of the Irish sector in the global market. The presented results are focused on volumes and production flow. A financial approach focused on costs, sales prices and profitability for example, could suggest shifting in the conflicting key performance metrics.

Ultimately, chemical transformation, temperature, pressure, composition and elements observable in a traditional physical pilot plant are outside of the scope of this research.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1. Contributions to the field

Given the new positioning of the Irish market in encouraging companies to increase their competitiveness to fulfil future demand, there is an evident requirement for innovative research capable of investigating the initial steps in the dairy manufacturing processes and the potential impact on the subsequent upstream, improving service levels and managing internal challenges identified in this environment.

Therefore, the contribution of this research to the field is fourfold:

I. The understanding of the implication and challenges faced by the dairy bulk powder manufacturing, the variability at the initial stages in this environment under limited storage capacity between manufacturing stages, constant interruptions caused by CIP process, perishability due to the short life span of raw material, seasonality which dictates the volumes available to be processed and internal and external stochastic events.

II. A novel environment for the bulk powder dairy sector for performing current and future state analyses through simulation is proposed to support decision-makers in visualising the impact of their decisions on the manufacturing plant through the ePMPS cloud-based simulation framework. Through the development of an innovative cloud-based simulation framework focused on the particularities found in this sector, to be used by dairies since the manufacturing environment can be easily scaled according to the structured files. The model is accessed through a cloud-based structure with a user-friendly interface. The production plant (such as production flow and capacities) is built according to spreadsheet input files in order to facilitate the subject-matter expert (SMEs) decisions when comparing the current state and the impact of simulated future state strategies. The simulated scenarios are then demonstrated on a dashboard available for multi-devices as described in Chapter 3.

III. The results and benefits of investigating the traditional lean pull-type PCS adapted to control the manufacturing flow to avoid waste in the production flow embracing the main challenges identified in this sector. In addition, the analysis of the best key parameters was fundamental to define how to improve the traditional push-type system. As presented in section 5.6.1 - ePMPS for Peak Seasons, extra volumes represent a significant number of extra trucks to be managed and the potential risk of perishability caused by excessive WIP levels.

IV. A simplified adaptive pull-type PCS has been designed specifically for dairy bulk powder manufacturing to support decision-makers according to seasonality. For high seasons, the strategy relies on recommending the appropriate volume to be processed within the manufacturing system whereas for medium seasons, the appropriate set of equipment to be utilised is recommended.

7.2. Conclusion

The results presented in this research are grounded on solid foundations. Essential gaps in the literature relative to the research field were investigated, exploring fundamental aspects observed for dairy bulk powder manufacturing.

For companies that traditionally rely on push-type approaches, several implications to convince senior managers to adopt lean and pull-type strategies are observed. Primarily owing to the natural disbelief that lean thinking could benefit the dairy sector and the lack of visibility of a globally optimised process by implementing such controls as opposed to local optimisations. In addition, cross-functional activities such as VSM, for example, require staff involvement and financial investment restricting the resources available from distinct departments.

The benefits of an innovative cloud-based simulation designed to operate as SaaS to support decision-making processes include accessibility and business scalability for those Irish Dairy manufacturers that are looking forward to obtaining insights through the simulated scenarios.

The results suggested that a well-designed pull-type PCS combined with appropriate key performance metrics eliminates potential waste in the production flow. Significant improvements were presented by adapting the current push system to the main mature methods of pull-type systems widely explored in discrete manufacturing environments. Despite the nature of the bulk powder dairy manufacturing in allowing extra WIP within the manufacturing flow, valuable findings demonstrate the benefits of adopting pull-type systems. Therefore, the main challenges identified in this sector were addressed in this research and generalised into other dairy markets due to the nature of this environment, outlined as follows.

First, for the short lifespan of the raw material and a lower level of intermediate Work-In-Progress (WIP) storage at different stages in the manufacturing process. Second, regarding inventory levels, due to the raw material perishability, a fast rate for processing the WIP is required. Constant interruptions caused by Cleaning In-Place (CIP) cycles compromise the system's processing capacity. In addition, since seasonality plays a fundamental role in defining strategies for production since the volume diverges throughout the year, this research explores the impact of seasonality on the manufacturers' operations volume provided by suppliers.

The results suggest that among the traditional pull-type explored, KCS is the more appropriate system to address the challenges of this sector for high seasons since it is possible to control WIP levels at each stage individually. The implications of identifying the best authorisation volumes for each stage are also addressed through an adaptive algorithm to determine the appropriate volume to be authorised. Finally, for medium and off-seasons, the challenges identified in this research are addressed through the recommendation algorithm to optimise the internal equipment set according to the criteria defined by the decision-maker. The results obtained by the recommendation schedule were published in a high-impact factor journal, as previously referred to in section 5.6.2.

In this context, research addressing the main aspects of the dairy bulk powder environment has been missing. This gap is now closed since the contributions of this research allow academia and industries to foresee new possibilities for the Irish Dairy Sector.

7.3. Directions for Future Research

During this research, an initiative to create a robust benchmarking process to the Irish dairy sector faced several challenges owing to the gap in a generalised manufacturing environment and the possibility to extrapolate the current manufacturing to an ideal process. Therefore, four main areas will be benefited from this research as described as follows.

7.3.1. Benchmarking tool for Irish Dairy Sector

As explored in section **2.2 - Supply Chain Management Overview** the increase in SCM complexity requires a more connected and efficient flow. Waste reduction and increase in efficiency is sought by all sectors, especially in a global market. During this research, it is observed that Benchmark tools have not been fully adopted by the Irish Dairy sector. This sector would benefit from the lessons-learnt process from all dairies since similar problems such as seasonality, CIP cycle-time schedules, downstream, WIP levels and equipment utilisation are similar for the initial stages in the manufacturing process. In addition, by strengthening a cooperative environment, the entire domestic operation would benefit from such collaboration.

Successful benchmarking metrics depend on the quality of the information collected and processed. Thus, the framework proposed by this research would support a benchmarking programme in comparing several dairies and their individual performance. The framework developed is capable of processing the information received in structured files and provides a consistent comparison among distinct companies. Few adjustments to receive distinct metrics as explored in this research would be required. Research exploring manufacturing costs and global exportation, for example, would enhance the objectives for optimisation previously explored, since, as previously mentioned in section 6.2 - Limitations of this Research, it would suggest differences in the conflicting key performance metrics.

Ultimately, this research is focused on the Irish dairy sector, where redistribution of raw material between dairies is a potential practice. Therefore, the excess of WIP observed could be managed through a collaborative approach among dairies increasing even more their competitiveness of the dairy sector in the global market.

7.3.2. Sustainable performance metrics in Dairy Manufacturing

As also investigated in section **2.2 - Supply Chain Management Overview,** green initiatives to incorporate sustainability in SCM have been studied by several sectors. Regarding this vital and current topic, it was observed that there is a lack of research regarding wastewater treatment in the Irish Dairy sector. Water is a natural resource widely used to perform CIP cycles and also to recover fines during the production process.

According to the CIP cycle times, the volume of water utilised could be evaluated by the framework developed to capture the volume of waste produced by specific processes and simulated in order to identify improvements in this sector. Such information would shift scheduling plans for operational decisions or even a future capital investment for long-term and strategic decisions.

7.3.3. Scalability of ePMPS to other Manufacturing Sectors

As explored in section **3.4.6 - Elasticity and Scalability of the ePMPS Framework**, from the technology development perspective, characteristics such as Elasticity and Scalability are inherited with respect to the network and cloud computing environment. Therefore, the framework is scalable for other dairies and also for other sectors.

However, the limitations regarding the current manufacturing plant, such as production process, capacity flows, CIP cycle times and indicator metrics that diverge from the proposed design by the ePMPS framework, must be mapped to be adapted in the current structure.

7.3.4. Integration between ePMPS and MES

As stated in section **2.6.4 - Integration and Interoperability between Models**, a fully automated industrialised process is also a future communication trend between Machine-to-Machine (M2M) reducing time to transferring data from pieces of equipment. The main benefit of integrating M&S and Manufacturing Execution Systems (MES) is the accuracy in data collections due to the reduction of errors in data manually collected. Regarding WIP authorisation in the manufacturing environment, the speed in the response between the current process and the ideal process is increased.

In 2019, during this project, initiatives to liaise with Orbis MES Ltd **(see https://orbismes.com/)** to create a real time framework in a format suitable for the creation of the user interface for real time process monitoring for Case Study 1 was started. However, at that stage the level of maturity of the industrial partner required more raw data treatment and the ability to connect the cloud framework through the Application Programming Interfaces (APIs) was restricted. There are potential benefits of integrating ePMPS to other MES systems. Though, it depends on the Technology Readiness Levels (TRLs), a method for estimating the maturity of technologies for specific programs and it requires technical professionals to develop such integration.

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LIST OF PUBLICATIONS AND CONTRIBUTIONS

1) C. Eccher, B. Minardi and J. Geraghty, "Application of Modelling and Simulation as the primary research methodology in Sustainable Supply Chain Management: an analysis of the literature," in 1st Conference of the EURO Working Group on Sustainable Supply Chains, 2016. (**see Appendix L.1**)

2) C. Eccher and J. Geraghty, "MODELLING & SIMULATION AS A STRATEGIC TOOL FOR DECISION-MAKING PROCESS IN THE DAIRY INDUSTRY," in International Conference on Decision Making in Manufacturing and Services (DMMS 2017), 2017, pp. 97–107.C. – **Best Student Paper Award.** (**see Appendix L.2**)

3) C. Eccher and J. Geraghty, "INDUSTRY 4 . 0 AND THE FUTURE FOR DAIRY SUPPLY CHAINS," Int. J. Mech. Prod. Eng., vol. 8, no. 2, pp. 7–13, 2020. (**see Appendix L.3**)

4) C. Eccher and J. Geraghty, "Incorporating sustainable criteria in a dynamic multi-objective recommendation planning tool for a continuous manufacturing process : A dairy case study," J. Manuf. Syst., vol. 55, no. April, pp. 159–170, 2020. https://doi.org/10.1016/j.jmsy.2020.02.008. Impact Factor: 5.105. (**see Appendix L.4**)

5) C. Eccher and J. Geraghty, "Modelling & Simulation as a Strategic Tool for Decision-Making Process: A Dairy Case Study," *Int. J. Decis. Mak. Manuf. Serv.*, vol. 14, no. 1, 2020. https://doi.org/10.7494/dmms.2020.14.1.2785 (**see Appendix L.5**)

Notes:

In the previous list, paper 2 was awarded as the "**Best Student Paper Award**", selected for expansion and publication in the International Decision Making in Manufacturing and Service as listed in item 5.

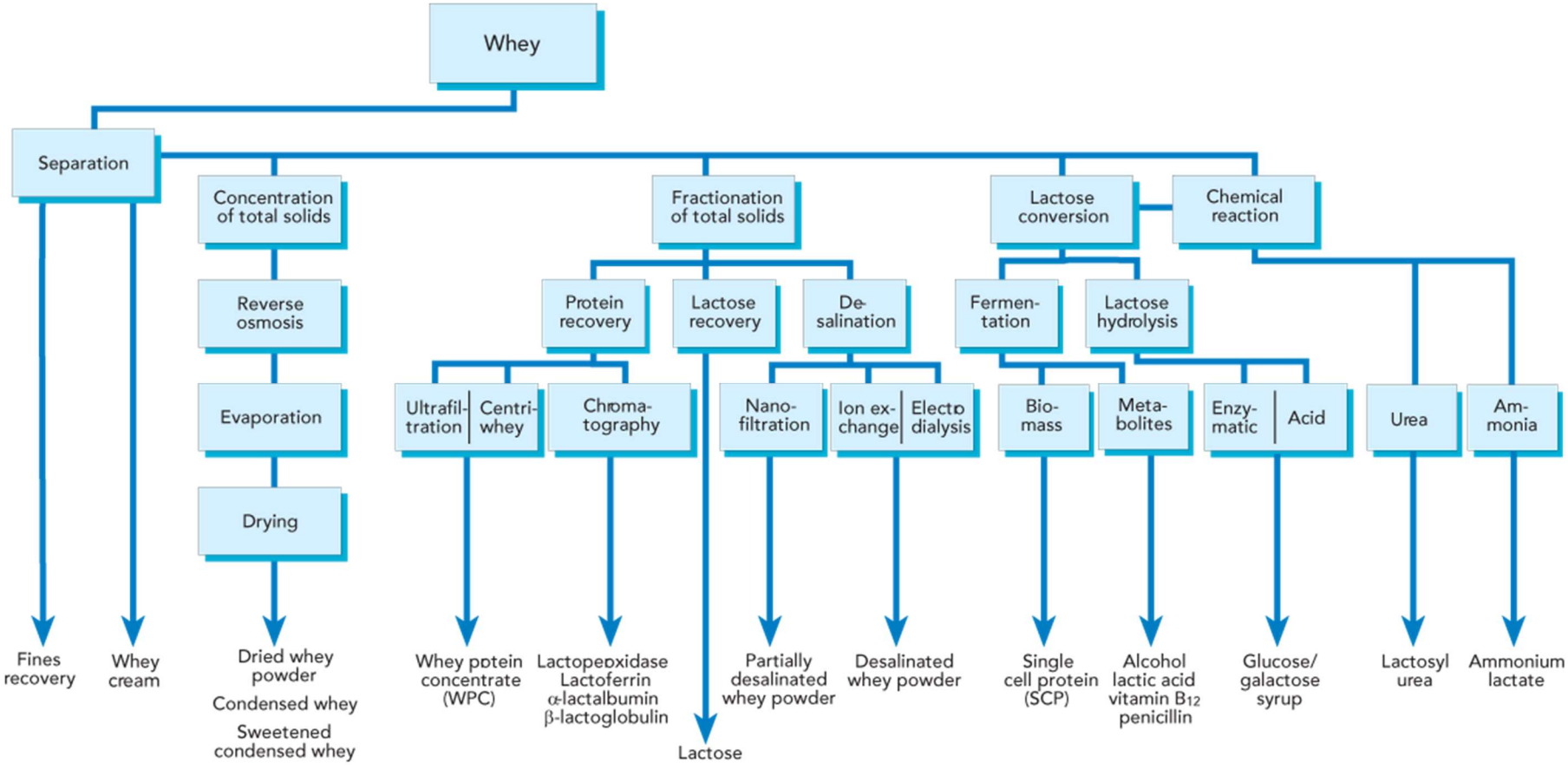
In addition, throughout the years 2016 and 2017, a workshop was conducted at the University of Limerick on the 19th and 20th of October 2016. The DPTC industrial partners attended a demonstration of the ExtendSim package and the application of simulation in dairy manufacturing processes[1]. In October- 2019, the final results of the project were presented in the last DPTC workshop among the Irish Dairies. Two new dairy companies demonstrated interest in the cloud-based framework ePMPS. Individual workshops were conducted presenting the ePMPS for two of these additional dairy companies in Feb-2020 and March-2020.

The manual of how to operating the system was release for all industrial partners involved in the DPTC project. One example from one specific Industrial Partner with values undisclosed (see **Appendix M – ePMPS User Guide.**

[1] https://dptc.ie/uncategorised/dcu-runs-sumilation-modelling-workshop-for-dairy-industry/

APPENDIX A - DAIRY SUPPLY CHAIN – PRODUCTS

A.1 Whey Potential Division



Source: [36]

A.2 Gross Composition and Milk Properties

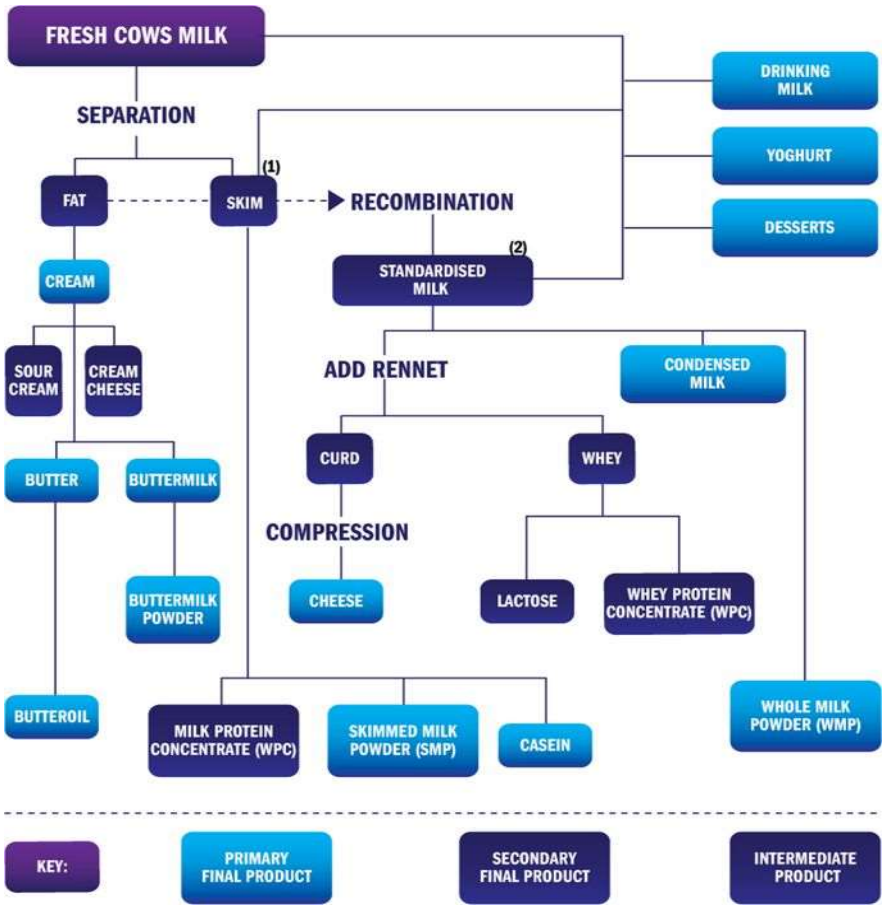
Milk Product Heat Treatment[a]	Fresh Milk No	Beverage Milk LP	Beverage Milk ST	Skim Milk[b] LP	Whipping Cream HP	Evaporated Milk ST	Whey (Sweet)[b] LP	Buttermilk (Sour)[c] HP	Yogurt (Plain)[d] HP
Contents (% w/w)									
Fat	4.0	3.5	3.5	0.07	35	8.0	0.05	0.4	3.5
Casein	2.6	2.6	2.6	2.7	1.7	5.7	trace	2.6	2.5
Other proteins	0.70	0.70	0.70	0.66	1.15	1.5	0.81	0.9	0.8
Lactose	4.6	4.6	4.6	4.8	3.1	9.5	5.0	3.9	3.7
Salts	0.85	0.85	0.85	0.88	0.57	1.85	0.66	0.88	0.85
Water	87.1	87.5	87.5	90.6	58.4	73.1	93.3	90.2	87.5
Properties									
pH	6.7	6.7	6.6	6.7	6.7	6.2	6.6	4.6	4.4
Viscosity (mPa·s)	1.9	1.8	1.9	1.65	8.7	17	1.2	100[e]	400[e]
Density (kg·m^{-3})	1029	1030	1030	1035	990	1070	1025	1034	1031
Fat globule size (μm[f])	3.4	0.5	0.3	0.4	4.0	0.3	—	—	0.4

Note: Approximate examples; values at room temperature.

[a] LP = low-pasteurized, HP = high-pasteurized, ST = sterilized.
[b] Centrifuged.
[c] Undiluted.
[d] Stirred yogurt.
[e] Highly variable.

Source: [53]

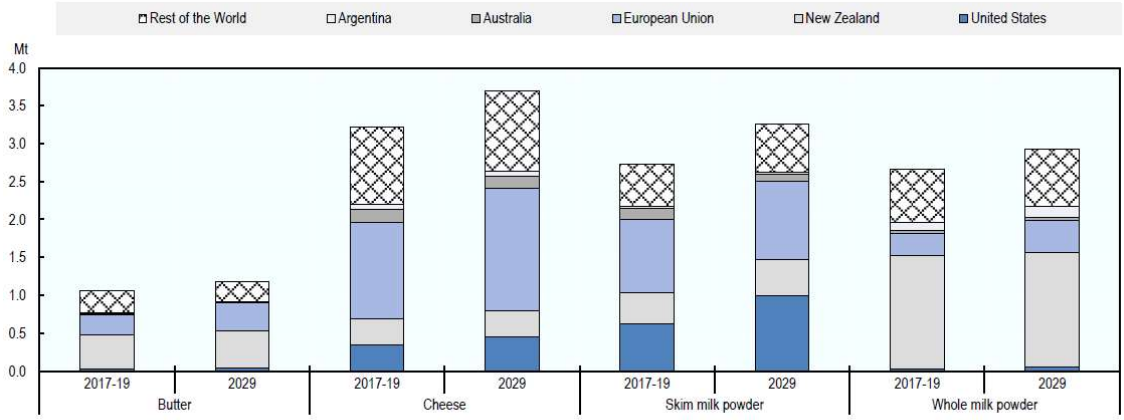
A.3 Dairy Products Manufactured



Source: [235]

APPENDIX B – Dairy Commodities – Global

B.1 Exports of Dairy products by Region



Source: OECD/FAO (2020), "OECD-FAO Agricultural Outlook", OECD Agriculture statistics (database), http://dx.doi.org/10.1787/agr-outl-data-en.

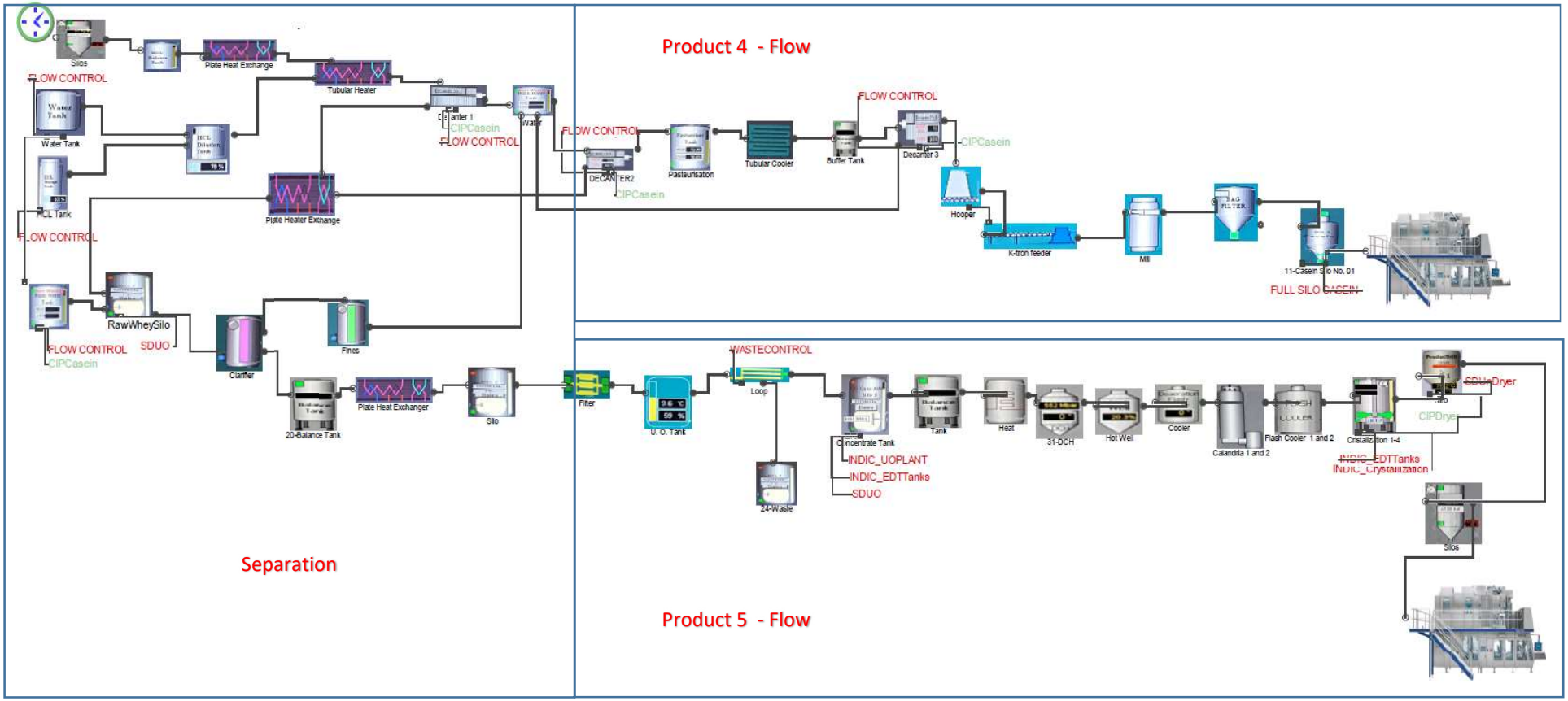
B.2 OECD-FAO – Dairy Agricultural Outlook 2018-2027 – Production

Country	European Union-28										
Variable	Production										
Time / Commodity	2017	2018	2019	2020	2021	2022	2023	2024	2025	2026	2027
Milk	163 584.07	166 973.28	167 436.04	168 694.22	169 824.13	171 044.01	172 180.92	173 388.71	174 485.08	175 661.61	176 719.48
Fresh dairy products	46 275.72	46 670.91	46 705.75	46 552.52	46 409.51	46 252.50	46 173.49	46 117.14	46 065.89	46 001.35	45 900.27
Butter (pw)	2 314.16	2 379.73	2 395.12	2 420.01	2 447.27	2 481.59	2 510.99	2 542.20	2 571.11	2 602.33	2 631.79
Cheese (pw)	10 255.70	10 550.89	10 669.64	10 780.11	10 879.87	10 988.42	11 095.26	11 192.60	11 287.71	11 389.02	11 471.30
Skim milk powder (pw)	1 491.67	1 533.15	1 532.07	1 539.66	1 555.58	1 586.90	1 606.71	1 629.93	1 646.81	1 668.33	1 687.44
Whole milk powder (pw)	720.53	730.47	750.02	757.23	770.46	783.27	797.82	814.03	826.58	841.58	853.64
Whey powder (pw)	1 867.44	1 914.92	1 936.55	1 956.07	1 973.71	1 993.04	2 012.15	2 029.55	2 046.52	2 064.63	2 079.22
Casein (pw)	156.11	122.57	142.89	139.07	143.23	143.11	144.15	145.57	146.51	147.97	149.20

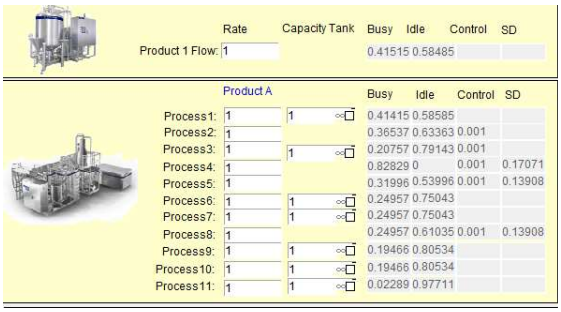
Source: [33]

APPENDIX C – SIMULATION MODELS FOR INDUSTRIAL PARTNERS

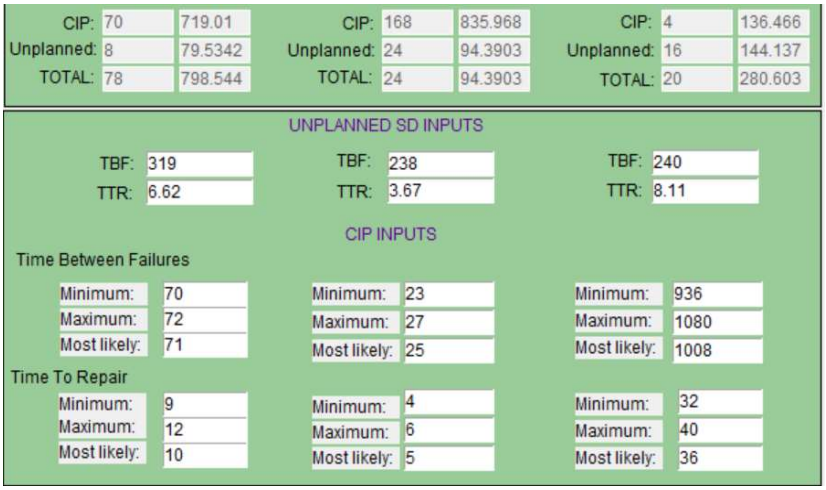
C.1 Model developed through ExtendSim – Case Study 1



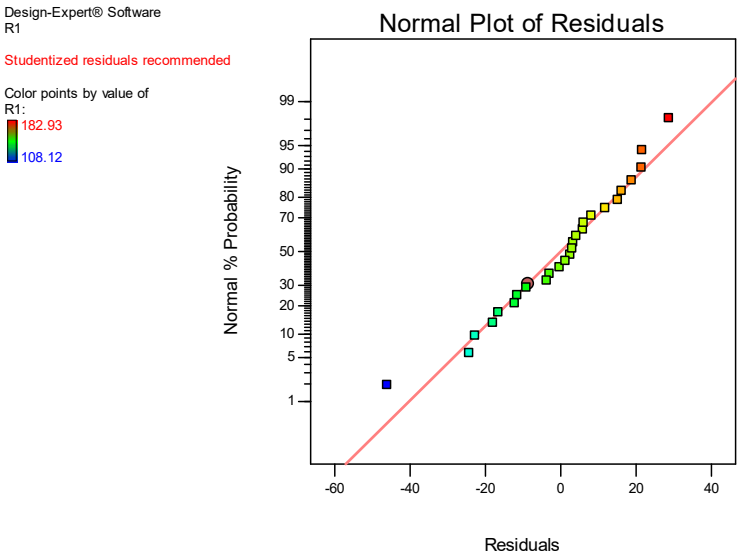
C.2 ExtendSim and Excel Interface for input process flow information - Case Study 1



C.3 ExtendSim Input CIP - Case Study 1



C.4 Checking the normality of Product 4 – Real - Case Study 1



C.5 Independent t-Test for Product 4 - Case Study 1

T-Test

Group Statistics

	1-REAL/2-SIMULATION	N	Mean	Std. Deviation	Std. Error Mean
PRODUCTA	1.00	30	136.1183	21.48116	3.92191
	2.00	30	137.7880	5.92367	1.08151

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PRODUCTA	Equal variances assumed	25.720	.000	-.410	58	.683	-1.66967	4.06829	-9.81324	6.47391
	Equal variances not assumed			-.410	33.385	.684	-1.66967	4.06829	-9.94304	6.60371

ANOVA

PRODUCTA

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	41.817	1	41.817	.168	.683
Within Groups	14399.375	58	248.265		
Total	14441.192	59			

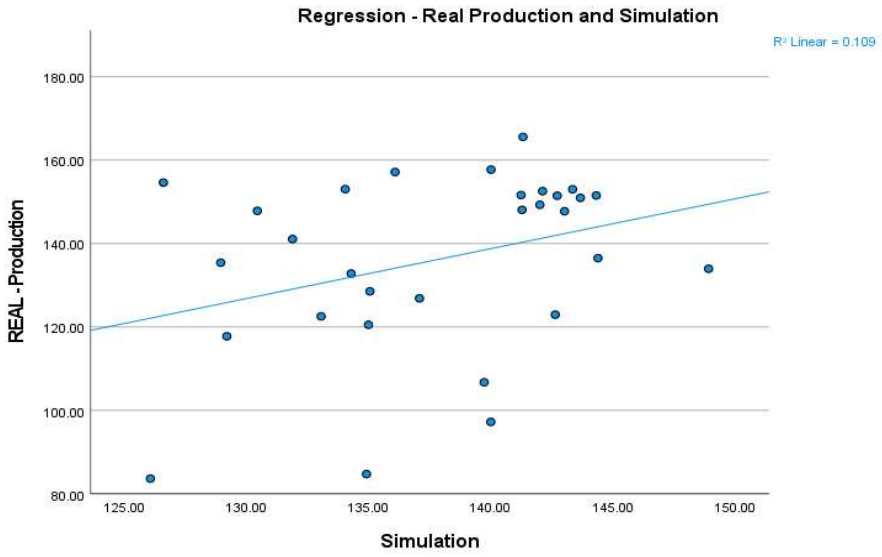
C.6 Regression Assessment for Real Production and Simulated

Model Summary

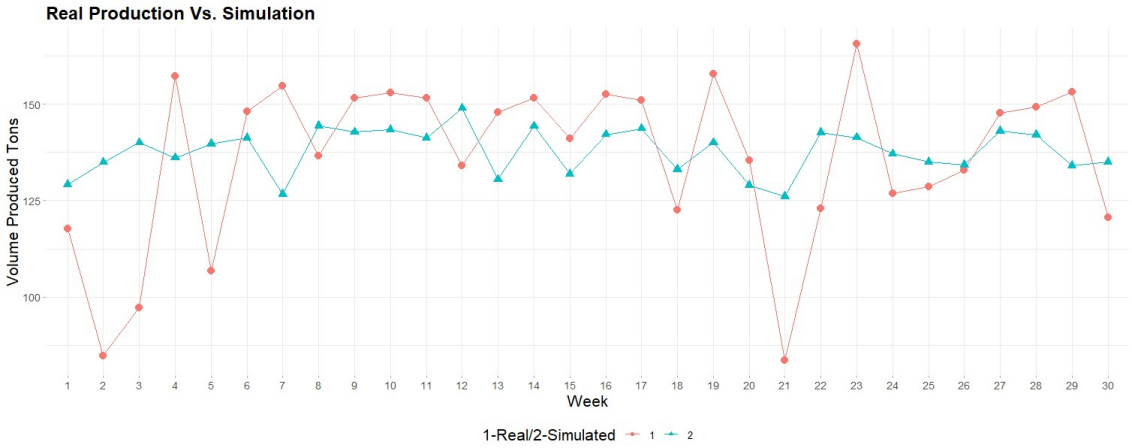
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.330[a]	.109	.077	20.63951

a. Predictors: (Constant), VAR00002

C.7 Regression Assessment Real Production Vs. Simulated – Scatterplot



C.8 Real Production Vs. Simulated for 30 weeks

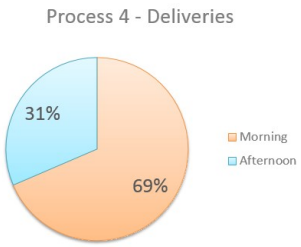


C.9 Supply Source - Case Study 2

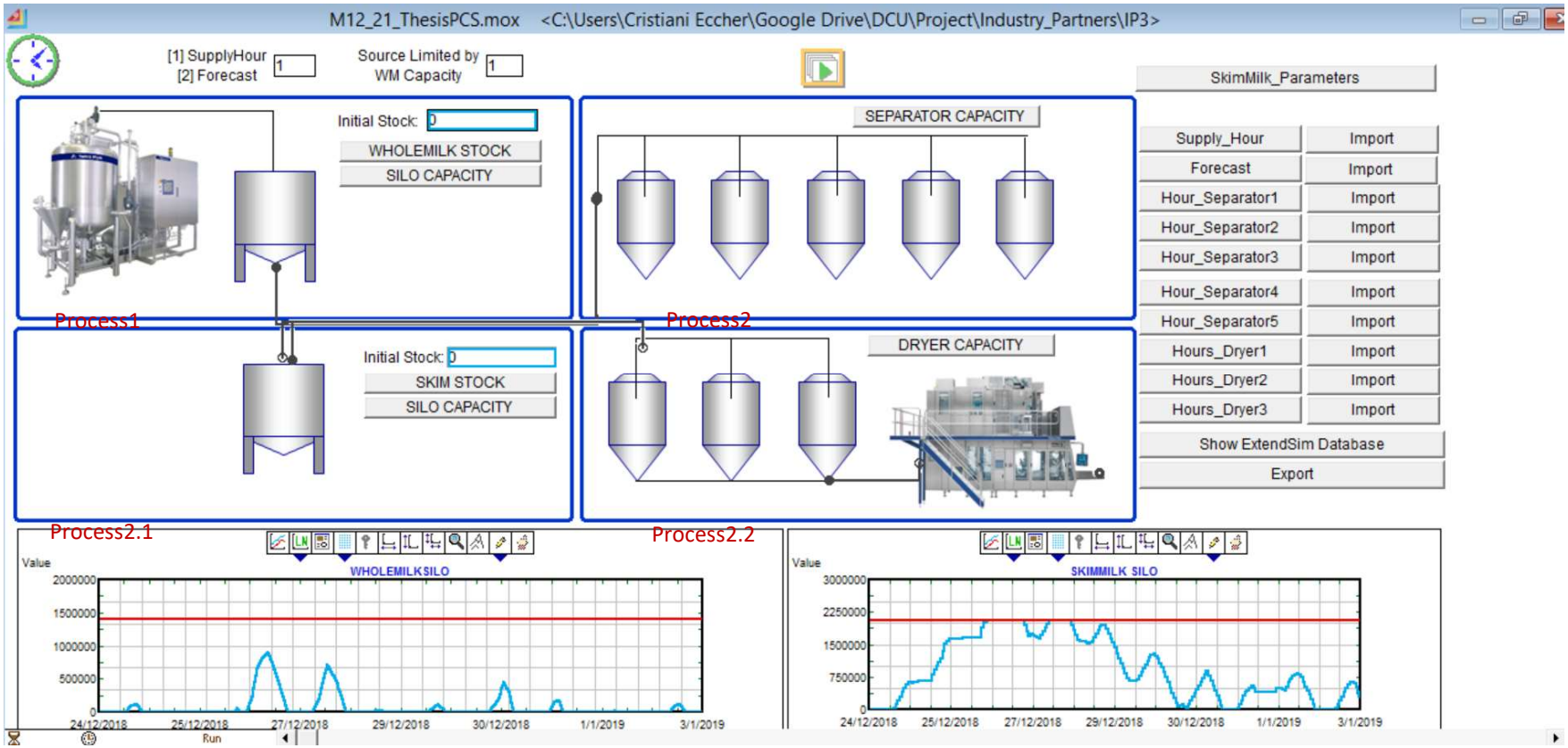
Table 7.1 – Supply Source RM3

SUPPLIER	PROCESS 4
Dairy 1	32%
Dairy 2	31%
Dairy 3	25%
Other Dairies	12%

C.10 Frequency of deliveries – Case Study 2



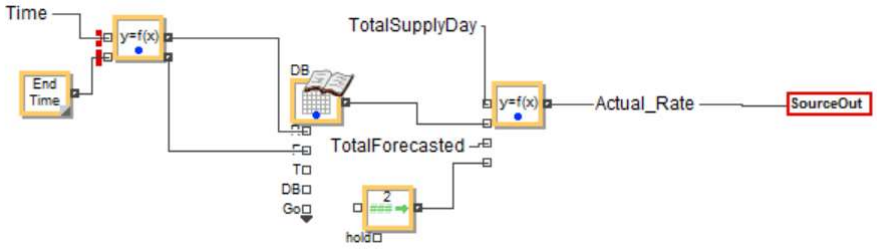
C.11 Model 2 developed in ExtendSim – Case Study 3



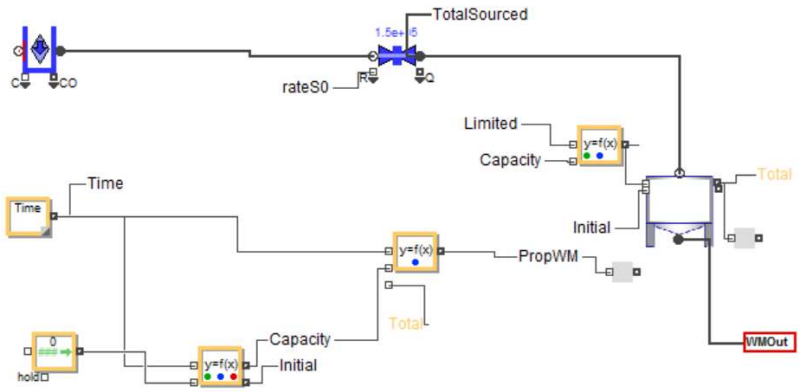
Buffer WIP Levels - Whole Milk (Process 1)

Buffer WIP Levels – Skim Milk (Proces 2.1)

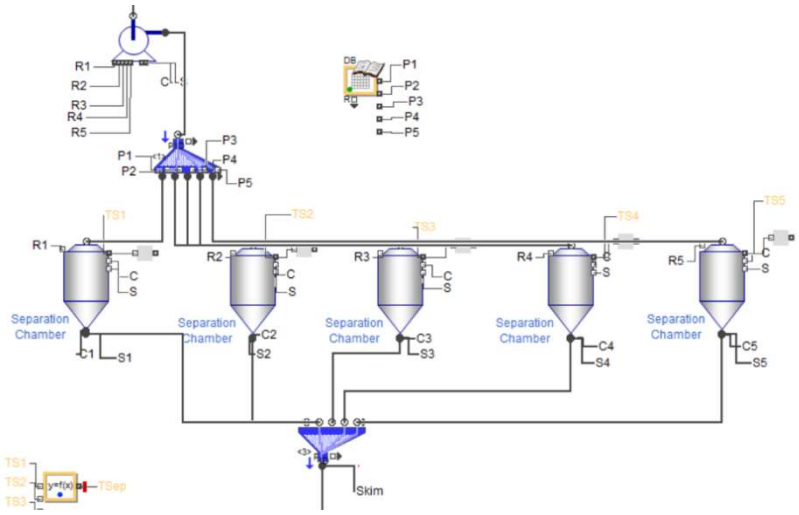
C.12 Blocks designed to import the milk supply spreadsheet and convert into hour rate



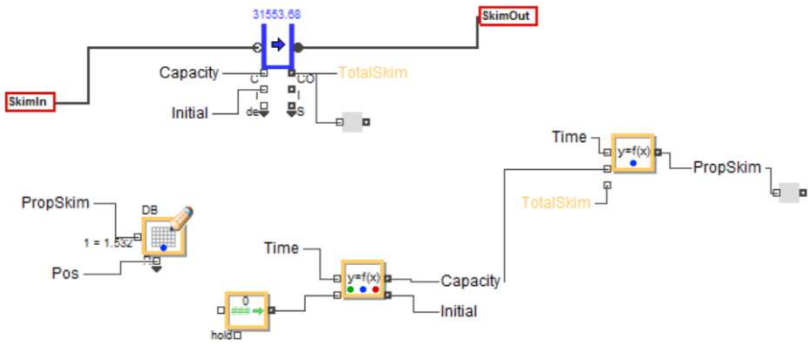
C.13 Blocks designed to store the raw milk received into the process flow



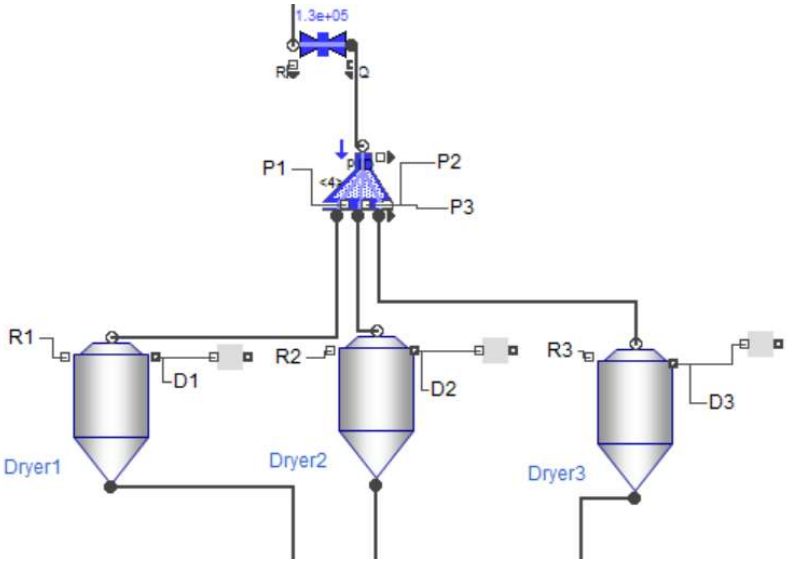
C.14 Blocks designed to separate the raw milk into fat and skimmed milk



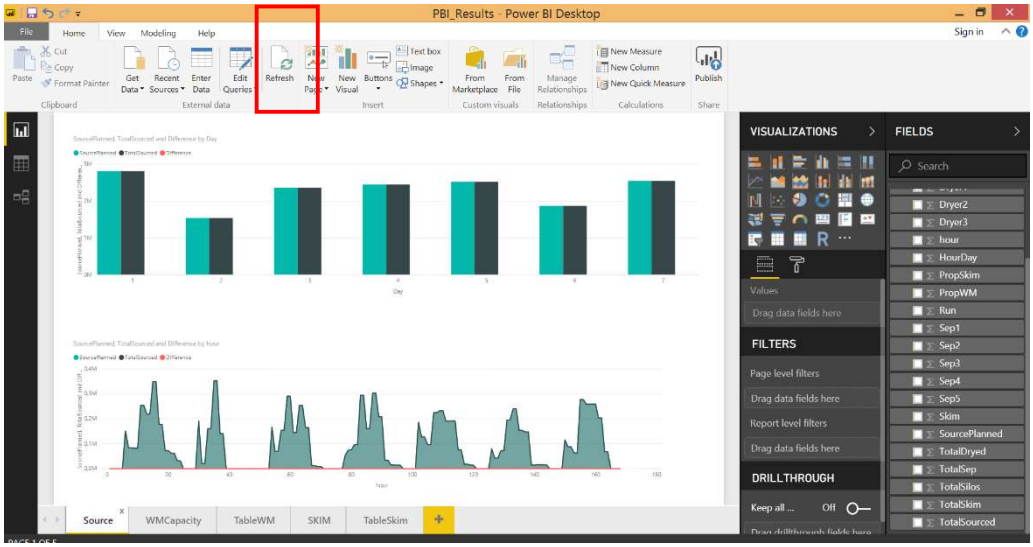
C.15 Blocks designed to store skimmed milk



C.16 Blocks designed for skimmed milk process



C.17 Power BI – Dashboard for Results Visualisation



C.18 Independent t-Test for Supply Volumes Comparison - Case Study 3

T-Test

Group Statistics

	Simul/Real	N	Mean	Std. Deviation	Std. Error Mean
Supply	Simulated	216	92973.3306	99104.19020	6743.18604
	Real	216	92973.3305	99104.19009	6743.18603

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Supply	Equal variances assumed	.000	1.000	.000	430	1.000	.00009	9536.30514	-18743.57135	18743.57153
	Equal variances not assumed			.000	430.000	1.000	.00009	9536.30514	-18743.57135	18743.57153

C.19 Independent t-Test for Process 2 – Separation Volumes Comparison - Case Study 3

T-Test

Group Statistics

	Simul/Real	N	Mean	Std. Deviation	Std. Error Mean
Separated	Simulated	216	92973.3304	96365.39986	6556.83496
	Real	216	92973.3304	96365.39986	6556.83496

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Separated	Equal variances assumed	.000	1.000	.000	430	1.000	.00000	9272.76493	-18225.58415	18225.58415
	Equal variances not assumed			.000	430.000	1.000	.00000	9272.76493	-18225.58415	18225.58415

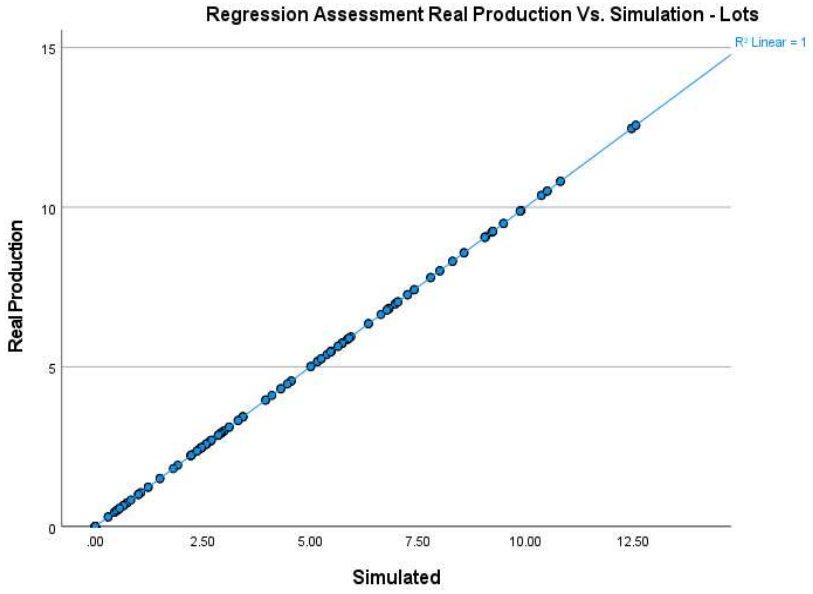
C.20 Regression Assessment for Real Production Vs. Simulated

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	1.000[a]	1.000	1.000	.000

a. Predictors: (Constant), Simulated

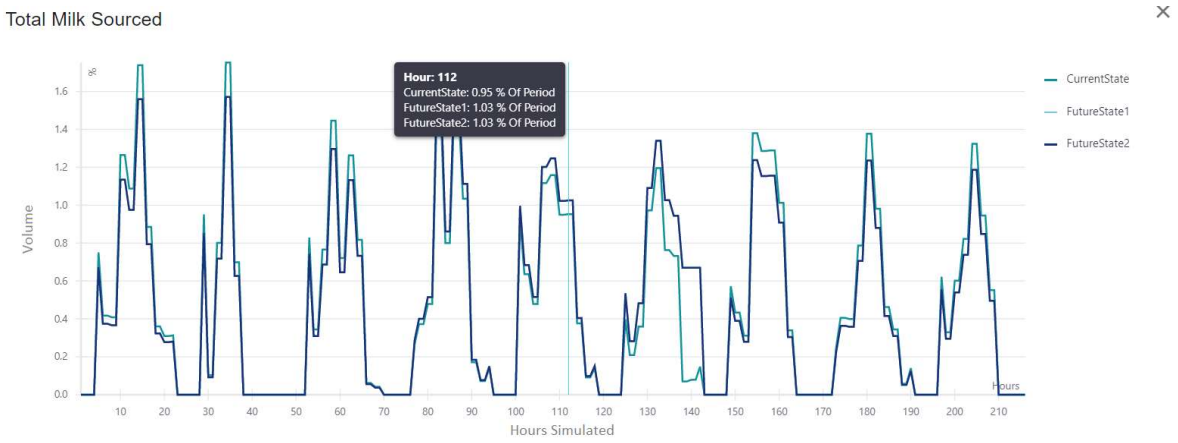
C.21 Regression Assessment for Real Production Vs. Simulated - Scatterplot



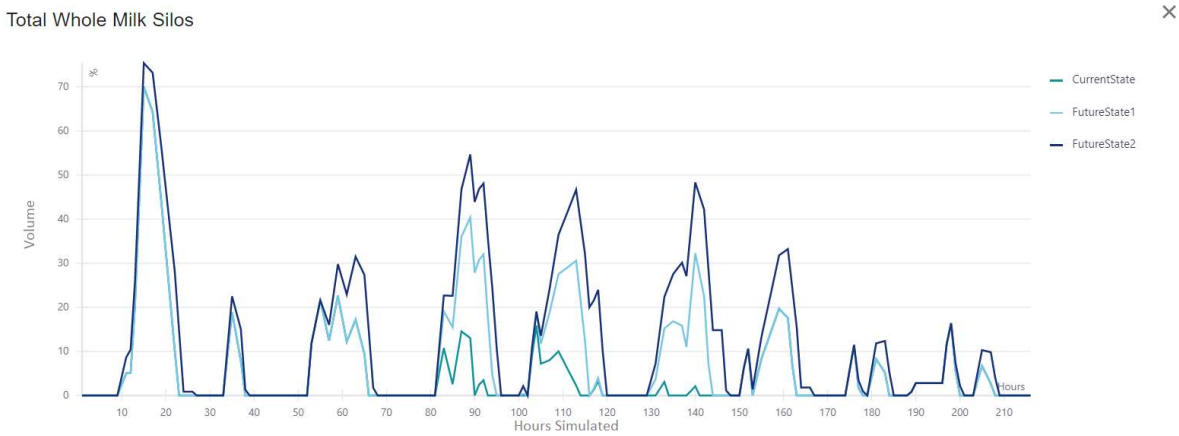
C.22 Example of scheduling plan for 9 days

	RUNNING HOURS ASSUMPTION								
TIMES	24/12/2017	25/12/2017	26/12/2017	27/12/2017	28/12/2017	29/12/2017	30/12/2017	31/12/2017	01/01/2018
Before 6AM	4	4	0	2	4	4	4	4	
6AM - 8AM	2	2	1	2	0	2	0	2	2
8AM - 10AM	2	2	2	2	2	2	2	2	2
10AM -12PM	2	2	2	2	2	2	2	2	2
12PM - 2PM	0	2	2	2	2	2	2	2	2
2PM - 4PM	1	2	2	2	2	2	2	2	2
4PM - 6PM	2	2	2	2	2	2	2	2	2
6PM - 8PM	2	2	2	0	2	0	2	2	2
8PM - 10PM	2	2	2	2	0	2	0		0
10PM - 12AM	2		2	2	2	2	2		2
TOTAL	19	20	17	18	18	20	18	18	16

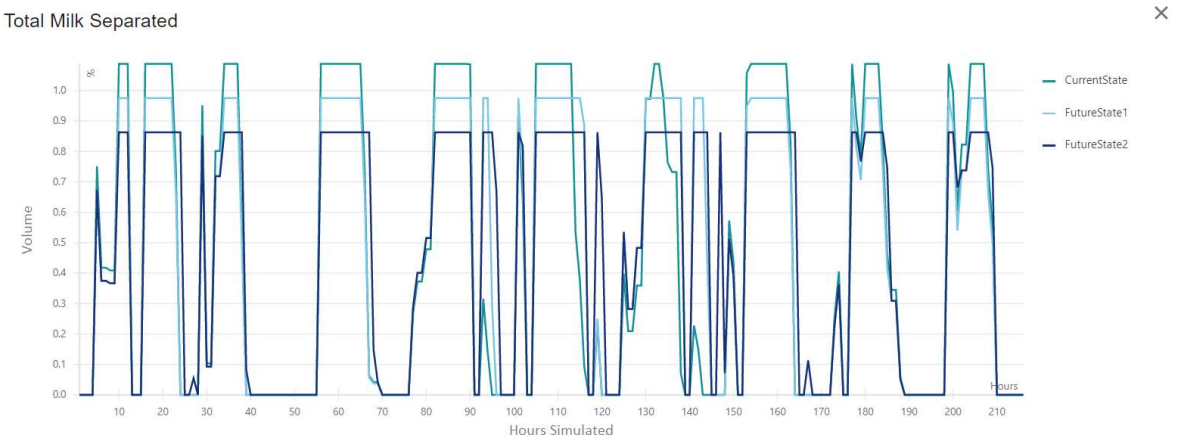
C.23 Total Milk Supplied – (Stage 1)



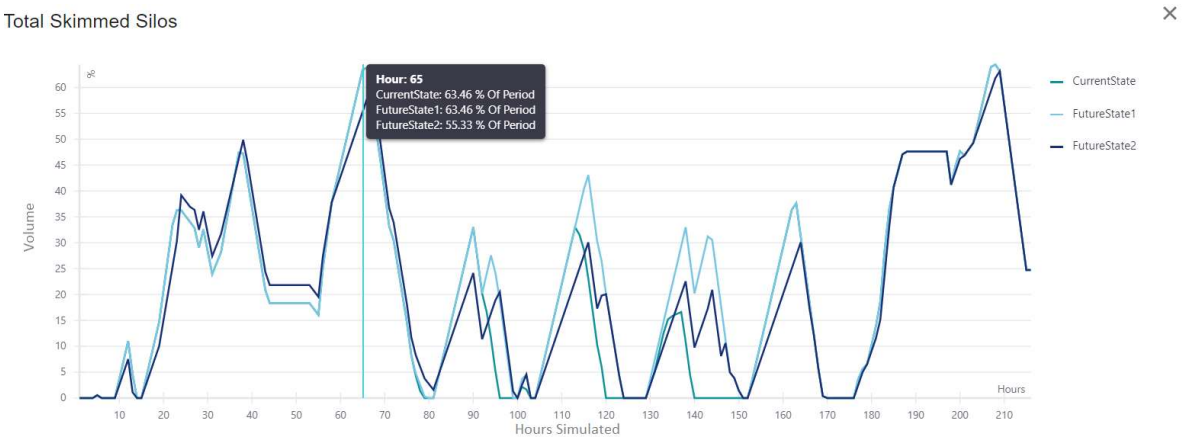
C.24 Total Whole Milk Silos – (Stage B1)



C.25 Total Milk Separated– (Stage 2)



C.26 Total Skimmed Silos – (Stage B2)



APPENDIX D – DATA ANALYSIS INDUSTRIAL PARTNERS' PROCESSES

D.1 Statistics Analysis peak season – Lots per hour – Month 1

Days	Mean	SD	Min	Max	CV	Skewness	Most Likely Statistic Distribution (Density Function)	Rank
1	2.101	1.14	0.649	4.965	0.543	0.959	Logistic,3.98e-002,3.38e-002	98.2
2	2.744	1.788	0.583	7.194	0.651	0.863	Pearson Type 5,-4.32e-002,6.64,0.482	99.4
3	2.5	1.068	0.667	4.866	0.427	0.625	Cauchy, 4.41e-002,1.21e-002,	96.8
4	2.274	1.337	0.558	4.841	0.588	0.437	Power Function,-1.75e-003,0.102,0.761,	99.2
5	2.57	1.501	0.84	6.492	0.584	0.929	Johnson SU,-3.31e-002,1.78e-002,-5.75,2.76	99.8
6	1.994	1.232	0.601	5.339	0.618	0.789	Weibull,-3.07e-003,1.51,4.94e-002	61.2
7	2.172	1.321	0.234	5.712	0.608	1.478	Laplace,4.08e-002,1.96e-002,	89.5
8	2.38	1.12	0.585	4.802	0.471	0.361	Normal,4.17e-002,2.8e-002	97
9	2.418	1.146	0.86	5.62	0.474	0.839	Logistic,4.12e-002,2.44e-002	100
10	2.302	1.221	0.71	4.721	0.53	0.151	Power Function,-3.16e-003,0.103,0.826,	68.6
11	2.361	1.608	0.93	7.83	0.681	1.99	Extreme Value IA,4.11e-002,3.26e-002	98.9
12	1.937	1.006	0.468	4.173	0.519	0.602	Weibull,-6.12e-003,2.16,5.39e-002	99.9
13	2.046	1.216	0.787	4.829	0.595	1.054	Pearson Type 5,-6.26e-002,13.1,1.26	99.4
14	2.053	1.154	0.634	4.442	0.562	0.619	Triangular,-7.27e-003,0.112,1.84e-002	96.7
15	2.165	1.186	0.772	4.741	0.548	0.609	Inverse Gaussian,-4.51e-002,8.68e-002,0.622	98.2
16	2.24	1.814	0.755	6.947	0.81	1.549	Johnson SU,1.62e-002,3.41e-003,-1.1,0.616	100
17	2.775	1.327	0.853	5.731	0.478	0.301	Normal,4.17e-002,2.83e-002	97.9
18	2.622	1.359	0.677	5.063	0.518	0.034	Power Function,-2.48e-003,0.104,0.705,	100
19	2.257	1.165	0.785	5.219	0.516	0.65	Weibull,-8.45e-003,2.07,5.65e-002	98.3
20	2.178	1.506	0.769	6.313	0.691	1.074	Erlang,-3.84e-003,4.55e-002,2.	67
21	2.499	1.352	0.747	5.247	0.541	0.351	Weibull,-7.63e-003,1.95,5.55e-002	95.2
22	2.215	1.052	0.838	4.072	0.475	0.153	Gamma,-1.1,8.75e-004,1.3e+003	99.8
23	2.544	1.529	0.835	7.422	0.601	1.614	Laplace,3.91e-002,1.84e-002,	98.3
24	2.487	1.481	0.844	5.815	0.596	0.656	LogNormal,-2.96e-002,7.16e-002,3.6e-002	96.5
25	2.375	1.18	0.483	4.764	0.497	0.377	Gamma,-0.215,2.48e-003,104	100
26	2.207	1.741	0.733	5.699	0.789	1.051	Inverse Weibull,-3.36e-002,2.36,19.4,	100
27	2.042	1.47	0	5.212	0.72	0.694	LogNormal,-1.51e-002,5.79e-002,4.42e-002	94.5
28	2.014	1.527	0.002	6.27	0.758	1.086	Inverse Weibull,-0.172,8.14,5.09,	98.5
29	2.625	1.869	0.776	6.707	0.712	1.121	LogLogistic,-0.18,9.63,0.213	100
30	2.34	1.509	0.88	5.83	0.645	1.126	Johnson SU,2.49e-002,1.18e-002,-0.353,0.467	100

D.2 Statistics Analysis peak season – Lots per hour – Month 2

Days	Mean	SD	Min	Max	CV	Skewness	Most Likely Statistic Distribution (Density Function)	Rank
1	2.35	1.071	0.693	4.166	0.456	0.136	Pearson Type 5,-0.154,66.9,12.9	90.2
2	2.388	1.575	0.578	5.41	0.66	0.476	Power Function,-1.11e-003,0.111,0.617,	100
3	2.33	1.394	0.266	6.227	0.598	0.855	Beta,-9.98e-003,0.176,2.31,5.71	100
4	2.284	1.537	0.721	5.283	0.673	0.841	Inverse Weibull,-0.109,5.55,7.56,	100
5	2.399	1.585	0.157	6.333	0.661	0.944	Johnson SU,-2.79e-002,3.2e-002,-3.77,2.6	100
6	2.363	1.776	0.75	6.271	0.752	0.901	Pearson Type 5,-2.69e-002,3.96,0.207	94
7	2.452	1.316	0.927	5.378	0.537	0.815	Rayleigh,-7.71e-003,4.04e-002,	92.9
8	2.462	1.4	0.614	6.211	0.569	1.056	Johnson SU,-3.46e-002,4.7e-002,-4.32,3.51	99.8
9	2.253	1.338	0.164	5.355	0.594	0.772	Extreme Value IA,4.12e-002,3.24e-002	99.6
10	2.133	1.236	0.83	5.219	0.58	1.073	LogLogistic,-0.162,12.9,0.2	93.1
11	2.294	1.304	0.709	5.439	0.568	0.977	Extreme Value IA,4.32e-002,2.6e-002	100
12	2.182	1.52	0.795	6.071	0.697	1.098	Inverse Gaussian,-1.93e-002,6.1e-002,0.169	99.8
13	2.365	1.147	0.538	4.684	0.485	0.306	Gamma,-0.336,1.92e-003,196	95
14	1.971	1.202	0.514	4.99	0.61	0.969	Erlang,-8.2e-003,5.03e-002,3.	82.8
15	2.876	1.327	0.812	5.344	0.462	0.089	Extreme Value IB,3.91e-002,4.71e-002	100
16	2	0.96	0.723	4.698	0.48	1.063	LogLogistic,-0.177,15.8,0.217	97.6
17	2.069	1.135	0.607	4.883	0.549	0.642	Logistic,4.11e-002,2.56e-002	90.4
18	2.252	0.883	0.906	3.838	0.392	0.112	Extreme Value IB,4.13e-002,3.03e-002	98.3
19	1.995	1.137	0.632	4.249	0.57	0.502	Power Function,-1.43e-003,9.14e-002,0.954,	77.2
20	1.998	0.941	0.6	4.461	0.471	0.724	Gamma,-0.144,4.22e-003,43.9	89.6
21	2.78	1.306	0.635	6.561	0.47	1.03	Normal,4.13e-002,2.99e-002	94.6
22	2.36	1.272	0.855	4.263	0.539	0.144	Power Function,-6.67e-003,0.101,0.826,	70.8
23	2.366	1.298	0.787	4.881	0.549	0.672	Extreme Value IA,4.23e-002,2.8e-002	100
24	2.399	0.969	0.579	4.179	0.404	-0.219	Extreme Value IB,4.1e-002,3.58e-002	100
25	2.048	1.129	0.609	4.458	0.551	0.412	Power Function,-1.11e-003,0.116,0.618,	88.2
26	1.897	1.377	0.712	6.262	0.726	1.872	LogLogistic,-0.11,8.22,0.146	94.7
27	2.038	1.079	0.608	3.837	0.529	0.395	Logistic,3.89e-002,3.7e-002	99.2
28	1.859	0.887	0.848	4.152	0.477	0.784	Gamma,-9.35e-002,6.79e-003,19.9	93.4
29	2.221	1.01	0.573	3.825	0.455	0.186	LogNormal,-0.297,0.338,2.8e-002	90.8
30	2.011	1.094	0.814	3.71	0.544	0.389	Extreme Value IA,4.14e-002,3.48e-002	100
31	2.127	1.217	0.738	5.025	0.572	0.83	Logistic,4.03e-002,3.53e-002	100

D.3 Statistics Analysis off-season – Lots per hour – Month 1

Days	Mean	SD	Min	Max	CV	Skewness	Most Likely Statistic Distribution (Density Function)	Rank
1	1.743	1.115	0.358	4.637	0.64	1.02	LogLogistic,-0.207,12.6,0.243	97.7
2	1.963	0.864	0.505	3.995	0.44	0.421	Extreme Value IB,3.9e-002,4.77e-002	100
3	1.878	1.251	0.608	4.757	0.666	0.868	Inverse Weibull,-8.62e-002,4.43,9.26,	100
4	1.65	0.869	0.733	3.713	0.526	0.92	Logistic,3.82e-002,4.09e-002	92.8
5	1.733	1.157	0.32	4.43	0.668	0.868	Power Function,-8.69e-004,0.153,0.454,	96
6	2.113	1.599	0.569	6.535	0.757	1.459	LogLogistic,-0.142,8.23,0.174	100
7	1.741	1.037	0.597	3.491	0.596	0.561	LogLogistic,-0.29,13.7,0.325	60
8	1.835	0.956	0.676	4.066	0.521	0.583	Logistic,3.99e-002,3.67e-002	98.4
9	1.704	1.146	0.57	4.135	0.672	0.952	Inverse Weibull,-8.57e-002,4.43,9.3,	100
10	2.022	1.128	0.592	4.897	0.558	1.084	Logistic,3.74e-002,4.45e-002	95.1
11	1.348	0.847	0.49	2.963	0.628	0.866	Laplace,3.25e-002,3.48e-002,	98
12	1.739	0.801	0.613	3.74	0.46	0.773	Logistic,4.13e-002,3.14e-002	97.1
13	1.829	0.984	0.701	3.549	0.538	0.487	Logistic,3.77e-002,4.54e-002	52.4
14	1.384	0.787	0.592	3.293	0.569	1.059	Laplace,3.6e-002,2.88e-002,	95.7
15	1.627	0.629	0.806	2.699	0.387	0.215	Extreme Value IB,4.e-002,4.64e-002	98.5
16	1.617	0.831	0.529	4.003	0.514	1.133	Normal,4.17e-002,3.64e-002	99.2
17	2.299	1.383	0.565	4.672	0.602	0.344	Logistic,3.51e-002,5.26e-002	16.6
18	1.129	0.536	0.515	2.043	0.475	0.56	Extreme Value IB,3.7e-002,6.95e-002	17.2
19	1.667	1.037	0.23	4.006	0.622	0.851	Extreme Value IA,4.11e-002,3.48e-002	100
20	1.744	1.174	0.04	3.792	0.673	0.506	Laplace,3.44e-002,3.52e-002,	67.9
21	1.424	0.983	0.513	3.586	0.69	1.174	LogLogistic,-0.174,9.72,0.207	89.7
22	1.304	0.713	0.518	3.508	0.547	1.734	Logistic,3.94e-002,3.75e-002	94.8
23	1.689	1.332	0.534	4.527	0.789	1.003	Inverse Weibull,-6.79e-002,3.55,11.7,	73
24	1.723	0.852	0.658	3.156	0.494	0.129	Extreme Value IB,3.75e-002,6.87e-002	12.3
25	1.133	0.791	0.051	2.757	0.698	0.514	Logistic,3.31e-002,5.4e-002	32.1
26	1.609	1.027	0.685	4.109	0.638	1.114	Inverse Weibull,-0.156,7.17,5.58,	99
27	1.717	1.238	0.374	4.157	0.721	0.812	Power Function,-1.33e-003,0.135,0.502,	93.8
28	1.471	0.815	0.674	2.895	0.554	0.698	Logistic,3.27e-002,5.54e-002	13.8
29	1.422	1.156	0.256	3.919	0.813	0.964	Power Function,-9.02e-004,0.189,0.352,	64.7
30	2.068	1.759	0.556	5.992	0.85	1.286	Power Function,-2.18e-003,0.209,0.373,	71.9

D.4 Statistics Analysis off-season – Lots per hour – Month 2

Days	Mean	SD	Min	Max	CV	Skewness	Most Likely Statistic Distribution (Density Function)	Rank
1	1.587	0.881	0.662	3.302	0.555	0.767	Logistic,3.62e-002,4.72e-002	86.3
2	1.006	0.383	0.653	1.956	0.381	1.839	Extreme Value IB,3.27e-002,9.19e-002	36.7
3	1.464	1.064	0.549	4.683	0.727	1.966	Laplace,3.43e-002,3.23e-002,	100
4	1.409	0.763	0.2	3.269	0.542	0.789	Logistic,3.61e-002,5.06e-002	100
5	0.906	0.559	0.248	1.773	0.617	0.563	Logistic,2.79e-002,6.22e-002	4.27
6	2.003	1.715	0.579	5.026	0.856	0.925	Beta,-3.63e-005,0.308,0.122,0.749	59.4
7	1.752	1.343	0.474	4.424	0.766	0.98	LogLogistic,-0.18,9.6,0.211	72.7
8	1.212	0.635	0.273	2.23	0.524	0.096	Extreme Value IB,3.81e-002,6.42e-002	13.5
9	0.996	0.631	0.078	2.031	0.634	0.286	Extreme Value IB,2.28e-002,0.154	0.6
10	1.347	0.925	0.328	3.929	0.687	1.412	Laplace,3.46e-002,3.58e-002,	100
11	1.369	0.947	0.457	3.58	0.691	1.292	Logistic,3.14e-002,5.58e-002	100
12	0.982	0.713	0.237	2.038	0.726	0.419	Logistic,1.93e-002,6.93e-002	0.34
13	1.57	0.83	0.703	2.917	0.529	0.529	Extreme Value IB,3.29e-002,9.81e-002	3.29
14	1.326	0.974	0.411	3.54	0.735	1.279	Laplace,2.87e-002,3.97e-002,	78.6
15	1.586	0.816	0.875	2.993	0.515	0.836	Extreme Value IB,1.65e-002,0.192	0.161
16	0.92	0.7	0.191	1.899	0.761	0.275	LogLogistic,-0.123,6.56,0.144	31.5
17	1.299	1.078	0.25	3.33	0.83	0.793	Logistic,3.09e-002,6.47e-002	1.39
18	1.405	0.396	0.843	1.95	0.282	-0.077	Not found	-
19	1.111	0.222	0.982	1.442	0.2	1.114	Not found	-
20	0.801	0.273	0.353	1.099	0.341	-0.782	Logistic,2.73e-002,6.79e-002	1.24
21	0.96	0.441	0.28	1.623	0.459	-0.056	Extreme Value IB,2.81e-002,0.131	0.47
22	1.191	0.859	0.364	2.696	0.721	0.739	Logistic,2.29e-002,6.67e-002	2.51
23	0.909	0.324	0.482	1.552	0.357	0.587	Extreme Value IB,3.75e-002,6.79e-002	40.1
24	0.911	0.056	0.84	0.994	0.061	0.373	Not found	-
26	1.474	1.114	0.173	3.856	0.756	1.014	Logistic,2.64e-002,6.28e-002	2.84
27	0.97	0.424	0.413	1.817	0.436	0.757	Extreme Value IB,3.35e-002,9.23e-002	10.1
28	1.214	0.443	0.868	1.835	0.365	0.679	Extreme Value IB,3.55e-002,8.45e-002	25.2
29	0.944	0.85	0	2.571	0.901	0.948	Logistic,2.68e-002,6.28e-002	6.73
30	1.007	0.637	0.251	2.061	0.633	0.395	Logistic,2.74e-002,6.25e-002	2.5
31	1.303	0.738	0.514	2.191	0.566	0.167	Not found	-

D.5 CIP Data Layout – Data collected for one Day

Date: 01/01/1900

CID Production Traceability System - INDUSTRIAL PARTNER X
Milk Separator Daily Log

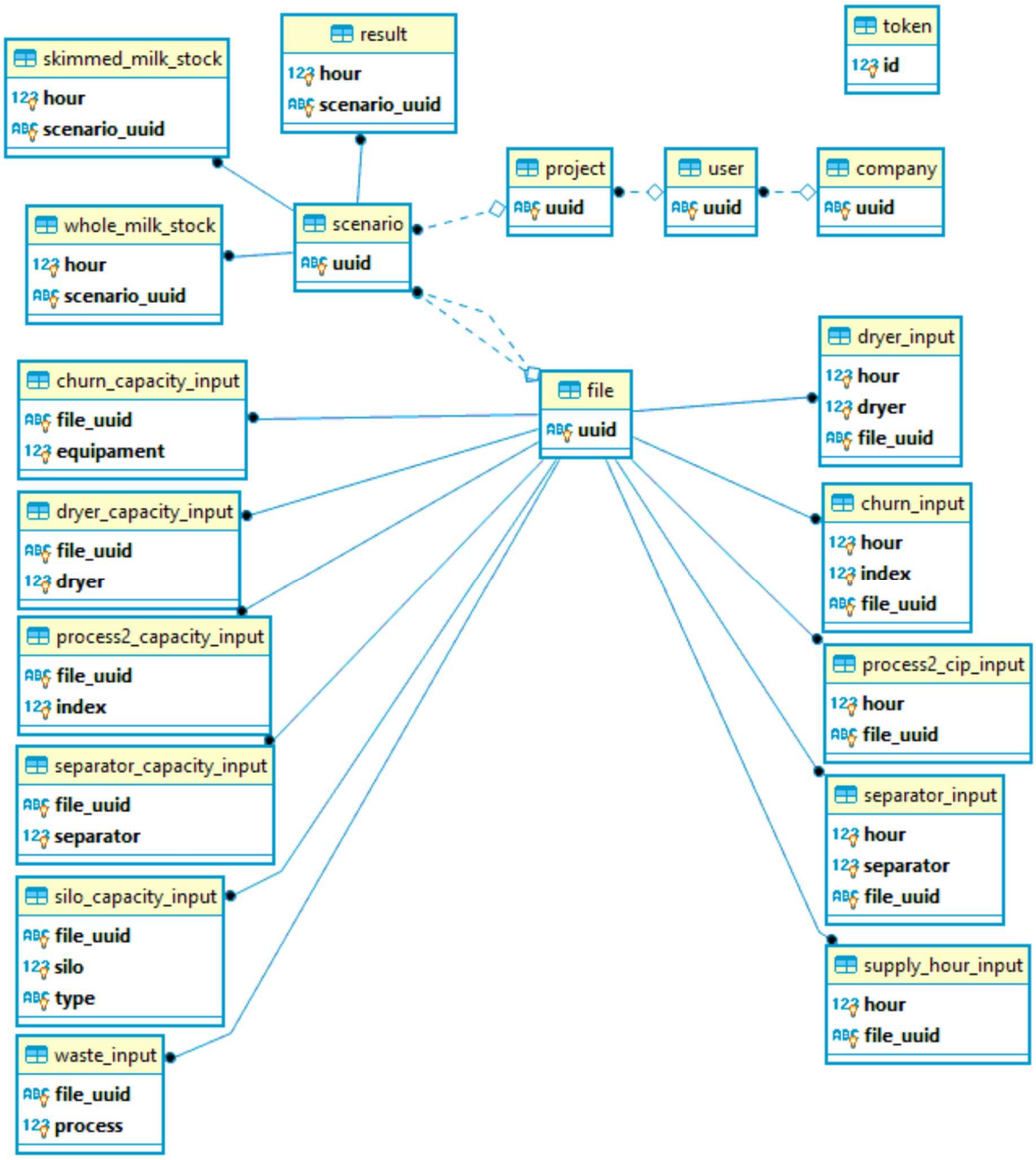
										Separator No. 1						Separator No. 2							Cream													Tempering		Raw Cream Storage		Separator No. 3							Separator No. 6							
	Time	WM Silo	WM Litres	Trace Code	WM Temp	Skim Silo	K/Litres	Skim Temp.	Trace Code	Past. Temp. PLC	Skim Temp.	% Fat Skim	Pres. In	Pres. Out	Back Pres.	Past. Temp. PLC	Past. Temp. Online	Skim Temp.	% Fat Skim	Press In	Pres. Out	Back Pres.	Butter	Melt Temp.	Melt Level	Past. Temp. Display	Cool Temp Display	Crea m Silo	Cream Litres	Trace Code	Cream Temp.	Flow Litres	Silo	Step	Level %	Temp	Past. Temp. PLC	Past. Temp. Online	Skim Temp.	% Fat Skim	Pres. In	Pres. Out	Back Pres.	Past. Temp. PLC	Past. Temp. Online	Skim Temp.	% Fat Skim	Pres. In	Pres. Out	Back Pres.	Initia
8	00:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	90	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	aaa
9	01:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	90	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	aaa
10	02:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	90	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	aaa
11	03:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	90	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	aaa
12	04:00	9	999	999	999.0	9	999	9.0	########	CIP						CIP							//	9.0	9.0	90	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	aaa
13	05:00		0					0.0		CIP						CIP							//	9.0	9.0	90	9.0	9	9999	01/01/1900	9.0	9			9999	9999	CIP							CIP							
14	06:00		0					0.0		CIP													//	9.0	9.0	CIP			0				9	9	9999	9999	CIP							CIP							
15	07:00		0					0.0								Water							//	9.0	9.0	CIP			0				9	9	9999	9999								CIP							
16	08:00		0					0.0		Water						Water							//	9.0	9.0				0				9	9	9999	9999	Water													
17	09:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	Water			0				9	9	9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0								bbbb
18	10:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	Water			0						9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0								bbbb
19	11:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	Water			0						9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	Water							bbbb
20	12:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	Water			0						9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0								bbbb
21	13:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	CIP							bbbb
22	14:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	CIP							bbbb
23	15:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0								bbbb
24	16:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	CIP							//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9			9999	9999						9	9.0	9.0	9.00	9.0	9.0	9.0	bbbb
25	17:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	CIP							//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9			9999	9999	CIP					9	9.0	9.0	9.00	9.0	9.0	9.0	bbbb
26	18:00	9	999	999	999.0	9	999	9.0	########							CIP							//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9			9999	9999	CIP					9	9.0	9.0	9.00	9.0	9.0	9.0	bbbb
27	19:00	9	999	999	999.0	9	999	9.0	########	CIP						9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9			9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	bbbb
28	20:00	9	999	999	999.0	9	999	9.0	########	CIP						9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9	9	9	9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	ccc
29	21:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9	9	9	9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	ccc
30	22:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0	9	9.0	9.0	9.00	9.0	9.0	9.0	//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9	9	9	9999	9999	9	9.0	9.0	9.00	9.0	9.0	9.0	CIP							ccc
31	23:00	9	999	999	999.0	9	999	9.0	########	99	9.0	9.00	9.0	9.0	9.0								//	9.0	9.0	99	9.0	9	9999	01/01/1900	9.0	9	9	9	9999	9999								CIP							ccc

D.6 Heat Map Algorithm Data Visualisation

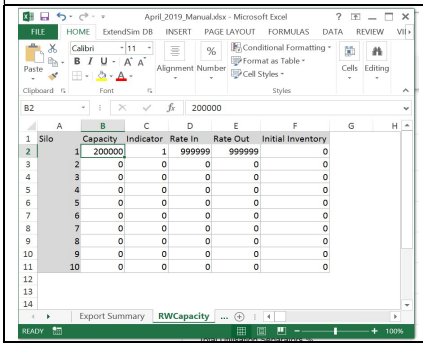
```
library(readxl)
library(ggplot2)
library(reshape2)
library(grid)
library(ggpubr)
library(MASS)
library(dplyr)

#IMPORTANT VARIABLES
folder = "C:/Temp/folder"
m  = 999
year = 999

setwd(folder)

file.list <- list.files( pattern='*.xls')
df.list <- lapply(file.list,function(x) {
  sheets <- excel_sheets(x)
  dfs <- lapply(sheets, function(y) {
    read_excel(x, sheet = y,skip=5, n_max = 24, col_names = TRUE)
  })
  names(dfs) <- sheets
  dfs
})

data = as.data.frame(df.list[[1]][[1]])
data$day = 1
data$month = 1
data$year = year

for (x in 2:length(file.list)) {
  namefile = file.list[x]
  d = as.numeric(substr(namefile, 1, 2))
  m = as.numeric(substr(namefile, 4, 5))
  y = as.numeric(substr(namefile, 7, 9)) + 2000
  dat_aux = as.data.frame(df.list[[x]][[1]])
  dat_aux$day = d
  dat_aux$month = m
  dat_aux$year = y
  data = rbind.data.frame(data,dat_aux)
}

cols = c("Time", "test2", "test3", "test4", "WMSilo", "WMLitres",
"test5",          "TraceCode",          "test6",          "test7",
"test70","WMTemp","SkimSilo",    "test10",    "test10a","KLitres",
"test11",  "test12",    "SkimTemp",  "test16",  "test17",  "test18",
"test19",  "TraceCode2","test20",  "test21",   "test22",  "test23",
"PastT5","test22",   "test23",   "SkimT5",    "PercFat5","test21a",
"test21b","PresI5",
"test27","test28","test29","PresO5","test27a","test28b","test29c",
"test30a","BackPres5","test33","PastT2","PastT2Online","test31a","
SkimT2","test35",est36","test37","PresI2","PresO2","test39","BackP
res2"Test41","Test42"Test43","ButterTrace","test44","MeltTemp","te
st46","test46","MeltLevel","CreamPastT","test47","CoolTemp","Cream
Silo","test49", "test50","CreamLitres","TraceCodeButter", "test53",
"test54",   "CreamTemp","FlowLitres","Silo",   "test55","PercLevel",
"CreamStoreTemp","test56","test57","PastT3","Temp3","SkimT3","Perc
Fat3","PresI3","PresO3",             "BackPres3","test58","test59",
"PastT4","PastT4Online","test60","test61","SkimT4","PercFat4","tes
t62",   "PresI4","test63",   "PresO4","BackPres4","Initials","Day",
"Month","Year")

colnames(data) = cols
col2 = grep("test", cols,ignore.case = TRUE)
data3 <- data[ -c(col2) ]
data3 = data
m = c("4","5")
data2 = data3 %>%
        filter(month %in% m)

#change by factors
data2$Month = as.factor(data2$Month)
data2$Day   = as.factor(data2$Day)

data2$Sep1CIP = as.integer(data2$PastT5 == "CIP")
data2$Sep1Water = as.integer(data2$PastT5 == "Water")
data2$Sep1Blank = as.integer(is.na(data2$PastT5))
data2$Sep1Working = as.integer(as.integer(data2$PastT5) > 70)
data2$Sep2CIP = as.integer(data2$PastT2 == "CIP")
data2$Sep2Water = as.integer(data2$PastT2 == "Water")
data2$Sep2Blank = as.integer(is.na(data2$PastT2))
data2$Sep2Working = as.integer(as.integer(data2$PastT2) > 70)
data2$Sep3CIP = as.integer(data2$PastT3 == "CIP")
data2$Sep3Water = as.integer(data2$PastT3 == "Water")
data2$Sep3Blank = as.integer(is.na(data2$PastT3))
data2$Sep3Working = as.integer(as.integer(data2$PastT3) > 70)
data2$Sep4CIP = as.integer(data2$PastT4 == "CIP")
data2$Sep4Water = as.integer(data2$PastT4 == "Water")
data2$Sep4Blank = as.integer(is.na(data2$PastT4))
data2$Sep4Working = as.integer(as.integer(data2$PastT4) > 70)

#TREATMENT FOR EXCELS
datacsv = data2 %>% filter(Month ==4)

graphdata                                                    <-
melt(datacsv[,c("Day","Month","Time","Sep2Working")],id.vars      =
c(1,2,3))
colgraphdata = c("Day","Month","Time","Working","Utilisation")
colnames(graphdata) = colgraphdata
tab  =  table(graphdata$Time,  graphdata$Day,graphdata$Utilisation,
exclude = NA)

g2 = ggplot(graphdata,aes(Day,Time,fill=Utilisation))+
  geom_tile(color= "white",size=0.1) +
  scale_fill_continuous(high = "#132B43", low = "#56B1F7") +
  facet_grid(~Month) +
  theme(strip.background = element_rect(colour="white")) +
  theme(axis.text.x = element_text(angle=65, vjust=0.6)) +
  labs(title="Separator 1 - Working Times")
```

APPENDIX E - ePMPS FILE STRUCTURE

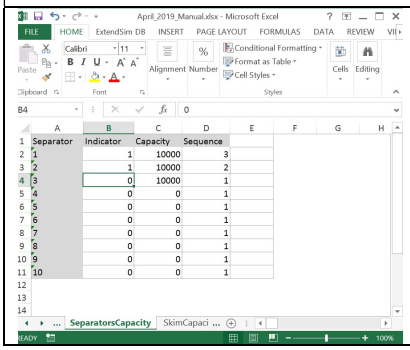
E.1 Entity-Relationship Diagram – ePMPS



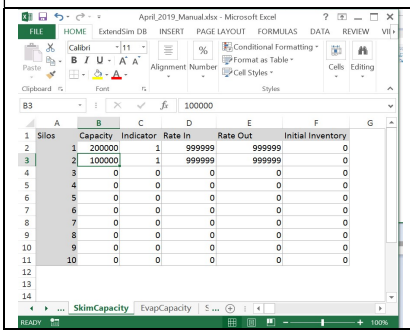
E.2 Stage B1 – Silos - RWCapacity

CSV file: RWCapacity	Description
	• This spreadsheet is limited to 10 silos at any capacity. • The binary indicator (0/1) activates/deactivates an extra capacity • *Rate In* and *Rate Out* control the flow. • Initial inventory is considered as presented in column F

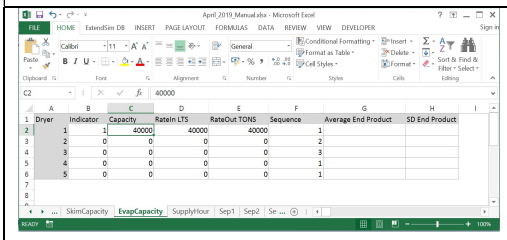
E.3 Stage 2 – Separation - SeparatorsCapacity

CSV file: SeparatorsCapacity	Information
	• This spreadsheet is limited to 10 separators • The binary indicator (0/1) activates/deactivates an extra equipment • The sequence defines the priority among separators

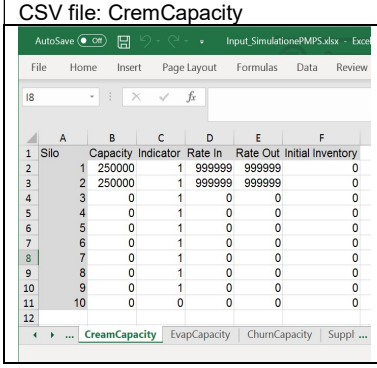
E.4 Stage B2 – Silos - SkimCapacity

CSV file: SkimCapacity	Information
	• This spreadsheet is limited to 10 silos • The binary indicator (0/1) activates/deactivates an extra capacity • *Rate In* and *Rate Out* control the flow. • It is also possible to fill it up an initial inventory as presented in column F

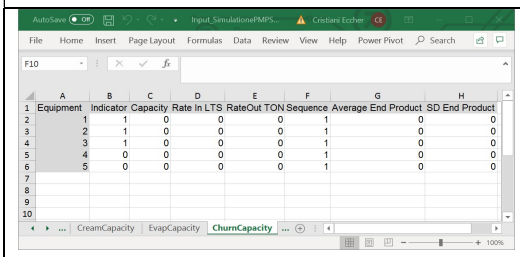
E.5 Stage 3 – Silos - EvapCapacity

CSV file: EvapCapacity	Information
	• This spreadsheet is limited to 5 dryers • The binary indicator (0/1) activates/deactivates an extra equipment • *Rate In* and *Rate Out* control the flow. • The sequence defines the priority among dryers • Through the Average and SD is possible to incorporate variability at the final production

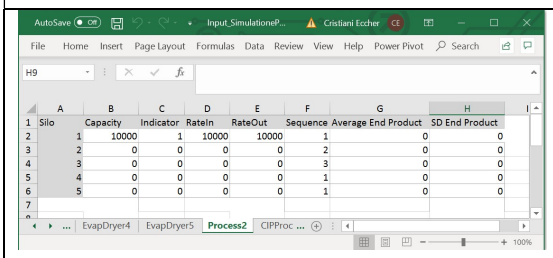
E.6 Stage B2.1 – Silos - CreamCapacity

CSV file: CremCapacity	Information
	This spreadsheet is limited to 10 silos The binary indicator (0/1) activates/deactivates an extra capacity *Rate In* and *Rate Out* control the flow. It is also possible to fill it up an initial inventory as presented in column F

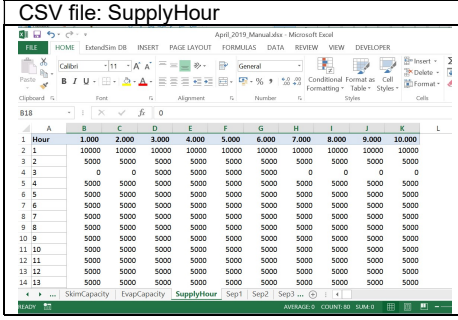
E.7 Stage 2.2 – Churn – ChurnCapacity

CSV file: ChurnCapacity	Information
	• This spreadsheet is limited to 5 equipment • The binary indicator (0/1) activates/deactivates an extra equipment • *Rate In* and *Rate Out* control the flow. • The sequence defines the priority among equipment • Through the Average and SD is possible to incorporate variability at the final production

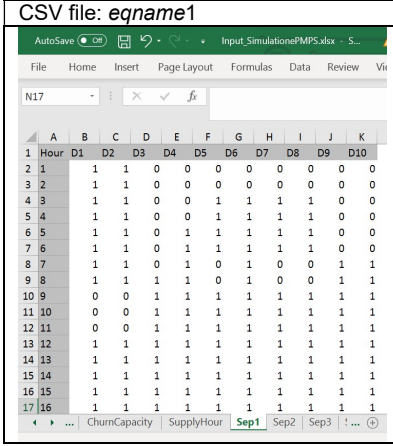
E.8 Stage 4 – Process 2

CSV file: Process2	Information
	• This spreadsheet is limited to 5 equipment • The binary indicator (0/1) activates/deactivates an extra equipment • *Rate In* and *Rate Out* control the flow. • The sequence defines the priority among equipment • Through the Average and SD is possible to incorporate variability at the final production

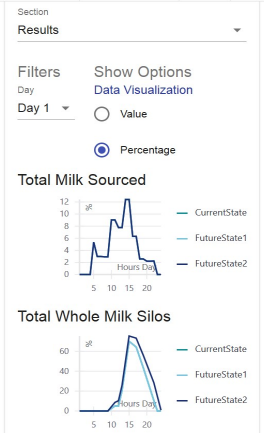
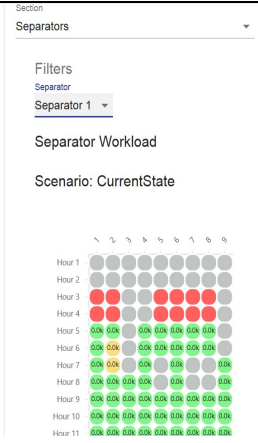
E.9 Stage 0 – Raw Material Supply - Hourly

CSV file: SupplyHour	Information
	This spreadsheet is limited to 10 days The amount of milk received per hour should be fill up in this file

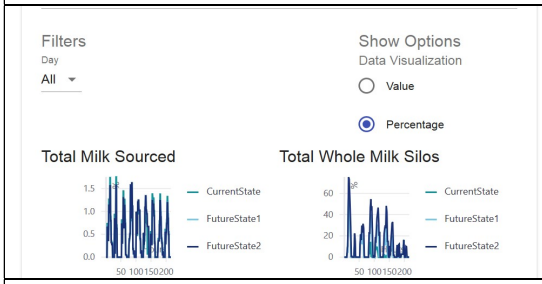
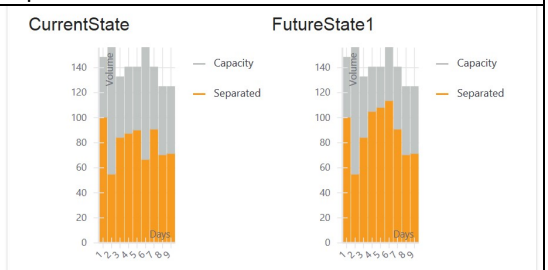
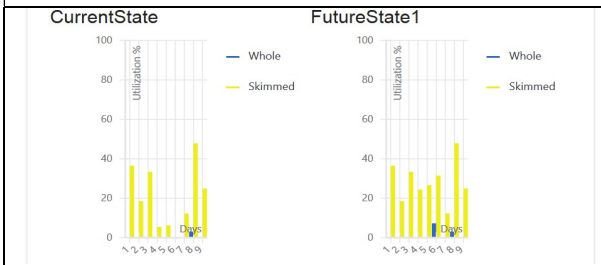
E.10 Stages 2,2.2,3 and 4 – Equipment Scheduling - Hourly

CSV file: *eqname*1	Information
	This spreadsheet is limited to 10 days The binary indicator (0/1) activates/deactivates the running hours

E.11 Mobile Dashboard Vertical Visualisations

Results Dashboard	Separator Dashboard	Whole and Skimmed Milk Silos	Separators Utilisation
			

E.12 Mobile Dashboard Horizontal Visualisations

Results Dashboard	Separators Utilisation
	
Whole and Skimmed Milk Silos	**Comparison Dashboard**
	

APPENDIX F - EXPERIMENTS DATA AND ALGORITHMS

F.1 Supply Volumes per Day

1-Day Period	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	Stage2Rate	Stage2Util	SLA	Lot
1	2.232	1.908	53.57	8.083	14.15	47.77	5.908	7.125	22.63	1	0.982	0.564	0.761	53.57
2	2.232	1.399	53.57	5.939	9.642	33.58	3.282	4.418	16.34	1	0.928	0.533	0.705	53.57
3	2.232	1.415	53.57	5.017	8.125	27.44	3.631	5.047	16.39	1	0.966	0.555	0.704	53.57
4	2.232	1.497	53.57	7.22	11.49	44.19	3.622	5.457	19.03	1	0.907	0.521	0.689	53.57
5	2.232	1.344	53.57	5.639	10.39	37.71	3.7	4.098	12.64	1	0.936	0.538	0.68	53.57
6	2.232	1.163	53.57	6.169	10.49	38.52	4.995	5.752	19.03	1	0.955	0.549	0.688	53.57
1	2.381	2.035	57.14	9.77	15.41	52.82	7.543	8.174	25.37	1	0.982	0.602	0.815	57.14
2	2.381	1.493	57.14	7.026	11.03	37.68	4.864	4.979	19.03	1	0.928	0.569	0.75	57.14
3	2.381	1.509	57.14	6.604	9.97	32.99	4.876	5.83	19.03	1	0.966	0.592	0.772	57.14
4	2.381	1.597	57.14	8.166	12.55	47.14	4.82	5.845	19.13	1	0.907	0.556	0.719	57.14
5	2.381	1.433	57.14	6.244	11.13	40.22	5.03	4.885	14.73	1	0.936	0.574	0.757	57.14
6	2.381	1.24	57.14	7.045	11.38	41.09	6.431	6.365	22.06	1	0.955	0.585	0.759	57.14
1	2.53	2.162	60.71	11.68	16.86	57.86	9.38	9.07	26.85	1	0.982	0.639	0.833	60.71
2	2.53	1.586	60.71	8.349	12.49	41.78	6.532	5.481	19.03	1	0.928	0.604	0.796	60.71
3	2.53	1.604	60.71	8.469	12.04	38.53	6.451	6.775	20.89	1	0.966	0.629	0.85	60.71
4	2.53	1.697	60.71	9.137	13.72	50.09	6.118	6.462	22.22	1	0.907	0.591	0.785	60.71
5	2.53	1.523	60.71	6.852	11.92	42.73	7.808	6.414	19.16	1	0.936	0.61	0.816	60.71
6	2.53	1.318	60.71	7.921	12.40	43.66	8.13	7.06	25.34	1	0.955	0.622	0.804	60.71
1	2.679	2.29	64.28	13.60	18.60	62.91	11.29	10.26	31.48	1	0.982	0.677	0.851	64.29
2	2.679	1.679	64.28	9.728	14.1	45.87	9.109	6.776	21.44	1	0.928	0.64	0.851	64.29
3	2.679	1.698	64.28	10.34	14.38	44.08	9.088	8.569	27.29	1	0.966	0.666	0.909	64.29
4	2.679	1.797	64.28	10.15	14.96	53.03	8.506	7.885	27.65	1	0.907	0.625	0.849	64.29
5	2.679	1.613	64.28	7.5	12.74	45.27	11.08	8.255	25.64	1	0.936	0.646	0.871	64.29
6	2.679	1.395	64.28	9.067	13.42	46.23	10.24	7.884	26.42	1	0.955	0.659	0.873	64.29
1	2.827	2.417	67.85	15.89	20.34	67.95	13.01	11.38	35.60	1	0.982	0.715	0.892	67.86
2	2.827	1.772	67.85	11.14	15.81	49.97	12.39	8.532	28.10	1	0.928	0.676	0.902	67.86
3	2.827	1.792	67.85	12.60	16.71	49.63	12.56	10.37	30.10	1	0.966	0.703	0.917	67.86
4	2.827	1.896	67.85	11.48	16.1	55.98	11.62	9.528	31.63	1	0.907	0.66	0.903	67.86
5	2.827	1.702	67.85	8.526	14	49.33	14.48	10.12	32.01	1	0.936	0.682	0.875	67.86
6	2.827	1.473	67.85	10.22	14.62	48.80	14.53	9.881	33.27	1	0.955	0.695	0.875	67.86
1	2.976	2.544	71.42	18.37	22.22	73.00	15.60	12.93	42.53	1	0.982	0.752	0.917	71.43
2	2.976	1.866	71.42	12.68	17.55	54.07	15.78	10.50	33.72	1	0.928	0.711	0.913	71.43
3	2.976	1.887	71.42	14.85	19.29	55.17	16.63	12.81	38.52	1	0.966	0.74	0.917	71.43
4	2.976	1.996	71.42	12.82	17.37	58.93	15.39	11.30	35.96	1	0.907	0.695	0.917	71.43
5	2.976	1.792	71.42	9.648	15.26	53.40	17.85	12.31	37.75	1	0.936	0.717	0.884	71.43
6	2.976	1.55	71.42	11.43	15.93	51.37	18.97	12.33	41.6	1	0.955	0.732	0.875	71.43
1	3.125	2.671	75	21.26	24.11	78.04	19.39	14.97	49.87	1	0.982	0.79	0.917	75.00
2	3.125	1.959	75	14.46	19.25	58.17	19.70	12.81	40.07	1	0.928	0.747	0.917	75.00
3	3.125	1.981	75	17.12	22.03	60.72	20.70	15.49	47.27	1	0.966	0.777	0.917	75.00
4	3.125	2.096	75	14.77	19.42	63.99	19.50	13.39	42.67	1	0.907	0.729	0.917	75.00
5	3.125	1.881	75	11.11	16.43	57.46	21.05	14.48	43.89	1	0.936	0.753	0.898	75.00
6	3.125	1.628	75	12.93	17.17	53.93	23.27	14.83	47.17	1	0.955	0.768	0.875	75.00
1	3.274	2.798	78.57	24.44	26.15	83.08	23.04	16.93	55.76	1	0.982	0.827	0.917	78.57
2	3.274	2.052	78.57	16.26	21.08	62.27	23.90	15.41	48.84	1	0.928	0.782	0.917	78.57
3	3.274	2.075	78.57	19.97	24.5	67.34	24.47	17.87	56.14	1	0.966	0.814	0.917	78.57
4	3.274	2.196	78.57	16.99	21.78	69.70	23.48	15.65	50.03	1	0.907	0.764	0.917	78.57
5	3.274	1.971	78.57	12.75	17.67	61.52	24.16	16.74	50.67	1	0.936	0.789	0.912	78.57
6	3.274	1.705	78.57	14.48	18.56	56.50	27.54	17.44	54.18	1	0.955	0.805	0.875	78.57
1	3.423	2.926	82.14	28.12	28.08	88.13	26.44	18.86	64.08	1	0.977	0.861	0.917	82.14
2	3.423	2.145	82.14	18.15	22.93	66.50	28.04	18.07	57.61	1	0.928	0.818	0.917	82.14
3	3.423	2.17	82.14	23.19	26.97	74.20	28.06	20.06	63.43	1	0.966	0.851	0.917	82.14
4	3.423	2.296	82.14	19.55	24.07	75.40	27.29	17.87	56.21	1	0.907	0.799	0.917	82.14
5	3.423	2.06	82.14	14.88	18.76	65.59	27.73	19.16	55.18	1	0.936	0.825	0.917	82.14
6	3.423	1.783	82.14	16.19	20.18	59.39	31.74	20.15	63.36	1	0.955	0.842	0.875	82.14

F.2 5-Day Supply Validation – Rstudio Algorithm Graphs

```
library(dplyr) # handle datasets
library(readxl) # handle excel files
library(ggplot2) # graphs
library(plyr) # grid
library(reshape2)
library("e1071")

folder = "C://model/"
ext = ".xlsx"
ext2 = ".csv"
lot = ?????

folder = "C://model/"
ext = ".xlsx"

file = paste(folder,"supply5days",ext, sep ="")
supply1  <- read_excel(file,sheet = "P1")
supply2  <- read_excel(file,sheet = "P2")
supply3  <- read_excel(file,sheet = "P3")

colnames(supply1) = c("Supply","Day")
colnames(supply2) = c("Supply","Day")
colnames(supply3) = c("Supply","Day")

supply1$Period = "Period 1"
supply2$Period = "Period 2"
supply3$Period = "Period 3"

supply1$Supply = supply1$Supply / lot
supply2$Supply = supply2$Supply / lot
supply3$Supply = supply3$Supply / lot

SupplyTot = NULL
SupplyTot = supply1
SupplyTot = as.data.frame(SupplyTot)

SupplyTot = rbind(SupplyTot, supply2, supply3)
SupplyTot$Period = as.factor(SupplyTot$Period)

SupplyTot$Day = as.factor(SupplyTot$Day)

SupplyTot$Supply[is.na(SupplyTot$Supply)] = 0

round(sd(supply1$Supply,na.rm = TRUE)/mean(supply1$Supply,na.rm = TRUE),3)
round(sd(supply2$Supply,na.rm = TRUE)/mean(supply2$Supply,na.rm = TRUE),3)
round(sd(supply3$Supply,na.rm = TRUE)/mean(supply3$Supply,na.rm = TRUE),3)

round(skewness(supply1$Supply,na.rm = TRUE, type = 3),3)
round(skewness(supply2$Supply,na.rm = TRUE, type = 3),3)
round(skewness(supply3$Supply,na.rm = TRUE, type = 3),3)

data_summary <- function(data, varname, groupnames){
  require(plyr)
  summary_func <- function(x, col){
    c(mean = mean(x[[col]], na.rm=TRUE),
      sd = sd(x[[col]], na.rm=TRUE))
  }

  data_sum<-ddply(data, groupnames, .fun=summary_func,
                  varname)
  data_sum <- rename(data_sum, c("mean" = varname))
  return(data_sum)
}

df3 <- data_summary(SupplyTot, varname="Supply",
                    groupnames=c("Day", "Period"))
```

```
#### PLOTING A BOXPLOT
box1 =  ggplot(SupplyTot,aes(x = Day, y = Supply, colour = Day)) +
  geom_boxplot() +
   facet_grid(~Period) +
  # ylim(0,10) +
  labs(title="Supply 5-Day Period",
       y="Volume per Day" ) +

  scale_color_brewer(palette="Dark2") +
  theme_bw()

box1 +  theme(legend.position="bottom")

g = ggplot(df3, aes(x=Period, y=Supply, group=Period, color=Period)) +
  geom_errorbar(aes(ymin=Supply-3*sd, ymax=Supply+3*sd), width=.1) +
  geom_line() + geom_point()+
  scale_color_brewer(palette="Paired")+theme_minimal() +
  labs(title="Supply 5-Day Period - Average -/+ 3SD",
       y="Volume per Day" )

ggarrange(box2,g,
          ncol=2, nrow=1,
          common.legend = TRUE,
          legend = "none")

box2 =  ggplot(SupplyTot,aes(x = Period, y = Supply, colour = Period)) +
  geom_boxplot() +

  # ylim(0,10) +
  labs(title="Supply 5-Day Period - BoxPlot",
       y="Volume per Day" ) +

  scale_color_brewer(palette="Dark2") +
  theme_minimal()

ggarrange(box2,g,
          ncol=2, nrow=1,
          common.legend = TRUE,
          legend = "none")


par(mfrow = c(1, 3))
qqnorm(supply1$Supply, pch = 1, frame = FALSE, main = "Normal Q-Q Plot - Period 1", xlim=c(-3,3),ylim=c(0,10))
qqline(supply1$Supply, col = "steelblue", lwd = 2)

qqnorm(supply2$Supply, pch = 1, frame = FALSE, main = "Normal Q-Q Plot - Period 2",xlim=c(-3,3),ylim=c(0,10))
qqline(supply2$Supply, col = "steelblue", lwd = 2)

qqnorm(supply3$Supply, pch = 1, frame = FALSE, main = "Normal Q-Q Plot - Period 3",xlim=c(-3,3),ylim=c(0,10))
qqline(supply3$Supply, col = "steelblue", lwd = 2)
```

F.3 Pareto Frontier Graph – Rstudio Algorithm

```
library(readxl)
library(ggplot2)
#library(igraph)
#library(rPref)
library(dplyr)

folder = "… /algorithms_graphs/kanban/"
ext = ".xlsx"

file = paste(folder,"KH",ext, sep ="")
datafile1  <- read_excel(file,sheet = "k1")
datafile2  <- read_excel(file,sheet = "k2")
datafile3  <- read_excel(file,sheet = "k3")

datafile1$Period = 1
datafile2$Period = 2
datafile3$Period = 3

data = datafile1
data = rbind(data, datafile2)
data = rbind(data, datafile3)

for (x in 1:3) {
    dataaux = subset(data, data$Period == x)
    dataaux4 = dataaux
    dataaux4$gd = 0
    dataaux4$euclidean = 0
    dataaux4$euclidean2= 0
    dataaux4 = dataaux4[-c(1:648),]

    while (nrow(dataaux) > 0) {

      #gaussian
      variance = ((dataaux$Stage1_Mean - dataaux$`SL%`) ^ 2)
      gd  = exp(((sqrt(variance) / (2*variance))) * -1)

    #get the first point
      dataaux$gd = gd
      min = min(gd, na.rm = TRUE)

      #min = max(gd,na.rm = TRUE)

      #create a subset of the first point
      dataaux2 = subset(dataaux, dataaux$gd == min)
      dataaux2$euclidean = 0
      dataaux2$euclidean2= 0

      #get the measures of the first point
      meaneuc = min(dataaux2$Stage1_Mean)
      sleuc = min(dataaux2$`SL%`)

      #calculate the euclidian distance for the first point to the rest of the dataset
      dataaux$euclidean =  sqrt(((dataaux$Stage1_Mean - meaneuc)^2) + (dataaux$`SL%` - sleuc)^2)
      dataaux$euclidean2= dataaux$euclidean * #dataaux$Stage1_Mean < meaneuc)
                          (dataaux$`SL%` > sleuc)

      #select only the dataset that satisfies the condition
      dataaux3  = subset(dataaux,dataaux$euclidean2 > 0)

      # update the dataset and aggregate to a nondominant dataset
      dataaux = dataaux3
      dataaux4 = rbind(dataaux4,dataaux2)

    }

    # plot the nondominant dataset
```

```
    # plot the nondominant dataset
    if (x == 1 ){
      data1 = dataaux4
    }

    if (x == 2 ){
      data2 = dataaux4
    }

    if (x == 3 ){
      data3 = dataaux4
    }
}


g1 =
  ggplot() +
  geom_point(data = datafile1,aes(x = Stage1_Mean, y = `SL%`), colour = "gray") +
  geom_point(data = data1, aes(x = Stage1_Mean, y = `SL%`), colour = "red") +
  geom_line(data = data1, aes(x = Stage1_Mean, y = `SL%`), colour = "blue") +
  labs(title=" Pareto Front - Supply Dist 1 ",
       y= "SLA",
       x = "Stage 1 - Mean") +
  ylim(0.5, 0.95)


g2 =
  ggplot() +
  geom_point(data = datafile2,aes(x = Stage1_Mean, y = `SL%`), colour = "gray") +
  geom_point(data = data2, aes(x = Stage1_Mean, y = `SL%`), colour = "red") +
  geom_line(data = data2, aes(x = Stage1_Mean, y = `SL%`), colour = "blue") +
  labs(title=" Pareto Front - Supply Dist 2 ",
       y= "SLA",
       x = "Stage 1 - Mean") +
  ylim(0.5, 0.95)

g3 =
  ggplot() +
  geom_point(data = datafile3,aes(x = Stage1_Mean, y = `SL%`), colour = "gray") +
  geom_point(data = data3, aes(x = Stage1_Mean, y = `SL%`), colour = "red") +
  geom_line(data = data3, aes(x = Stage1_Mean, y = `SL%`), colour = "blue") +
  labs(title=" Pareto Front - Supply Dist 3 ",
       y= "SLA",
       x = "Stage 1 - Mean") +
  ylim(0.5, 0.95)


ggarrange(g1,g2,g3,
          ncol=3, nrow=1, common.legend = TRUE, legend="bottom")


ggplot() +
  geom_point(data = data1,aes(x = Stage1_Mean, y = `SL%`), colour = "blue") +
  geom_line(data = data1,aes(x = Stage1_Mean, y = `SL%`), colour = "blue") +
  geom_point(data = data2,aes(x = Stage1_Mean, y = `SL%`), colour = "red") +
  geom_line(data = data2,aes(x = Stage1_Mean, y = `SL%`), colour = "red") +
  geom_point(data = data3,aes(x = Stage1_Mean, y = `SL%`), colour = "green") +
  geom_line(data = data3,aes(x = Stage1_Mean, y = `SL%`), colour = "green") +
  labs(title="Pareto Front - Supply Distributions 1,2,3 ",
       y= "SLA",
       x = "Stage 1 - Mean") +
  ylim(0.6, 0.95)
```

APPENDIX G - INPUT FACTORS AND RESPONSES

G.1 Tables Input Factors and Responses High Season – CONWIP

Run	A:Supply	B:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utilisation	Period
			R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	
	Lot	Lot	Lots	Lots	Lots	%	%	%	%	%	%				
1	57.14	28.57	2.38	1.64	285.71	6.15	10.81	43.37	17.15	12.73	48.70	1.000	0.829	0.577	1
2	57.14	10.71	2.26	1.59	271.26	5.34	9.87	38.53	9.92	8.37	30.55	0.949	0.796	0.548	1
3	71.43	28.57	2.71	1.98	325.39	8.30	12.89	48.17	51.11	22.10	85.52	0.911	0.901	0.650	1
4	71.43	10.71	2.46	1.78	294.94	5.48	10.06	45.54	15.96	10.05	37.90	0.826	0.851	0.593	1
5	64.29	19.64	2.56	1.82	306.87	6.93	11.28	43.35	25.14	15.14	57.29	0.955	0.876	0.614	1
6	64.29	19.64	2.56	1.82	306.87	6.93	11.28	43.35	25.14	15.14	57.29	0.955	0.876	0.614	1
7	64.29	10.71	2.37	1.68	283.83	5.87	10.15	41.70	12.67	9.31	36.66	0.883	0.823	0.567	1
8	71.43	19.64	2.63	1.89	316.06	7.26	12.07	48.17	36.29	14.34	60.43	0.885	0.901	0.632	1
9	64.29	19.64	2.56	1.82	306.87	6.93	11.28	43.35	25.14	15.14	57.29	0.955	0.876	0.614	1
10	64.29	19.64	2.56	1.82	306.87	6.93	11.28	43.35	25.14	15.14	57.29	0.955	0.876	0.614	1
11	64.29	19.64	2.56	1.82	306.87	6.93	11.28	43.35	25.14	15.14	57.29	0.955	0.876	0.614	1
12	64.29	32.14	2.68	1.85	321.43	8.35	12.73	48.79	33.20	23.32	72.55	1.000	0.876	0.642	1
13	57.14	19.64	2.38	1.64	285.02	6.08	10.72	43.37	16.73	12.55	48.70	0.998	0.829	0.575	1
1	71.43	28.57	2.71	2.02	325.27	9.37	15.83	79.08	51.95	24.11	84.880	0.911	0.884	0.655	2
2	57.14	10.71	2.24	1.53	268.24	4.70	9.04	37.12	9.94	9.17	31.050	0.939	0.755	0.545	2
3	57.14	28.57	2.38	1.69	285.71	5.83	10.75	57.49	13.85	10.52	37.960	1.000	0.840	0.577	2
4	71.43	10.71	2.43	1.64	291.02	5.10	9.68	41.37	13.97	10.17	36.280	0.815	0.851	0.589	2
5	64.29	19.64	2.58	1.85	309.65	7.31	13.06	68.29	27.49	15.42	56.370	0.963	0.876	0.623	2
6	71.43	19.64	2.63	1.97	315.52	8.36	14.95	79.08	34.43	15.90	60.730	0.883	0.884	0.634	2
7	64.29	19.64	2.58	1.85	309.65	7.31	13.06	68.29	27.49	15.42	56.370	0.963	0.876	0.623	2
8	64.29	19.64	2.58	1.85	309.65	7.31	13.06	68.29	27.49	15.42	56.370	0.963	0.876	0.623	2
9	64.29	32.14	2.68	1.91	321.43	8.03	13.30	68.29	33.03	21.19	76.180	1.000	0.876	0.644	2
10	64.29	19.64	2.58	1.85	309.65	7.31	13.06	68.29	27.49	15.42	56.370	0.963	0.876	0.623	2
11	64.29	10.71	2.37	1.51	284.00	4.98	9.28	37.23	12.60	9.70	31.790	0.884	0.825	0.579	2
12	64.29	19.64	2.58	1.85	309.65	7.31	13.06	68.29	27.49	15.42	56.370	0.963	0.876	0.623	2
13	57.14	19.64	2.38	1.69	285.71	5.83	10.75	57.49	13.85	10.52	37.960	1.000	0.840	0.577	2
1	57.14	10.71	2.08	1.84	249.77	5.72	11.48	65.38	9.70	9.38	32.230	0.874	0.680	0.499	3
2	71.43	28.57	2.73	2.43	327.04	14.00	21.65	89.69	41.24	23.93	85.140	0.916	0.893	0.649	3
3	71.43	10.71	2.29	1.95	274.27	5.99	11.42	49.64	12.60	10.64	34.480	0.768	0.748	0.550	3
4	57.14	28.57	2.38	2.11	285.40	9.60	16.19	71.75	21.20	17.47	71.250	0.999	0.799	0.567	3
5	64.29	19.64	2.46	2.15	295.57	9.37	16.66	80.72	22.59	16.90	54.360	0.920	0.835	0.588	3
6	64.29	10.71	2.16	1.96	259.26	6.21	11.65	48.97	11.45	10.51	34.460	0.807	0.716	0.516	3
7	64.29	32.14	2.61	2.27	313.05	12.49	18.91	80.72	32.81	20.97	84.080	0.974	0.876	0.620	3
8	71.43	19.64	2.62	2.32	314.76	11.55	19.47	84.77	26.42	17.89	56.410	0.881	0.868	0.626	3
9	64.29	19.64	2.46	2.15	295.57	9.37	16.66	80.72	22.59	16.90	54.360	0.920	0.835	0.588	3
10	64.29	19.64	2.46	2.15	295.57	9.37	16.66	80.72	22.59	16.90	54.360	0.920	0.835	0.588	3
11	64.29	19.64	2.46	2.15	295.57	9.37	16.66	80.72	22.59	16.90	54.360	0.920	0.835	0.588	3
12	57.14	19.64	2.29	1.97	275.08	8.01	14.26	71.75	17.71	15.28	51.010	0.963	0.774	0.548	3
13	64.29	19.64	2.46	2.15	295.57	9.37	16.66	80.72	22.59	16.90	54.360	0.920	0.835	0.588	3

G.2 Tables Input Factors and Responses Medium Season – CONWIP

Run	A:Supply	B:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili	Period
			R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	
	Lot	Lot	Lots	Lots	Lots	%	%	%	%	%	%				
1	53.57	7.14	2.01	1.47	241.53	4.36	8.47	36.13	4.98	5.83	28.56	0.90	0.69	0.49	1
2	46.43	14.29	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47	1
3	53.57	14.29	2.22	1.54	266.80	5.28	9.81	40.66	10.74	9.83	36.78	1.00	0.78	0.54	1
4	46.43	7.14	1.11	1.45	133.62	2.42	6.47	31.31	1.51	3.19	17.56	0.58	0.34	0.29	1
5	50.00	10.72	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50	1
6	50.00	10.72	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50	1
7	50.00	10.72	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50	1
8	53.57	10.72	2.19	1.54	262.78	5.16	9.70	40.66	8.82	8.18	30.55	0.98	0.77	0.53	1
9	50.00	7.14	1.99	1.41	239.27	4.36	8.74	37.95	4.87	5.73	26.96	0.96	0.66	0.48	1
10	50.00	10.72	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50	1
11	46.43	10.72	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47	1
12	50.00	10.72	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50	1
13	50.00	14.29	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50	1
1	53.57	7.14	1.94	1.35	232.93	3.71	7.43	31.02	4.82	5.72	20.29	0.87	0.64	0.47	2
2	46.43	14.29	1.93	1.38	232.14	3.65	7.73	41.30	4.86	6.43	23.77	1.00	0.61	0.47	2
3	53.57	14.29	2.23	1.59	267.86	4.93	9.68	52.10	8.95	8.95	33.27	1.00	0.76	0.54	2
4	46.43	7.14	1.45	1.27	174.40	2.62	6.17	26.89	2.48	4.54	19.58	0.75	0.44	0.35	2
5	53.57	10.72	2.19	1.48	262.60	4.53	8.74	36.54	7.96	7.96	28.41	0.98	0.74	0.53	2
6	50.00	14.29	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50	2
7	46.43	10.72	1.93	1.34	231.26	3.56	7.45	36.54	4.74	6.21	22.18	1.00	0.61	0.46	2
8	50.00	7.14	1.92	1.27	230.42	3.52	7.18	28.96	4.43	5.48	19.90	0.92	0.61	0.46	2
9	50.00	10.72	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50	2
10	50.00	10.72	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50	2
11	50.00	10.72	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50	2
12	50.00	10.72	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50	2
13	50.00	10.72	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50	2
1	53.57	7.14	1.73	1.66	207.04	3.93	8.64	46.15	4.66	6.46	25.06	0.77	0.56	0.41	3
2	46.43	14.29	1.92	1.68	229.96	5.28	10.98	58.30	7.97	9.76	34/.52	0.99	0.63	0.46	3
3	53.57	14.29	2.08	1.83	249.99	6.31	12.19	67.27	10.75	10.63	35.93	0.93	0.69	0.50	3
4	46.43	7.14	1.67	1.48	200.62	3.56	8.11	46.15	4.45	6.03	22.83	0.86	0.53	0.40	3
5	50.00	10.72	1.96	1.72	235.01	5.44	10.92	62.78	7.85	9.10	30.55	0.94	0.65	0.47	3
6	53.57	10.72	2.03	1.80	243.76	5.65	11.20	65.38	8.91	9.15	31.12	0.91	0.67	0.49	3
7	50.00	10.72	1.96	1.72	235.01	5.44	10.92	62.78	7.85	9.10	30.55	0.94	0.65	0.47	3
8	50.00	14.29	2.03	1.77	243.99	6.03	12.08	62.78	10.58	11.58	38.57	0.98	0.68	0.49	3
9	50.00	10.72	1.96	1.72	235.01	5.44	10.92	62.78	7.85	9.10	30.55	0.94	0.65	0.47	3
10	50.00	10.72	1.96	1.72	235.01	5.44	10.92	62.78	7.85	9.10	30.55	0.94	0.65	0.47	3
11	46.43	10.72	1.87	1.61	224.23	4.86	10.28	58.30	6.93	8.77	31.43	0.97	0.59	0.44	3
12	50.00	10.72	1.96	1.72	235.01	5.44	10.92	62.78	7.85	9.10	30.55	0.94	0.65	0.47	3
13	50.00	7.14	1.68	1.65	201.02	3.91	8.44	46.15	4.60	6.34	23.94	0.80	0.56	0.40	3

G.3 Tables Input Factors and Responses High Season – KCS - Period 1

Run	A:Supply	B: K1	C: K2	D:K3	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
					R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lots	Lots	Lots	%	%	%	%	%	%			
1	57.14	12.50	16.07	2.14	2.38	1.64	285.71	7.21	11.84	53.17	16.62	11.94	42.53	1.00	0.83	0.58
2	57.14	12.50	8.93	2.14	2.34	1.63	280.58	13.40	17.71	67.42	10.06	7.74	32.23	0.98	0.81	0.57
3	57.14	12.50	12.50	3.21	2.37	1.64	284.44	9.57	14.36	66.91	14.64	10.20	35.41	1.00	0.83	0.57
4	71.43	12.50	12.50	3.21	2.61	2.08	313.35	23.99	24.14	88.73	22.78	8.22	41.05	0.88	0.90	0.63
5	64.29	12.50	8.93	3.21	2.51	1.88	300.82	19.80	21.81	76.89	12.37	7.54	32.23	0.94	0.86	0.61
6	64.29	8.93	12.50	3.21	2.48	1.82	298.08	10.31	14.33	54.58	16.19	9.68	34.85	0.93	0.86	0.60
7	57.14	16.07	12.50	2.14	2.38	1.64	285.71	9.85	14.54	69.07	15.31	10.50	35.41	1.00	0.83	0.58
8	64.29	12.50	8.93	1.07	2.26	1.90	271.59	30.61	22.56	92.02	16.58	6.75	33.24	0.84	0.68	0.54
9	71.43	12.50	16.07	2.14	2.64	2.10	317.11	23.08	24.15	87.77	30.98	9.36	52.18	0.89	0.90	0.63
10	57.14	12.50	12.50	1.07	2.28	1.63	273.16	15.37	18.32	70.07	20.69	9.72	38.69	0.96	0.67	0.54
11	64.29	8.93	16.07	2.14	2.53	1.82	303.46	9.11	13.61	48.79	20.60	12.06	44.30	0.94	0.87	0.61
12	64.29	8.93	12.50	1.07	2.26	1.84	271.54	15.62	18.88	76.25	23.26	7.83	41.21	0.84	0.68	0.55
13	71.43	16.07	12.50	2.14	2.62	2.10	314.61	36.14	28.65	100.00	24.12	7.86	42.41	0.88	0.90	0.63
14	71.43	12.50	8.93	2.14	2.56	2.10	306.89	26.20	24.40	90.28	13.90	7.14	32.23	0.86	0.88	0.62
15	71.43	12.50	12.50	1.07	2.31	1.97	276.98	36.43	22.14	82.76	26.40	7.61	43.35	0.78	0.68	0.55
16	71.43	8.93	12.50	2.14	2.57	2.05	308.64	13.41	17.45	64.68	18.85	8.66	34.60	0.86	0.89	0.62
17	64.29	16.07	16.07	2.14	2.61	1.84	312.83	18.41	22.39	89.55	23.97	13.58	44.93	0.97	0.88	0.62
18	64.29	12.50	16.07	3.21	2.59	1.83	310.31	13.78	17.87	68.32	23.91	13.32	44.93	0.97	0.88	0.62
19	64.29	12.50	12.50	2.14	2.56	1.84	307.14	16.23	19.80	77.69	18.85	10.03	41.05	0.96	0.88	0.61
20	64.29	12.50	16.07	1.07	2.33	1.90	279.11	25.43	23.23	76.02	33.92	9.44	53.46	0.87	0.68	0.55
21	64.29	16.07	12.50	1.07	2.32	1.91	278.69	40.89	27.25	98.37	26.18	7.62	43.35	0.87	0.68	0.55
22	64.29	8.93	8.93	2.14	2.40	1.85	288.12	13.44	17.16	61.39	10.84	7.18	32.23	0.90	0.84	0.58
23	57.14	8.93	12.50	2.14	2.33	1.63	280.08	7.90	12.29	43.74	12.54	9.85	35.17	0.98	0.80	0.57
24	64.29	16.07	12.50	3.21	2.58	1.83	309.04	21.71	24.35	91.06	19.11	10.44	41.05	0.96	0.88	0.61
25	64.29	16.07	8.93	2.14	2.54	1.84	305.23	27.55	25.30	96.12	12.93	7.70	32.23	0.95	0.86	0.60
26	64.29	12.50	12.50	2.14	2.56	1.84	307.14	16.23	19.80	77.69	18.85	10.03	41.05	0.96	0.88	0.61
27	64.29	12.50	12.50	2.14	2.56	1.84	307.14	16.23	19.80	77.69	18.85	10.03	41.05	0.96	0.88	0.61
28	64.29	12.50	12.50	2.14	2.56	1.84	307.14	16.23	19.80	77.69	18.85	10.03	41.05	0.96	0.88	0.61
29	64.29	12.50	12.50	2.14	2.56	1.84	307.14	16.23	19.80	77.69	18.85	10.03	41.05	0.96	0.88	0.61
30	64.29	12.50	12.50	2.14	2.56	1.84	307.14	16.23	19.80	77.69	18.85	10.03	41.05	0.96	0.88	0.61

G.4 Tables Input Factors and Responses High Season – KCS - Period 2

Run	A:Supply	B: K1	C: K2	D:K3	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
					R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	57.14	12.50	16.07	2.14	2.38	1.67	285.09	5.69	10.48	54.12	13.73	10.51	36.86	1.00	0.84	0.58
2	57.14	12.50	8.93	2.14	2.37	1.67	284.43	12.41	16.10	57.65	10.18	7.76	31.52	1.00	0.82	0.58
3	57.14	12.50	12.50	3.21	2.38	1.67	285.09	7.20	11.90	54.12	12.97	9.77	34.16	1.00	0.84	0.58
4	71.43	12.50	12.50	3.21	2.59	1.99	311.34	23.12	24.22	84.38	20.16	10.10	42.35	0.87	0.88	0.62
5	64.29	12.50	8.93	3.21	2.47	1.79	296.64	20.13	21.46	78.90	11.70	7.84	32.34	0.92	0.85	0.59
6	64.29	8.93	12.50	3.21	2.45	1.72	294.42	9.40	14.75	57.86	13.78	9.93	34.04	0.92	0.84	0.59
7	57.14	16.07	12.50	2.14	2.38	1.69	285.71	7.48	12.12	57.49	13.03	9.74	34.16	1.00	0.84	0.58
8	64.29	12.50	8.93	1.07	2.25	1.79	270.03	29.34	24.14	89.02	15.68	7.37	33.25	0.84	0.66	0.54
9	71.43	12.50	16.07	2.14	2.63	2.01	315.51	22.66	24.73	87.82	28.38	12.78	52.58	0.88	0.88	0.62
10	57.14	12.50	12.50	1.07	2.26	1.62	271.18	18.04	19.99	84.56	21.05	10.62	42.43	0.95	0.66	0.53
11	64.29	8.93	16.07	2.14	2.52	1.70	302.76	7.70	12.48	50.99	20.24	12.99	44.10	0.94	0.86	0.61
12	64.29	8.93	12.50	1.07	2.26	1.72	270.63	13.82	18.76	66.83	19.58	10.13	36.54	0.84	0.66	0.54
13	71.43	16.07	12.50	2.14	2.61	2.12	312.90	36.77	28.57	100.00	22.19	9.68	42.47	0.88	0.88	0.61
14	71.43	12.50	8.93	2.14	2.56	2.01	306.62	26.87	25.94	89.81	13.36	7.75	32.36	0.86	0.86	0.60
15	71.43	12.50	12.50	1.07	2.31	1.87	277.37	32.31	24.37	100.00	24.80	9.04	43.35	0.78	0.67	0.55
16	71.43	8.93	12.50	2.14	2.53	1.89	303.30	12.91	18.46	75.83	16.43	10.18	34.01	0.85	0.87	0.61
17	64.29	16.07	16.07	2.14	2.62	1.94	314.62	18.66	22.94	100.00	25.31	13.49	45.95	0.98	0.88	0.62
18	64.29	12.50	16.07	3.21	2.58	1.84	309.11	12.95	18.39	78.80	24.16	13.47	44.29	0.96	0.88	0.62
19	64.29	12.50	12.50	2.14	2.53	1.82	303.89	15.88	20.12	78.66	17.85	10.70	38.32	0.95	0.87	0.60
20	64.29	12.50	16.07	1.07	2.31	1.79	277.55	23.84	23.87	85.90	31.12	12.55	53.47	0.86	0.66	0.55
21	64.29	16.07	12.50	1.07	2.31	1.86	277.49	40.04	27.01	100.00	24.46	9.64	43.35	0.86	0.66	0.54
22	64.29	8.93	8.93	2.14	2.38	1.72	285.75	11.96	16.66	68.30	9.79	7.39	27.12	0.89	0.81	0.58
23	57.14	8.93	12.50	2.14	2.31	1.55	277.61	5.79	10.51	45.82	10.77	8.94	34.16	0.97	0.80	0.56
24	64.29	16.07	12.50	3.21	2.59	1.90	310.89	24.70	24.21	100.00	19.52	10.50	42.16	0.97	0.88	0.61
25	64.29	16.07	8.93	2.14	2.55	1.88	306.46	31.11	25.79	100.00	12.80	8.01	32.34	0.95	0.85	0.60
26	64.29	12.50	12.50	2.14	2.53	1.82	303.89	15.88	20.12	78.66	17.85	10.70	38.32	0.95	0.87	0.60
27	64.29	12.50	12.50	2.14	2.53	1.82	303.89	15.88	20.12	78.66	17.85	10.70	38.32	0.95	0.87	0.60
28	64.29	12.50	12.50	2.14	2.53	1.82	303.89	15.88	20.12	78.66	17.85	10.70	38.32	0.95	0.87	0.60
29	64.29	12.50	12.50	2.14	2.53	1.82	303.89	15.88	20.12	78.66	17.85	10.70	38.32	0.95	0.87	0.60
30	64.29	12.50	12.50	2.14	2.53	1.82	303.89	15.88	20.12	78.66	17.85	10.70	38.32	0.95	0.87	0.60

G.5 Tables Input Factors and Responses High Season – KCS - Period 3

Run	A:Supply	B: K1	C: K2	D:K3	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
					R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
57.14	12.50	16.07	2.14	2.28	2.03	273.31	9.29	15.43	71.75	14.35	12.47	44.03	0.96	0.77	0.54	57.14
57.14	12.50	8.93	2.14	2.18	1.99	262.06	14.96	18.77	71.75	8.87	8.13	32.23	0.92	0.72	0.52	57.14
57.14	12.50	12.50	3.21	2.26	2.04	271.69	12.56	18.91	80.95	12.39	10.33	34.09	0.95	0.76	0.54	57.14
71.43	12.50	12.50	3.21	2.49	2.32	298.65	18.82	23.36	89.69	15.82	11.15	36.93	0.84	0.84	0.58	71.43
64.29	12.50	8.93	3.21	2.29	2.15	275.07	18.98	21.44	84.68	9.87	8.29	32.23	0.86	0.78	0.54	64.29
64.29	8.93	12.50	3.21	2.25	2.05	270.04	9.35	16.48	79.45	12.22	10.30	33.07	0.84	0.74	0.54	64.29
57.14	16.07	12.50	2.14	2.31	2.03	277.71	16.27	22.30	82.89	14.46	11.24	39.43	0.97	0.77	0.55	57.14
64.29	12.50	8.93	1.07	2.21	2.11	264.76	24.45	24.64	92.95	12.85	8.47	33.21	0.82	0.64	0.51	64.29
71.43	12.50	16.07	2.14	2.59	2.33	311.22	17.71	22.04	89.69	24.02	14.02	49.44	0.87	0.86	0.60	71.43
57.14	12.50	12.50	1.07	2.18	2.00	261.67	15.31	20.39	75.95	16.79	11.09	36.21	0.92	0.64	0.52	57.14
64.29	8.93	16.07	2.14	2.29	2.06	275.27	7.07	13.75	79.45	14.31	12.37	41.95	0.86	0.75	0.55	64.29
64.29	8.93	12.50	1.07	2.16	2.06	259.10	11.80	18.21	79.45	15.42	11.06	36.13	0.81	0.62	0.51	64.29
71.43	16.07	12.50	2.14	2.61	2.44	313.25	27.38	28.10	95.90	17.96	10.78	40.67	0.88	0.88	0.60	71.43
71.43	12.50	8.93	2.14	2.39	2.25	287.23	23.02	24.33	94.96	10.47	8.18	32.23	0.80	0.80	0.56	71.43
71.43	12.50	12.50	1.07	2.31	2.28	277.61	27.00	25.42	89.69	21.53	10.20	43.35	0.78	0.66	0.53	71.43
71.43	8.93	12.50	2.14	2.35	2.23	282.00	11.73	19.17	82.94	13.23	10.60	34.19	0.79	0.76	0.56	71.43
64.29	16.07	16.07	2.14	2.55	2.24	305.93	18.06	24.01	83.22	23.09	13.33	45.14	0.95	0.87	0.61	64.29
64.29	12.50	16.07	3.21	2.48	2.21	297.98	13.67	19.43	80.72	18.79	12.98	44.11	0.93	0.84	0.59	64.29
64.29	12.50	12.50	2.14	2.41	2.20	289.18	16.33	21.38	80.72	14.67	11.04	34.78	0.90	0.82	0.57	64.29
64.29	12.50	16.07	1.07	2.34	2.19	280.36	20.78	23.42	93.84	27.94	14.17	53.46	0.87	0.66	0.54	64.29
64.29	16.07	12.50	1.07	2.37	2.23	284.17	31.20	28.34	100.00	21.74	10.55	43.35	0.88	0.66	0.54	64.29
64.29	8.93	8.93	2.14	2.13	1.98	255.50	9.96	16.13	79.45	8.44	7.62	25.17	0.79	0.70	0.51	64.29
57.14	8.93	12.50	2.14	2.11	1.87	253.34	7.34	13.82	71.75	10.15	9.40	31.19	0.89	0.69	0.50	57.14
64.29	16.07	12.50	3.21	2.49	2.23	299.30	22.23	25.66	98.02	16.81	11.27	39.43	0.93	0.85	0.58	64.29
64.29	16.07	8.93	2.14	2.40	2.22	287.97	27.05	25.23	100.00	10.56	8.39	32.23	0.90	0.81	0.55	64.29
57.14	12.50	16.07	2.14	2.28	2.03	273.31	9.29	15.43	71.75	14.35	12.47	44.03	0.96	0.77	0.54	57.14
57.14	12.50	8.93	2.14	2.18	1.99	262.06	14.96	18.77	71.75	8.87	8.13	32.23	0.92	0.72	0.52	57.14
57.14	12.50	12.50	3.21	2.26	2.04	271.69	12.56	18.91	80.95	12.39	10.33	34.09	0.95	0.76	0.54	57.14
71.43	12.50	12.50	3.21	2.49	2.32	298.65	18.82	23.36	89.69	15.82	11.15	36.93	0.84	0.84	0.58	71.43
64.29	12.50	8.93	3.21	2.29	2.15	275.07	18.98	21.44	84.68	9.87	8.29	32.23	0.86	0.78	0.54	64.29

G.6 Tables Input Factors and Responses Medium Season – KCS - Period 1

Run	A:Supply	B: K1	C: K2	D:K3	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	46.43	12.50	16.07	2.14	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
2	53.57	12.50	16.07	2.14	2.23	1.54	267.86	6.06	10.26	40.94	10.58	9.33	31.57	1.00	0.78	0.54
3	46.43	16.07	12.50	2.14	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
4	50.00	8.93	16.07	2.14	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
5	50.00	12.50	8.93	1.07	2.08	1.44	250.00	5.32	9.59	40.25	16.69	12.08	39.77	1.00	0.62	0.50
6	50.00	12.50	12.50	2.14	2.08	1.44	250.00	5.75	9.51	37.95	6.63	6.89	28.25	1.00	0.71	0.50
7	53.57	12.50	8.93	2.14	2.23	1.54	267.50	5.94	10.23	40.73	10.45	9.22	31.01	1.00	0.78	0.54
8	50.00	12.50	16.07	3.21	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
9	46.43	12.50	8.93	2.14	1.93	1.33	232.14	7.02	11.49	55.49	8.78	7.59	27.09	1.00	0.59	0.47
10	50.00	8.93	12.50	1.07	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
11	50.00	12.50	16.07	1.07	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
12	50.00	16.07	12.50	3.21	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
13	50.00	12.50	8.93	3.21	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
14	50.00	12.50	12.50	2.14	2.06	1.42	246.90	6.69	11.43	43.90	13.90	9.94	36.21	0.99	0.62	0.50
15	50.00	16.07	16.07	2.14	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
16	50.00	8.93	8.93	2.14	2.08	1.44	250.00	5.75	9.51	37.95	6.63	6.89	28.25	1.00	0.71	0.50
17	50.00	12.50	12.50	2.14	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
18	53.57	16.07	12.50	2.14	2.19	1.53	262.32	11.10	16.26	63.14	17.99	10.85	35.96	0.98	0.64	0.53
19	53.57	8.93	12.50	2.14	2.23	1.54	267.86	6.06	10.26	40.94	10.58	9.33	31.57	1.00	0.78	0.54
20	50.00	8.93	12.50	3.21	2.08	1.44	250.00	7.49	12.62	60.31	15.61	10.77	36.21	1.00	0.62	0.51
21	50.00	12.50	12.50	2.14	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
22	46.43	8.93	12.50	2.14	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
23	50.00	12.50	12.50	2.14	2.08	1.44	250.00	7.49	12.62	60.31	15.61	10.77	36.21	1.00	0.62	0.51
24	46.43	12.50	12.50	1.07	1.93	1.33	232.14	4.33	8.38	35.24	4.80	5.65	24.94	1.00	0.63	0.47
25	53.57	12.50	12.50	1.07	2.23	1.54	267.86	9.77	13.96	61.13	8.73	7.60	31.57	1.00	0.78	0.54
26	46.43	12.50	12.50	3.21	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
27	50.00	16.07	12.50	1.07	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
28	50.00	12.50	12.50	2.14	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
29	53.57	12.50	12.50	3.21	2.23	1.54	267.86	9.77	13.96	61.13	8.73	7.60	31.57	1.00	0.78	0.54
30	50.00	16.07	8.93	2.14	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50

G.7 Tables Input Factors and Responses Medium Season – KCS - Period 2

Run	A:Supply	B: K1	C: K2	D:K3	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	46.43	12.50	16.07	2.14	1.93	1.38	232.14	3.65	7.73	41.30	4.86	6.43	23.77	1.00	0.61	0.47
2	53.57	12.50	16.07	2.14	2.23	1.59	267.86	4.93	9.68	52.10	8.95	8.95	33.27	1.00	0.76	0.54
3	46.43	16.07	12.50	2.14	1.93	1.38	232.14	3.65	7.73	41.30	4.86	6.43	23.77	1.00	0.61	0.47
4	50.00	8.93	16.07	2.14	2.06	1.40	247.44	3.96	7.90	32.93	6.15	7.18	27.07	0.99	0.67	0.50
5	50.00	12.50	8.93	1.07	2.08	1.48	250.00	9.42	13.33	49.82	10.75	7.58	26.06	1.00	0.63	0.51
6	50.00	12.50	12.50	2.14	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
7	53.57	12.50	8.93	2.14	2.23	1.59	267.86	7.88	12.12	52.10	7.52	7.14	28.41	1.00	0.76	0.54
8	50.00	12.50	16.07	3.21	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
9	46.43	12.50	8.93	2.14	1.93	1.38	232.14	3.99	7.91	41.30	4.71	6.11	21.89	1.00	0.61	0.47
10	50.00	8.93	12.50	1.07	2.06	1.40	247.44	4.40	8.22	32.93	12.48	9.34	32.13	0.99	0.62	0.50
11	50.00	12.50	16.07	1.07	2.08	1.48	250.00	4.25	8.67	46.70	13.32	9.78	33.89	1.00	0.63	0.50
12	50.00	16.07	12.50	3.21	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
13	50.00	12.50	8.93	3.21	2.08	1.48	250.00	5.61	9.73	46.70	5.88	6.67	24.58	1.00	0.67	0.50
14	50.00	12.50	12.50	2.14	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
15	50.00	16.07	16.07	2.14	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
16	50.00	8.93	8.93	2.14	2.06	1.40	247.44	4.96	8.80	37.51	5.71	6.48	24.58	0.99	0.66	0.50
17	50.00	12.50	12.50	2.14	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
18	53.57	16.07	12.50	2.14	2.23	1.59	267.86	5.03	9.79	52.10	8.90	8.90	33.27	1.00	0.76	0.54
19	53.57	8.93	12.50	2.14	2.20	1.48	263.68	4.59	8.76	33.91	8.26	8.23	31.97	0.98	0.75	0.53
20	50.00	8.93	12.50	3.21	2.06	1.40	247.44	3.96	7.90	32.93	6.15	7.18	27.07	0.99	0.67	0.50
21	50.00	12.50	12.50	2.14	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
22	46.43	8.93	12.50	2.14	1.92	1.32	230.41	3.49	7.22	31.95	4.63	6.02	22.18	0.99	0.61	0.46
23	50.00	12.50	12.50	2.14	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
24	46.43	12.50	12.50	1.07	1.93	1.38	232.14	3.65	7.73	41.30	8.50	8.07	28.83	1.00	0.57	0.47
25	53.57	12.50	12.50	1.07	2.20	1.60	264.23	11.04	15.96	68.58	18.34	10.92	36.06	0.99	0.66	0.53
26	46.43	12.50	12.50	3.21	1.93	1.38	232.14	3.65	7.73	41.30	4.86	6.43	23.77	1.00	0.61	0.47
27	50.00	16.07	12.50	1.07	2.08	1.48	250.00	4.71	8.94	46.70	13.10	9.50	33.18	1.00	0.63	0.51
28	50.00	12.50	12.50	2.14	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
29	53.57	12.50	12.50	3.21	2.23	1.59	267.86	5.03	9.79	52.10	8.90	8.90	33.27	1.00	0.76	0.54
30	50.00	16.07	8.93	2.14	2.08	1.48	250.00	5.61	9.73	46.70	5.88	6.67	24.58	1.00	0.67	0.50

G.8 Tables Input Factors and Responses Medium Season – KCS - Period 3

Run	A:Supply	B: K1	C: K2	D:K3	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	50.00	8.93	12.50	1.07	1.92	1.67	230.68	6.93	12.50	62.78	11.49	9.96	35.67	0.92	0.56	0.46
2	53.57	8.93	12.50	2.14	2.02	1.76	242.77	6.50	12.58	67.27	8.66	8.77	30.49	0.91	0.67	0.49
3	46.43	12.50	8.93	2.14	1.91	1.67	229.02	8.11	12.95	58.30	6.30	7.68	32.23	0.99	0.61	0.46
4	50.00	8.93	8.93	2.14	1.91	1.65	228.65	6.82	12.38	62.78	6.13	7.03	23.76	0.91	0.63	0.46
5	50.00	8.93	16.07	2.14	1.93	1.66	231.24	4.95	10.74	62.78	7.47	8.84	32.41	0.92	0.64	0.46
6	50.00	16.07	12.50	3.21	2.08	1.84	249.37	9.72	15.21	62.78	9.95	10.38	38.57	1.00	0.71	0.50
7	53.57	12.50	12.50	1.07	2.11	1.89	252.84	12.91	19.45	79.98	15.76	10.99	36.21	0.94	0.61	0.51
8	46.43	12.50	12.50	3.21	1.91	1.67	229.02	5.50	11.03	58.30	7.58	9.35	33.18	0.99	0.62	0.46
9	50.00	16.07	16.07	2.14	2.08	1.84	249.37	6.95	12.57	62.78	11.34	12.27	44.23	1.00	0.71	0.50
10	50.00	12.50	12.50	2.14	2.04	1.79	244.30	7.64	13.36	62.78	9.11	9.99	34.54	0.98	0.68	0.49
11	50.00	12.50	12.50	2.14	2.04	1.79	244.30	7.64	13.36	62.78	9.11	9.99	34.54	0.98	0.68	0.49
12	50.00	16.07	8.93	2.14	2.06	1.80	247.34	13.23	18.00	62.78	7.70	8.08	32.23	0.99	0.69	0.50
13	53.57	16.07	12.50	2.14	2.20	1.92	264.40	12.79	18.95	67.97	12.37	10.90	39.43	0.99	0.74	0.53
14	50.00	12.50	16.07	3.21	2.04	1.79	244.30	6.00	12.00	62.78	9.93	11.10	37.10	0.98	0.68	0.49
15	50.00	12.50	8.93	3.21	2.03	1.78	243.75	10.81	15.87	62.78	7.41	7.94	32.23	0.97	0.68	0.49
16	50.00	8.93	12.50	3.21	1.93	1.66	231.24	5.48	11.20	62.78	7.21	8.36	31.16	0.92	0.64	0.46
17	50.00	16.07	12.50	1.07	2.04	1.78	245.14	12.83	20.08	73.12	15.14	11.14	39.59	0.98	0.60	0.49
18	53.57	12.50	12.50	3.21	2.15	1.92	257.88	10.00	16.14	67.97	10.45	10.03	34.09	0.96	0.72	0.51
19	50.00	12.50	8.93	1.07	1.95	1.73	233.84	13.87	17.90	65.88	10.40	8.60	32.28	0.94	0.58	0.47
20	46.43	8.93	12.50	2.14	1.82	1.58	218.67	4.63	10.14	58.30	6.15	7.81	28.92	0.94	0.58	0.43
21	50.00	12.50	12.50	2.14	2.04	1.79	244.30	7.64	13.36	62.78	9.11	9.99	34.54	0.98	0.68	0.49
22	53.57	12.50	8.93	2.14	2.11	1.89	252.83	12.59	17.29	67.27	8.07	7.89	32.23	0.94	0.70	0.51
23	46.43	12.50	16.07	2.14	1.91	1.67	229.02	5.15	10.83	58.30	7.76	9.64	33.18	0.99	0.62	0.46
24	53.57	12.50	16.07	2.14	2.15	1.91	258.47	7.37	13.54	67.27	11.86	11.72	41.38	0.96	0.72	0.52
25	50.00	12.50	12.50	2.14	2.04	1.79	244.30	7.64	13.36	62.78	9.11	9.99	34.54	0.98	0.68	0.49
26	46.43	16.07	12.50	2.14	1.93	1.72	232.14	6.09	11.34	58.30	8.02	9.81	34.52	1.00	0.63	0.46
27	50.00	12.50	16.07	1.07	2.04	1.79	244.30	8.45	13.94	62.78	16.31	12.74	46.33	0.98	0.60	0.49
28	46.43	12.50	12.50	1.07	1.90	1.66	228.23	8.25	13.69	58.30	12.06	10.63	35.96	0.98	0.55	0.45
29	50.00	12.50	12.50	2.14	2.04	1.79	244.30	7.64	13.36	62.78	9.11	9.99	34.54	0.98	0.68	0.49
30	50.00	12.50	12.50	2.14	2.04	1.79	244.30	7.64	13.36	62.78	9.11	9.99	34.54	0.98	0.68	0.49

G.9 Tables Input Factors and Responses High Season – CONWIP/KCS - Period 1

Run	A:Supply	B: K1	C: K2	D:K3	E:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Staee2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	64.29	8.93	8.93	2.14	17.86	2.36	1.82	282.65	12.3	15.5	48.0	10.2	7.38	32.2	0.88	0.83	0
2	64.29	12.50	16.07	2.14	10.71	2.38	1.84	285.99	4.99	9.03	40.9	14.0	9.77	36.6	0.89	0.83	0
3	64.29	8.93	12.50	1.07	17.86	2.25	1.73	270.58	13.8	15.9	48.0	22.9	8.03	42.0	0.84	0.68	0
4	71.43	12.50	8.93	2.14	17.86	2.53	1.99	303.91	24.0	21.4	67.3	13.5	7.28	32.2	0.85	0.88	0
5	64.29	16.07	12.50	1.07	17.86	2.30	1.69	275.98	22.9	16.9	60.3	26.0	7.38	43.3	0.86	0.68	0
6	57.14	12.50	16.07	2.14	17.86	2.36	1.65	283.46	6.94	11.3	43.3	15.2	11.4	42.5	0.99	0.83	0
7	71.43	16.07	12.50	2.14	17.86	2.62	1.88	313.82	21.0	18.2	61.4	23.1	7.90	42.0	0.88	0.90	0
8	71.43	8.93	12.50	2.14	17.86	2.51	1.98	301.51	12.5	15.7	48.0	17.6	9.74	39.4	0.84	0.88	0
9	64.29	12.50	12.50	2.14	17.86	2.54	1.81	304.55	14.3	17.1	55.7	18.4	9.99	41.0	0.95	0.88	0
10	64.29	12.50	16.07	3.21	17.86	2.55	1.83	305.90	9.45	12.3	43.3	21.6	12.2	44.9	0.95	0.88	0
11	57.14	16.07	12.50	2.14	17.86	2.36	1.65	282.93	9.00	13.3	54.0	13.8	10.0	35.4	0.99	0.83	0
12	64.29	8.93	12.50	2.14	10.71	2.39	1.78	286.64	5.13	8.68	40.9	13.5	9.13	34.0	0.89	0.83	0
13	64.29	12.50	8.93	3.21	17.86	2.47	1.86	296.82	18.8	20.8	67.3	12.2	7.61	32.2	0.92	0.86	0
14	71.43	12.50	16.07	2.14	17.86	2.61	1.89	313.54	12.9	15.0	46.4	27.9	10.1	46.6	0.88	0.90	0
15	57.14	12.50	8.93	2.14	17.86	2.34	1.65	280.84	13.2	17.5	67.3	10.1	7.76	32.2	0.98	0.81	0
16	64.29	12.50	12.50	3.21	25.00	2.53	1.88	304.04	16.1	19.7	67.3	18.7	10.1	41.0	0.95	0.88	0
17	64.29	16.07	8.93	2.14	17.86	2.52	1.80	302.48	24.5	22.8	76.3	12.8	7.67	32.2	0.94	0.86	0
18	57.14	12.50	12.50	2.14	10.71	2.29	1.66	274.87	5.63	9.95	42.5	10.8	8.65	30.5	0.96	0.80	0
19	64.29	12.50	12.50	2.14	17.86	2.54	1.81	304.55	14.3	17.1	55.7	18.4	9.99	41.0	0.95	0.88	0
20	64.29	12.50	12.50	2.14	17.86	2.54	1.81	304.55	14.3	17.1	55.7	18.4	9.99	41.0	0.95	0.88	0
21	71.43	12.50	12.50	3.21	17.86	2.59	1.83	311.31	19.4	18.2	62.9	22.4	8.26	41.0	0.87	0.89	0
22	64.29	16.07	12.50	2.14	25.00	2.56	1.86	306.87	21.6	23.9	86.5	18.9	10.3	41.0	0.95	0.88	0
23	57.14	12.50	12.50	1.07	17.86	2.26	1.62	270.87	12.0	15.3	51.1	20.4	9.50	38.6	0.95	0.67	0
24	71.43	12.50	12.50	1.07	17.86	2.29	1.65	274.88	26.2	15.6	58.5	26.3	7.48	43.3	0.77	0.68	0
25	64.29	12.50	12.50	2.14	17.86	2.54	1.81	304.55	14.3	17.1	55.7	18.4	9.99	41.0	0.95	0.88	0
26	64.29	8.93	12.50	3.21	17.86	2.44	1.84	292.68	10.7	14.5	48.0	15.7	9.99	39.4	0.91	0.85	0
27	57.14	8.93	12.50	2.14	17.86	2.28	1.64	274.04	8.00	12.3	48.0	12.0	10.3	35.4	0.96	0.80	0
28	64.29	12.50	16.07	2.14	25.00	2.57	1.85	307.88	13.5	17.7	67.3	23.6	13.3	44.9	0.96	0.88	0
29	64.29	8.93	16.07	2.14	17.86	2.46	1.83	294.82	7.73	11.3	43.3	19.4	12.8	47.3	0.92	0.85	0
30	64.29	12.50	8.93	2.14	25.00	2.47	1.86	296.82	18.9	20.8	67.3	12.2	7.61	32.2	0.92	0.86	0
31	64.29	12.50	12.50	3.21	10.71	2.38	1.74	285.07	5.58	9.05	40.9	13.2	9.17	36.6	0.89	0.83	0
32	64.29	12.50	8.93	1.07	17.86	2.25	1.74	269.99	28.2	19.8	67.3	16.4	6.69	33.2	0.84	0.68	0
33	64.29	12.50	8.93	2.14	10.71	2.41	1.76	289.36	13.6	16.1	63.7	11.3	7.44	32.2	0.90	0.85	0
34	57.14	12.50	12.50	2.14	25.00	2.37	1.65	284.68	9.59	14.3	67.3	14.7	10.2	35.4	1.00	0.83	0
35	64.29	12.50	12.50	1.07	10.71	2.25	1.79	269.96	10.3	14.4	55.7	20.3	9.12	36.8	0.84	0.66	0
36	64.29	12.50	12.50	2.14	17.86	2.54	1.81	304.55	14.3	17.1	55.7	18.4	9.99	41.0	0.95	0.88	0
37	64.29	12.50	12.50	2.14	17.86	2.54	1.81	304.55	14.3	17.1	55.7	18.4	9.99	41.0	0.95	0.88	0
38	64.29	16.07	16.07	2.14	17.86	2.57	1.85	308.31	9.73	12.9	48.7	22.2	12.3	44.9	0.96	0.88	0
39	64.29	8.93	12.50	2.14	25.00	2.44	1.87	292.68	10.9	14.9	48.0	15.7	9.99	39.4	0.91	0.85	0
40	57.14	12.50	12.50	3.21	17.86	2.37	1.64	284.25	9.24	13.6	61.2	14.5	10.1	35.4	0.99	0.83	0
41	64.29	12.50	16.07	1.07	17.86	2.28	1.74	273.50	10.8	12.9	43.3	30.5	9.50	51.9	0.85	0.68	0
42	64.29	12.50	12.50	1.07	25.00	2.28	1.81	273.75	26.4	21.1	67.3	25.8	7.46	43.3	0.85	0.68	0
43	71.43	12.50	12.50	2.14	10.71	2.50	2.02	300.06	7.91	11.8	45.5	16.4	9.31	37.9	0.84	0.85	0
44	64.29	16.07	12.50	2.14	10.71	2.40	1.82	287.72	5.47	9.27	40.9	13.9	9.25	35.0	0.90	0.84	0
45	64.29	16.07	12.50	3.21	17.86	2.54	1.77	305.12	14.3	16.9	55.7	18.4	10.1	41.0	0.95	0.87	0
46	71.43	12.50	12.50	2.14	25.00	2.59	2.02	311.23	22.9	21.9	67.3	22.5	8.33	41.0	0.87	0.89	0

G.10 Tables Input Factors and Responses High Season – CONWIP/KCS - Period 2

Run	A:Supply	B: K1	C: K2	D:K3	E:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	64.29	12.50	12.50	2.14	17.86	2.48	1.68	297.19	12.94	16.73	63.48	16.87	10.85	36.40	0.92	0.86	0.60
2	64.29	12.50	8.93	2.14	25.00	2.45	1.72	293.63	18.73	20.27	67.31	11.62	8.09	32.34	0.91	0.83	0.58
3	64.29	16.07	16.07	2.14	17.86	2.54	1.79	305.28	9.01	12.85	57.69	22.58	13.06	44.31	0.95	0.88	0.62
4	64.29	12.50	12.50	2.14	17.86	2.48	1.68	297.19	12.94	16.73	63.48	16.87	10.85	36.40	0.92	0.86	0.60
5	71.43	12.50	16.07	2.14	17.86	2.58	1.74	309.50	11.08	13.13	49.92	25.55	13.14	52.36	0.87	0.88	0.62
6	71.43	8.93	12.50	2.14	17.86	2.48	1.87	298.19	11.61	15.70	48.08	15.99	10.39	34.60	0.83	0.85	0.60
7	64.29	12.50	12.50	2.14	17.86	2.48	1.68	297.19	12.94	16.73	63.48	16.87	10.85	36.40	0.92	0.86	0.60
8	64.29	12.50	16.07	2.14	25.00	2.55	1.73	305.45	11.89	16.95	67.31	23.24	13.92	44.29	0.95	0.87	0.61
9	57.14	12.50	12.50	2.14	25.00	2.35	1.59	282.18	6.66	11.19	45.82	12.46	9.64	34.16	0.99	0.81	0.57
10	64.29	8.93	12.50	1.07	17.86	2.23	1.65	267.85	12.01	15.47	48.08	18.80	10.79	36.27	0.83	0.66	0.54
11	64.29	12.50	12.50	2.14	17.86	2.48	1.68	297.19	12.94	16.73	63.48	16.87	10.85	36.40	0.92	0.86	0.60
12	64.29	12.50	12.50	2.14	17.86	2.48	1.68	297.19	12.94	16.73	63.48	16.87	10.85	36.40	0.92	0.86	0.60
13	64.29	16.07	8.93	2.14	17.86	2.53	1.75	303.66	27.89	22.84	77.75	12.31	8.26	32.34	0.94	0.85	0.59
14	64.29	16.07	12.50	2.14	25.00	2.57	1.81	308.96	23.67	23.22	86.54	18.86	10.96	42.06	0.96	0.88	0.60
15	71.43	16.07	12.50	2.14	17.86	2.60	1.83	311.54	22.13	19.00	65.22	20.29	10.24	42.45	0.87	0.88	0.61
16	57.14	8.93	12.50	2.14	17.86	2.27	1.52	272.94	5.28	9.71	45.82	10.16	8.75	34.16	0.96	0.77	0.55
17	64.29	16.07	12.50	1.07	17.86	2.28	1.69	273.51	21.81	17.43	60.91	23.39	9.67	43.36	0.85	0.66	0.54
18	64.29	16.07	12.50	3.21	17.86	2.52	1.79	302.97	16.16	18.08	63.48	18.09	10.79	41.75	0.94	0.88	0.60
19	57.14	12.50	12.50	3.21	17.86	2.35	1.59	282.18	6.66	11.19	45.82	12.46	9.64	34.16	0.99	0.81	0.57
20	71.43	12.50	12.50	3.21	17.86	2.57	1.69	308.41	17.77	17.56	63.51	18.81	10.77	42.22	0.86	0.88	0.61
21	57.14	12.50	12.50	2.14	10.71	2.30	1.57	276.44	5.64	10.26	39.97	11.31	9.37	34.16	0.97	0.80	0.56
22	64.29	12.50	8.93	1.07	17.86	2.27	1.67	271.93	26.31	21.13	67.31	15.00	7.64	33.24	0.85	0.66	0.53
23	64.29	12.50	16.07	2.14	10.71	2.40	1.74	288.38	5.06	9.45	37.23	14.38	10.73	40.18	0.90	0.82	0.58
24	57.14	12.50	16.07	2.14	17.86	2.35	1.59	282.18	5.21	9.56	38.46	13.19	10.36	36.86	0.99	0.81	0.57
25	64.29	12.50	8.93	2.14	10.71	2.39	1.75	287.08	13.22	15.57	57.84	10.34	7.88	32.34	0.89	0.83	0.58
26	64.29	8.93	12.50	2.14	25.00	2.44	1.71	292.29	9.22	13.66	48.08	13.69	10.16	34.19	0.91	0.83	0.59
27	57.14	12.50	12.50	1.07	17.86	2.22	1.49	266.48	13.60	16.25	60.79	19.87	11.07	40.43	0.93	0.66	0.54
28	64.29	12.50	8.93	3.21	17.86	2.45	1.71	293.63	18.72	20.25	67.31	11.62	8.09	32.34	0.91	0.83	0.58
29	71.43	12.50	12.50	2.14	25.00	2.58	1.87	309.83	20.82	21.27	67.31	18.85	10.84	42.22	0.87	0.88	0.61
30	64.29	12.50	16.07	3.21	17.86	2.51	1.69	301.46	7.91	11.57	45.36	20.53	13.11	44.08	0.94	0.87	0.61
31	64.29	16.07	12.50	2.14	10.71	2.41	1.69	288.62	7.14	11.50	46.90	13.65	9.92	35.25	0.90	0.83	0.59
32	64.29	12.50	16.07	1.07	17.86	2.28	1.65	273.60	10.34	12.48	41.89	27.92	12.82	52.14	0.85	0.66	0.55
33	64.29	12.50	12.50	1.07	10.71	2.21	1.68	265.26	8.05	13.79	65.38	17.91	10.22	38.96	0.83	0.66	0.54
34	64.29	8.93	8.93	2.14	17.86	2.36	1.68	283.30	10.34	14.42	48.08	9.63	7.38	27.01	0.88	0.81	0.57
35	64.29	12.50	12.50	2.14	17.86	2.48	1.68	297.19	12.94	16.73	63.48	16.87	10.85	36.40	0.92	0.86	0.60
36	71.43	12.50	12.50	2.14	10.71	2.49	1.87	299.15	10.74	14.46	55.79	16.27	10.23	39.41	0.84	0.86	0.60
37	64.29	8.93	12.50	3.21	17.86	2.43	1.71	291.57	9.04	13.49	48.08	13.62	10.08	34.19	0.91	0.83	0.59
38	64.29	12.50	12.50	1.07	25.00	2.30	1.72	275.69	23.68	21.81	67.31	22.03	10.38	43.36	0.86	0.66	0.54
39	71.43	12.50	8.93	2.14	17.86	2.54	1.87	304.54	23.56	21.72	67.31	12.55	7.93	32.36	0.85	0.87	0.60
40	57.14	16.07	12.50	2.14	17.86	2.38	1.69	285.71	7.48	12.12	57.49	13.03	9.74	34.16	1.00	0.84	0.58
41	71.43	12.50	12.50	1.07	17.86	2.31	1.55	277.66	23.78	16.45	61.06	24.22	9.08	43.35	0.78	0.67	0.54
42	64.29	8.93	16.07	2.14	17.86	2.48	1.74	297.89	6.75	10.70	45.36	18.35	12.98	44.08	0.93	0.85	0.60
43	64.29	8.93	12.50	2.14	10.71	2.41	1.66	289.00	6.38	10.27	37.68	13.26	9.53	34.12	0.90	0.83	0.59
44	57.14	12.50	8.93	2.14	17.86	2.34	1.59	281.28	11.07	15.13	57.65	10.09	7.88	31.52	0.98	0.81	0.57
45	64.29	12.50	12.50	3.21	25.00	2.49	1.74	298.94	14.39	19.03	67.31	17.06	10.97	36.40	0.93	0.86	0.60
46	64.29	12.50	12.50	3.21	10.71	2.40	1.66	288.10	6.54	10.48	37.23	13.84	10.04	34.31	0.90	0.82	0.59

G.11 Tables Input Factors and Responses High Season – CONWIP/KCS - Period 3

Run	A:Supply	B: K1	C: K2	D:K3	E:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	64.29	12.50	8.93	3.21	17.86	2.35	2.09	282.21	21.28	20.35	67.31	10.11	8.37	32.23	0.88	0.78	0.55
2	71.43	16.07	12.50	2.14	17.86	2.53	2.19	303.37	21.14	19.73	75.99	16.46	11.56	41.03	0.85	0.84	0.58
3	64.29	12.50	12.50	2.14	17.86	2.38	2.07	286.20	14.45	17.95	67.31	14.72	11.35	39.10	0.89	0.80	0.56
4	71.43	8.93	12.50	2.14	17.86	2.40	2.16	288.42	12.45	15.42	48.08	13.74	11.22	34.20	0.81	0.77	0.56
5	64.29	8.93	12.50	2.14	25.00	2.30	2.11	276.29	10.74	14.58	48.08	12.59	10.89	34.18	0.86	0.76	0.54
6	64.29	12.50	12.50	3.21	25.00	2.40	2.15	287.52	15.95	20.28	67.31	14.85	11.29	39.10	0.89	0.80	0.56
7	64.29	12.50	12.50	1.07	25.00	2.30	2.15	275.60	20.30	21.98	67.31	18.63	11.39	42.00	0.86	0.65	0.52
8	64.29	12.50	16.07	1.07	17.86	2.27	1.97	272.88	10.87	14.27	67.31	22.99	14.20	46.21	0.85	0.65	0.53
9	71.43	12.50	12.50	3.21	17.86	2.49	2.14	298.51	16.93	18.01	67.31	15.80	11.54	39.43	0.84	0.81	0.57
10	71.43	12.50	8.93	2.14	17.86	2.44	2.19	293.00	24.11	21.30	67.31	10.60	8.37	32.23	0.82	0.80	0.56
11	64.29	8.93	12.50	2.14	10.71	2.26	2.05	271.18	7.75	12.10	48.08	12.27	10.51	34.18	0.84	0.75	0.54
12	64.29	16.07	12.50	3.21	17.86	2.41	2.11	289.74	17.79	18.89	80.72	15.59	11.70	39.43	0.90	0.82	0.57
13	57.14	12.50	12.50	3.21	17.86	2.24	1.92	268.44	11.26	16.57	67.31	12.44	10.51	36.47	0.94	0.76	0.53
14	57.14	12.50	8.93	2.14	17.86	2.21	1.96	265.61	15.64	19.15	67.31	9.34	8.25	32.23	0.93	0.73	0.53
15	64.29	12.50	16.07	3.21	17.86	2.39	2.05	287.29	9.40	13.94	67.31	17.53	13.71	44.03	0.89	0.80	0.57
16	64.29	12.50	12.50	1.07	10.71	2.19	2.03	262.57	11.09	14.83	56.39	16.15	11.20	36.27	0.82	0.62	0.51
17	64.29	16.07	12.50	2.14	10.71	2.30	2.18	275.54	10.26	15.04	52.19	12.86	10.71	34.46	0.86	0.77	0.54
18	57.14	12.50	16.07	2.14	17.86	2.25	1.93	270.00	8.45	13.32	67.31	14.20	12.44	44.18	0.94	0.76	0.54
19	64.29	8.93	12.50	1.07	17.86	2.18	2.00	261.63	12.25	15.28	48.08	15.96	11.49	36.21	0.81	0.61	0.50
20	64.29	8.93	12.50	3.21	17.86	2.30	2.10	276.29	10.66	14.47	48.08	12.59	10.89	34.18	0.86	0.76	0.54
21	64.29	8.93	16.07	2.14	17.86	2.36	2.10	283.38	7.92	12.08	48.08	15.49	13.04	44.03	0.88	0.78	0.56
22	64.29	8.93	8.93	2.14	17.86	2.23	2.04	267.61	12.24	14.93	48.08	9.21	8.17	29.50	0.83	0.74	0.53
23	64.29	16.07	12.50	2.14	25.00	2.49	2.22	298.23	22.56	25.36	86.54	16.71	11.35	39.43	0.93	0.83	0.58
24	64.29	16.07	12.50	1.07	17.86	2.30	2.03	275.92	20.50	19.16	75.74	18.96	11.56	43.33	0.86	0.66	0.53
25	57.14	16.07	12.50	2.14	17.86	2.25	1.95	270.53	13.28	17.89	71.75	13.59	11.34	39.43	0.95	0.77	0.54
26	71.43	12.50	12.50	1.07	17.86	2.32	2.06	277.82	21.70	18.42	62.13	20.51	10.58	43.32	0.78	0.66	0.53
27	64.29	12.50	12.50	2.14	17.86	2.38	2.07	286.20	14.45	17.95	67.31	14.72	11.35	39.10	0.89	0.80	0.56
28	57.14	8.93	12.50	2.14	17.86	2.15	1.95	257.64	8.25	13.02	48.08	10.42	9.75	34.09	0.90	0.70	0.51
29	64.29	12.50	8.93	2.14	25.00	2.35	2.11	282.21	21.39	20.57	67.31	10.11	8.37	32.23	0.88	0.78	0.55
30	64.29	12.50	16.07	2.14	25.00	2.48	2.16	297.24	13.65	18.94	67.31	19.23	13.29	44.29	0.92	0.83	0.59
31	64.29	12.50	12.50	3.21	10.71	2.28	2.10	273.82	8.68	13.36	48.97	12.66	10.67	34.46	0.85	0.76	0.54
32	71.43	12.50	16.07	2.14	17.86	2.52	2.15	302.64	11.40	14.88	67.31	19.76	14.30	44.03	0.85	0.82	0.59
33	64.29	12.50	8.93	2.14	10.71	2.25	1.99	269.47	13.85	14.67	54.38	9.52	8.47	32.23	0.84	0.74	0.52
34	64.29	12.50	12.50	2.14	17.86	2.38	2.07	286.20	14.45	17.95	67.31	14.72	11.35	39.10	0.89	0.80	0.56
35	64.29	12.50	12.50	2.14	17.86	2.38	2.07	286.20	14.45	17.95	67.31	14.72	11.35	39.10	0.89	0.80	0.56
36	57.14	12.50	12.50	1.07	17.86	2.15	1.87	258.16	13.02	17.25	67.31	16.65	11.51	37.48	0.90	0.62	0.51
37	64.29	12.50	12.50	2.14	17.86	2.38	2.07	286.20	14.45	17.95	67.31	14.72	11.35	39.10	0.89	0.80	0.56
38	57.14	12.50	12.50	2.14	10.71	2.09	1.89	250.57	6.08	11.75	65.38	10.19	9.92	35.51	0.88	0.69	0.50
39	64.29	12.50	16.07	2.14	10.71	2.23	2.09	267.14	7.00	12.36	54.37	12.63	11.17	38.27	0.83	0.73	0.53
40	71.43	12.50	12.50	2.14	25.00	2.53	2.28	303.19	20.58	22.16	67.31	16.02	11.40	39.43	0.85	0.81	0.57
41	64.29	16.07	8.93	2.14	17.86	2.41	2.15	289.10	27.26	23.71	80.72	10.69	8.38	32.23	0.90	0.82	0.56
42	57.14	12.50	12.50	2.14	25.00	2.26	2.00	270.92	12.60	18.63	67.31	12.65	10.43	36.47	0.95	0.76	0.54
43	71.43	12.50	12.50	2.14	10.71	2.34	2.18	281.13	8.46	12.63	49.64	13.43	10.79	33.24	0.79	0.77	0.56
44	64.29	12.50	8.93	1.07	17.86	2.22	2.02	266.70	24.69	21.70	67.31	12.70	8.49	33.21	0.83	0.64	0.51
45	64.29	16.07	16.07	2.14	17.86	2.43	2.15	291.61	11.66	16.41	80.72	19.35	14.31	44.29	0.91	0.82	0.58
46	64.29	12.50	12.50	2.14	17.86	2.38	2.07	286.20	14.45	17.95	67.31	14.72	11.35	39.10	0.89	0.80	0.56

G.12 Tables Input Factors and Responses Medium Season – CONWIP/KCS - Period 1

Run	A:Supply	B: K1	C: K2	D:K3	E:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	53.57	12.50	16.07	2.14	17.86	2.23	1.54	267.86	5.37	9.94	40.66	10.93	9.89	36.78	1.00	0.78	0.54
2	50.00	12.50	16.07	1.07	17.86	2.07	1.44	248.51	5.19	9.32	37.95	15.79	11.56	39.56	0.99	0.62	0.50
3	50.00	12.50	8.93	2.14	25.00	2.08	1.44	250.00	5.75	9.51	37.95	6.63	6.89	28.25	1.00	0.71	0.50
4	46.43	16.07	12.50	2.14	17.86	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
5	50.00	16.07	12.50	3.21	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
6	53.57	16.07	12.50	2.14	17.86	2.23	1.54	267.86	6.06	10.26	40.94	10.58	9.33	31.57	1.00	0.78	0.54
7	53.57	8.93	12.50	2.14	17.86	2.19	1.52	262.90	5.69	9.87	40.94	10.16	9.50	31.57	0.98	0.77	0.53
8	50.00	8.93	12.50	2.14	25.00	2.06	1.42	247.16	4.50	8.89	37.95	6.97	7.57	28.25	0.99	0.69	0.50
9	50.00	8.93	8.93	2.14	17.86	2.06	1.42	247.16	5.56	9.30	37.95	6.44	6.88	28.25	0.99	0.69	0.50
10	53.57	12.50	12.50	3.21	17.86	2.23	1.54	267.86	6.06	10.26	40.94	10.58	9.33	31.57	1.00	0.78	0.54
11	46.43	12.50	16.07	2.14	17.86	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
12	50.00	8.93	12.50	2.14	10.71	2.06	1.42	246.76	4.50	8.89	37.95	6.71	7.31	28.25	0.99	0.69	0.50
13	50.00	16.07	8.93	2.14	17.86	2.08	1.44	250.00	5.75	9.51	37.95	6.63	6.89	28.25	1.00	0.71	0.50
14	50.00	16.07	12.50	1.07	17.86	2.07	1.45	248.32	7.01	12.19	51.28	14.75	10.28	36.21	0.99	0.62	0.50
15	53.57	12.50	8.93	2.14	17.86	2.23	1.54	267.86	9.77	13.96	61.13	8.73	7.60	31.57	1.00	0.78	0.54
16	50.00	12.50	16.07	2.14	10.71	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50
17	50.00	16.07	12.50	2.14	25.00	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
18	50.00	12.50	12.50	1.07	25.00	2.08	1.44	250.00	7.49	12.62	60.31	15.61	10.77	36.21	1.00	0.62	0.51
19	50.00	12.50	12.50	2.14	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
20	50.00	12.50	12.50	3.21	25.00	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
21	50.00	16.07	16.07	2.14	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
22	53.57	12.50	12.50	2.14	10.71	2.18	1.53	261.69	5.06	9.52	40.66	8.75	8.19	30.55	0.98	0.76	0.53
23	50.00	8.93	12.50	3.21	17.86	2.06	1.42	247.16	4.50	8.89	37.95	6.97	7.57	28.25	0.99	0.69	0.50
24	53.57	12.50	12.50	1.07	17.86	2.17	1.52	260.94	9.20	13.74	51.14	17.63	10.58	35.96	0.97	0.64	0.53
25	50.00	12.50	12.50	2.14	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
26	50.00	12.50	16.07	3.21	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
27	50.00	12.50	8.93	1.07	17.86	2.06	1.45	247.18	11.73	16.46	67.31	11.58	7.83	29.27	0.99	0.62	0.50
28	50.00	12.50	12.50	2.14	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
29	50.00	12.50	8.93	3.21	17.86	2.08	1.44	250.00	5.75	9.51	37.95	6.63	6.89	28.25	1.00	0.71	0.50
30	50.00	8.93	12.50	1.07	17.86	2.04	1.44	244.27	6.63	11.65	48.08	13.62	10.10	36.21	0.98	0.62	0.49
31	46.43	12.50	12.50	2.14	25.00	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
32	50.00	12.50	12.50	2.14	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
33	50.00	12.50	12.50	3.21	10.71	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50
34	46.43	8.93	12.50	2.14	17.86	1.92	1.33	230.97	4.06	8.24	35.24	4.83	5.78	24.94	0.99	0.62	0.46
35	46.43	12.50	8.93	2.14	17.86	1.93	1.33	232.14	4.33	8.38	35.24	4.80	5.65	24.94	1.00	0.63	0.47
36	53.57	12.50	12.50	2.14	25.00	2.23	1.54	267.86	6.06	10.26	40.94	10.58	9.33	31.57	1.00	0.78	0.54
37	50.00	8.93	16.07	2.14	17.86	2.06	1.42	247.16	4.50	8.89	37.95	6.97	7.57	28.25	0.99	0.69	0.50
38	50.00	12.50	12.50	2.14	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
39	50.00	12.50	8.93	2.14	10.71	2.07	1.44	248.98	5.26	9.21	37.95	6.26	6.58	28.25	1.00	0.70	0.50
40	50.00	12.50	12.50	1.07	10.71	2.01	1.43	240.95	4.43	8.70	37.95	11.37	9.21	34.66	0.96	0.60	0.48
41	50.00	12.50	12.50	2.14	17.86	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
42	46.43	12.50	12.50	2.14	10.71	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
43	46.43	12.50	12.50	3.21	17.86	1.93	1.33	232.14	4.13	8.34	35.24	4.91	5.81	24.94	1.00	0.63	0.47
44	50.00	12.50	16.07	2.14	25.00	2.08	1.44	250.00	4.69	9.13	37.95	7.16	7.56	28.25	1.00	0.71	0.50
45	50.00	16.07	12.50	2.14	10.71	2.08	1.44	249.60	4.69	9.13	37.95	6.90	7.31	28.25	1.00	0.71	0.50
46	46.43	12.50	12.50	1.07	17.86	1.93	1.33	232.14	4.42	8.41	35.24	10.08	9.10	29.01	1.00	0.59	0.47

G.13 Tables Input Factors and Responses Medium Season – CONWIP/KCS - Period 2

Run	A:Supply	B: K1	C: K2	D:K3	E:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	50.00	8.93	12.50	2.14	10.71	2.03	1.34	243.72	3.67	7.35	28.96	5.64	6.66	27.07	0.97	0.66	0.49
2	50.00	8.93	12.50	2.14	25.00	2.03	1.34	243.72	3.67	7.35	28.96	5.64	6.66	27.07	0.97	0.66	0.49
3	50.00	12.50	12.50	2.14	17.86	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
4	50.00	8.93	12.50	1.07	17.86	2.03	1.34	243.72	3.88	7.50	28.96	11.15	8.89	32.13	0.97	0.60	0.49
5	53.57	16.07	12.50	2.14	17.86	2.23	1.59	267.86	5.03	9.79	52.10	8.90	8.90	33.27	1.00	0.76	0.54
6	50.00	12.50	12.50	3.21	10.71	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50
7	50.00	12.50	8.93	2.14	10.71	2.07	1.42	248.11	5.10	9.00	37.51	5.76	6.53	24.58	0.99	0.66	0.50
8	50.00	12.50	16.07	2.14	25.00	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
9	50.00	12.50	12.50	2.14	17.86	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
10	46.43	16.07	12.50	2.14	17.86	1.93	1.38	232.14	3.65	7.73	41.30	4.86	6.43	23.77	1.00	0.61	0.47
11	50.00	12.50	12.50	1.07	10.71	2.03	1.42	244.15	3.98	7.94	36.54	11.42	9.12	32.13	0.98	0.62	0.50
12	46.43	12.50	16.07	2.14	17.86	1.93	1.36	231.61	3.59	7.56	38.46	4.79	6.30	22.35	1.00	0.61	0.47
13	53.57	12.50	12.50	3.21	17.86	2.21	1.51	265.32	4.68	8.96	38.46	8.52	8.46	31.97	0.99	0.75	0.53
14	50.00	16.07	16.07	2.14	17.86	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
15	50.00	12.50	12.50	2.14	17.86	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
16	50.00	16.07	12.50	2.14	10.71	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50
17	50.00	16.07	8.93	2.14	17.86	2.08	1.48	250.00	5.61	9.73	46.70	5.88	6.67	24.58	1.00	0.67	0.50
18	50.00	8.93	8.93	2.14	17.86	2.03	1.34	243.32	4.50	8.32	37.51	5.24	6.02	21.41	0.97	0.65	0.49
19	50.00	12.50	16.07	3.21	17.86	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
20	50.00	12.50	8.93	2.14	25.00	2.07	1.43	248.47	5.20	9.13	38.46	5.78	6.55	24.58	0.99	0.67	0.50
21	50.00	8.93	12.50	3.21	17.86	2.03	1.34	243.72	3.67	7.35	28.96	5.64	6.66	27.07	0.97	0.66	0.49
22	53.57	12.50	16.07	2.14	17.86	2.21	1.51	265.32	4.58	8.84	38.46	8.57	8.51	31.97	0.99	0.75	0.53
23	46.43	12.50	12.50	2.14	10.71	1.93	1.34	231.26	3.56	7.45	36.54	4.74	6.21	22.18	1.00	0.61	0.46
24	50.00	16.07	12.50	1.07	17.86	2.08	1.48	250.00	4.71	8.94	46.70	13.10	9.50	33.18	1.00	0.63	0.51
25	46.43	12.50	12.50	3.21	17.86	1.93	1.36	231.61	3.59	7.56	38.46	4.79	6.30	22.35	1.00	0.61	0.47
26	50.00	12.50	8.93	1.07	17.86	2.07	1.43	248.47	8.69	12.78	49.82	10.63	7.61	25.59	0.99	0.62	0.50
27	46.43	12.50	12.50	1.07	17.86	1.93	1.36	231.61	3.59	7.56	38.46	8.39	7.97	27.41	1.00	0.57	0.47
28	50.00	16.07	12.50	3.21	17.86	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
29	53.57	8.93	12.50	2.14	17.86	2.16	1.42	259.47	4.18	8.08	32.99	7.66	7.77	31.97	0.97	0.73	0.52
30	50.00	12.50	16.07	1.07	17.86	2.07	1.43	248.47	4.05	8.17	38.46	12.95	9.68	33.89	0.99	0.62	0.50
31	53.57	12.50	12.50	2.14	25.00	2.21	1.51	265.32	4.68	8.96	38.46	8.52	8.46	31.97	0.99	0.75	0.53
32	50.00	8.93	16.07	2.14	17.86	2.03	1.34	243.72	3.67	7.35	28.96	5.64	6.66	27.07	0.97	0.66	0.49
33	50.00	12.50	12.50	1.07	25.00	2.07	1.43	248.47	4.50	8.47	38.46	12.73	9.39	32.13	0.99	0.62	0.50
34	53.57	12.50	8.93	2.14	17.86	2.21	1.51	265.32	6.89	11.01	47.58	7.41	7.09	28.41	0.99	0.75	0.54
35	50.00	12.50	12.50	2.14	17.86	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
36	50.00	12.50	8.93	3.21	17.86	2.07	1.43	248.47	5.20	9.13	38.46	5.78	6.55	24.58	0.99	0.67	0.50
37	46.43	12.50	8.93	2.14	17.86	1.93	1.36	231.61	3.87	7.69	38.46	4.68	6.05	21.89	1.00	0.61	0.46
38	50.00	12.50	12.50	3.21	25.00	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
39	53.57	12.50	12.50	1.07	17.86	2.18	1.49	261.57	9.45	13.88	52.53	17.80	11.09	35.87	0.98	0.65	0.53
40	46.43	12.50	12.50	2.14	25.00	1.93	1.36	231.61	3.59	7.56	38.46	4.79	6.30	22.35	1.00	0.61	0.47
41	50.00	12.50	12.50	2.14	17.86	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
42	50.00	16.07	12.50	2.14	25.00	2.08	1.48	250.00	4.25	8.67	46.70	6.50	7.70	28.52	1.00	0.68	0.50
43	46.43	8.93	12.50	2.14	17.86	1.90	1.27	227.96	3.27	6.80	26.89	4.33	5.64	22.18	0.98	0.60	0.46
44	50.00	12.50	12.50	2.14	17.86	2.07	1.43	248.47	4.05	8.17	38.46	6.29	7.39	27.07	0.99	0.68	0.50
45	50.00	12.50	16.07	2.14	10.71	2.07	1.42	248.11	4.02	8.07	36.54	6.24	7.32	27.07	0.99	0.67	0.50
46	53.57	12.50	12.50	2.14	10.71	2.19	1.49	262.95	4.38	8.52	36.54	8.27	8.38	31.97	0.98	0.74	0.53

G.14 Tables Input Factors and Responses Medium Season – CONWIP/KCS - Period 3

Run	A:Supply	B: K1	C: K2	D:K3	E:CC	Stage0_Mean	Stage0_SD	Stage0_Sum	StageB1_Mean	StageB1_SD	StageB1_Max	StageB2_Mean	StageB2_SD	StageB2_Max	SupplyAccuracy	SLA	Stage2Utili
						R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12
	Lot	Lot	Lot	Lot	Lot	Lot	Lot	Lot	%	%	%	%	%	%			
1	50.00	12.50	12.50	2.14	17.86	2.05	1.82	246.39	8.15	13.22	62.78	9.07	9.92	34.05	0.99	0.69	0.49
2	46.43	8.93	12.50	2.14	17.86	1.85	1.61	221.51	4.29	8.93	48.08	6.56	8.31	30.22	0.95	0.59	0.44
3	50.00	8.93	12.50	2.14	25.00	1.96	1.73	235.08	5.66	10.85	48.08	7.69	8.88	32.71	0.94	0.65	0.47
4	53.57	12.50	8.93	2.14	17.86	2.14	1.90	257.02	13.74	18.32	67.27	8.44	7.94	32.23	0.96	0.71	0.52
5	50.00	8.93	8.93	2.14	17.86	1.94	1.72	232.65	7.28	11.92	48.08	6.33	7.22	24.91	0.93	0.64	0.47
6	46.43	12.50	12.50	2.14	25.00	1.92	1.70	230.58	5.65	10.85	58.30	7.76	9.61	32.65	0.99	0.61	0.46
7	46.43	12.50	8.93	2.14	17.86	1.92	1.70	230.58	8.58	13.37	58.30	6.32	7.67	32.23	0.99	0.60	0.46
8	46.43	12.50	12.50	1.07	17.86	1.90	1.65	228.05	8.03	13.29	58.30	11.94	10.57	35.96	0.98	0.55	0.45
9	50.00	12.50	12.50	1.07	25.00	2.03	1.79	243.01	11.29	17.82	66.50	14.29	10.70	35.97	0.97	0.60	0.49
10	50.00	16.07	12.50	2.14	10.71	1.96	1.71	235.28	5.47	10.98	62.78	7.86	9.09	32.88	0.94	0.65	0.47
11	50.00	16.07	12.50	2.14	25.00	2.08	1.85	250.00	9.98	15.63	62.78	10.00	10.37	38.57	1.00	0.71	0.50
12	50.00	12.50	12.50	3.21	25.00	2.05	1.82	246.39	8.15	13.22	62.78	9.07	9.92	34.05	0.99	0.69	0.49
13	53.57	12.50	12.50	2.14	25.00	2.17	1.93	260.64	10.89	16.56	67.31	10.87	10.09	35.15	0.97	0.73	0.52
14	50.00	16.07	16.07	2.14	17.86	2.07	1.82	248.50	6.66	12.41	62.78	11.26	12.25	44.23	0.99	0.70	0.50
15	46.43	12.50	16.07	2.14	17.86	1.92	1.70	230.58	5.16	10.65	58.30	8.00	9.95	33.01	0.99	0.61	0.46
16	50.00	12.50	12.50	2.14	17.86	2.05	1.82	246.39	8.15	13.22	62.78	9.07	9.92	34.05	0.99	0.69	0.49
17	50.00	8.93	12.50	1.07	17.86	1.93	1.73	232.01	7.46	12.55	48.08	11.48	9.98	36.28	0.93	0.57	0.46
18	50.00	12.50	16.07	1.07	17.86	1.99	1.73	238.92	6.57	11.57	62.78	15.38	12.80	45.15	0.96	0.59	0.47
19	50.00	12.50	16.07	2.14	25.00	2.05	1.82	246.39	5.95	11.50	62.78	10.17	11.46	38.85	0.99	0.69	0.49
20	50.00	12.50	16.07	2.14	10.71	1.96	1.70	234.75	5.42	10.97	62.78	7.78	8.99	30.55	0.94	0.65	0.47
21	46.43	12.50	12.50	2.14	10.71	1.90	1.70	227.70	5.34	10.61	58.30	7.48	9.37	31.69	0.98	0.61	0.45
22	50.00	12.50	12.50	2.14	17.86	2.05	1.82	246.39	8.15	13.22	62.78	9.07	9.92	34.05	0.99	0.69	0.49
23	50.00	12.50	8.93	1.07	17.86	1.98	1.75	237.41	14.66	18.88	66.37	10.71	8.52	32.28	0.95	0.59	0.47
24	50.00	12.50	8.93	3.21	17.86	2.05	1.82	246.39	11.48	16.54	62.78	7.41	7.89	32.23	0.99	0.69	0.49
25	50.00	8.93	12.50	3.21	17.86	1.96	1.73	235.08	5.66	10.85	48.08	7.69	8.88	32.71	0.94	0.65	0.47
26	53.57	12.50	16.07	2.14	17.86	2.17	1.90	259.98	7.42	12.52	67.27	12.40	12.21	44.26	0.97	0.72	0.52
27	53.57	8.93	12.50	2.14	17.86	2.05	1.84	246.35	6.90	11.76	48.08	9.02	9.30	34.09	0.92	0.67	0.49
28	46.43	12.50	12.50	3.21	17.86	1.92	1.70	230.58	5.65	10.85	58.30	7.76	9.61	32.65	0.99	0.61	0.46
29	50.00	12.50	12.50	1.07	10.71	1.88	1.67	225.71	4.78	10.17	62.78	11.75	10.33	33.89	0.90	0.56	0.45
30	50.00	12.50	16.07	3.21	17.86	2.05	1.82	246.39	5.95	11.50	62.78	10.17	11.46	38.85	0.99	0.69	0.49
31	53.57	16.07	12.50	2.14	17.86	2.17	1.87	260.62	11.23	16.68	67.27	12.02	11.00	39.43	0.97	0.73	0.52
32	50.00	12.50	8.93	2.14	25.00	2.05	1.82	246.39	11.48	16.54	62.78	7.41	7.89	32.23	0.99	0.69	0.49
33	50.00	12.50	12.50	2.14	17.86	2.05	1.82	246.39	8.15	13.22	62.78	9.07	9.92	34.05	0.99	0.69	0.49
34	50.00	8.93	12.50	2.14	10.71	1.91	1.65	229.68	4.35	8.97	48.08	7.11	8.37	27.90	0.92	0.63	0.46
35	50.00	12.50	12.50	3.21	10.71	1.95	1.68	233.87	5.27	10.67	62.78	7.69	8.95	32.88	0.94	0.64	0.47
36	50.00	12.50	12.50	2.14	17.86	2.05	1.82	246.39	8.15	13.22	62.78	9.07	9.92	34.05	0.99	0.69	0.49
37	53.57	12.50	12.50	2.14	10.71	2.04	1.82	245.22	5.96	11.51	65.38	9.15	9.32	33.88	0.92	0.66	0.49
38	50.00	16.07	8.93	2.14	17.86	2.07	1.81	248.10	13.54	18.49	62.78	7.73	8.07	32.23	0.99	0.70	0.50
39	50.00	12.50	8.93	2.14	10.71	1.99	1.76	239.24	9.02	13.09	62.78	6.94	7.87	32.23	0.96	0.67	0.48
40	53.57	12.50	12.50	1.07	17.86	2.07	1.82	248.97	11.27	16.66	67.27	15.41	11.20	36.21	0.93	0.60	0.50
41	50.00	16.07	12.50	1.07	17.86	2.00	1.72	240.43	10.68	16.36	62.78	14.43	11.26	39.59	0.96	0.59	0.48
42	46.43	16.07	12.50	2.14	17.86	1.93	1.72	232.14	6.09	11.34	58.30	8.02	9.81	34.52	1.00	0.63	0.46
43	50.00	8.93	16.07	2.14	17.86	1.97	1.72	235.98	4.46	9.12	48.08	8.40	10.01	36.85	0.94	0.66	0.47
44	53.57	12.50	12.50	3.21	17.86	2.17	1.93	259.93	10.67	16.18	67.27	10.82	10.11	35.15	0.97	0.72	0.52
45	50.00	16.07	12.50	3.21	17.86	2.07	1.81	248.20	9.25	14.55	62.78	9.90	10.40	38.57	0.99	0.70	0.49
46	50.00	12.50	12.50	2.14	17.86	2.05	1.82	246.39	8.15	13.22	62.78	9.07	9.92	34.05	0.99	0.69	0.49

APPENDIX H – ANOVA AND FINAL EQUATION ACTUAL FACTORS

H.1 ANOVA AND MODEL EQUATION RESPONSES 7, 11, 9 - HS – CONWIP – Period 1

ANOVA TABLE

Response 7 StageB2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	5.58	1	5.58			
Model	1457.73	5	291.55	1346.67	< 0.0001	significant
A-Supply	*590.97*	*1*	*590.97*	*2729.72*	*< 0.0001*	
B-CC	*657.84*	*1*	*657.84*	*3038.58*	*< 0.0001*	
AB	*194.92*	*1*	*194.92*	*900.37*	*< 0.0001*	
A^2	*2.45*	*1*	*2.45*	*11.34*	*0.0151*	
B^2	*30.14*	*1*	*30.14*	*139.22*	*< 0.0001*	
Residual	1.30	6	0.22			
Lack of Fit	*1.30*	*2*	*0.65*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	1464.61	12				

METRICS AND FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9991
Adj R-Squared	0.9984
Pred R-Squared	0.9807
Adeq Precision	118.249

StageB2_Mean =
+142.48546
-4.04954 * Supply
-4.37967 * CC
+0.10941 * Supply * CC
+0.025587 * Supply2
-0.038300 * CC2

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	1.509E-003	1	1.509E-003			
Model	0.011	4	2.627E-003	77.93	< 0.0001	significant
A-Supply	*6.536E-003*	*1*	*6.536E-003*	*193.92*	*< 0.0001*	
B-CC	*3.694E-003*	*1*	*3.694E-003*	*109.60*	*< 0.0001*	
A^2	*1.465E-004*	*1*	*1.465E-004*	*4.35*	*0.0755*	
B^2	*1.186E-003*	*1*	*1.186E-003*	*35.17*	*0.0006*	
Residual	2.359E-004	7	3.371E-005			
Lack of Fit	*2.359E-004*	*3*	*7.865E-005*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.012	12				

R-Squared	0.9780
Adj R-Squared	0.9655
Pred R-Squared	0.7862
Adeq Precision	29.068

SLA =
-0.38574
+0.030040 * Supply
+0.012159 * CC
-1.97721E-004 * Supply2
-2.40210E-004 * CC2

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	81.36	1	81.36			
Model	2469.08	4	617.27	93.30	< 0.0001	significant
A-Supply	*520.85*	*1*	*520.85*	*78.73*	*< 0.0001*	
B-CC	*1688.20*	*1*	*1688.20*	*255.17*	*< 0.0001*	
AB	*217.12*	*1*	*217.12*	*32.82*	*0.0007*	
B^2	*43.36*	*1*	*43.36*	*6.55*	*0.0375*	
Residual	46.31	7	6.62			
Lack of Fit	*46.31*	*3*	*15.44*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	2596.75	12				

R-Squared	0.9816
Adj R-Squared	0.9711
Pred R-Squared	0.8156
Adeq Precision	29.444

Stage2_Max =
+64.17722
-0.96380 * Supply
-3.84974 * CC
+0.11547 * Supply * CC
-0.044188 * CC2

H.2 ANOVA AND MODEL EQUATION RESPONSE 10 - HS – CONWIP – Period 1

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	2.049E-003	1	2.049E-003			
Model	0.028	2	0.014	91.02	< 0.0001	significant
A-Supply	*0.018*	*1*	*0.018*	*113.00*	*< 0.0001*	
B-CC	*0.011*	*1*	*0.011*	*69.04*	*< 0.0001*	
Residual	1.403E-003	9	1.558E-004			
Lack of Fit	*1.403E-003*	*5*	*2.805E-004*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.032	12				

R-Squared	0.9529
Adj R-Squared	0.9424
Pred R-Squared	0.8708
Adeq Precision	27.018

SupplyAcc =
+1.33518
-7.58265E-003 * Supply

+4.40885E-003 * CC

H.3 ANOVA AND MODEL EQUATION – RESPONSES 7,11,9 - HS – CONWIP – Period 2

ANOVA TABLE

Response 7 StageB2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	29.73	1	29.73			
Model	1630.33	5	326.07	18098.02	< 0.0001	significant
A-Supply	*655.24*	*1*	*655.24*	*36368.80*	*< 0.0001*	
B-CC	*678.26*	*1*	*678.26*	*37646.12*	*< 0.0001*	
AB	*290.24*	*1*	*290.24*	*16109.76*	*< 0.0001*	
A^2	*16.17*	*1*	*16.17*	*897.72*	*< 0.0001*	
B^2	*68.27*	*1*	*68.27*	*3789.49*	*< 0.0001*	
Residual	0.11	6	0.018			
Lack of Fit	*0.11*	*2*	*0.054*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	1660.17	12				

FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9999
Adj R-Squared	0.9999
Pred R-Squared	0.9988
Adeq Precision	423.790

StageB2_Mean =

-213.14474	
+7.28618	* Supply
-5.15121	* CC
+0.13351	* Supply * CC
-0.065689	* Supply2
-0.057644	* CC2

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	3.307E-003	1	3.307E-003			
Model	0.012	4	2.964E-003	41.50	< 0.0001	significant
A-Supply	*5.709E-003*	*1*	*5.709E-003*	*79.93*	*< 0.0001*	
B-CC	*5.328E-003*	*1*	*5.328E-003*	*74.60*	*< 0.0001*	
AB	*6.563E-004*	*1*	*6.563E-004*	*9.19*	*0.0191*	
B^2	*1.218E-003*	*1*	*1.218E-003*	*17.05*	*0.0044*	
Residual	5.000E-004	7	7.142E-005			
Lack of Fit	*5.000E-004*	*3*	*1.667E-004*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.016	12				

R-Squared	0.9595
Adj R-Squared	0.9364
Pred R-Squared	0.7370
Adeq Precision	24.913

SLA =

+0.17629	
+8.26002E-003	* Supply
+0.025368	* CC
-2.00751E-004	* Supply * CC
-2.34182E-004	* CC2

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	125.66	1	125.66			
Model	3117.11	4	779.28	65.84	< 0.0001	significant
A-Supply	*935.50*	*1*	*935.50*	*79.04*	*< 0.0001*	
B-CC	*1683.73*	*1*	*1683.73*	*142.26*	*< 0.0001*	
AB	*434.61*	*1*	*434.61*	*36.72*	*0.0005*	
A^2	*46.08*	*1*	*46.08*	*3.89*	*0.0891*	
Residual	82.85	7	11.84			
Lack of Fit	*82.85*	*3*	*27.62*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	3325.62	12				

R-Squared	0.9741
Adj R-Squared	0.9593
Pred R-Squared	0.8404
Adeq Precision	24.017

Stage2_Max =

-327.20150	
+12.25116	* Supply
-8.75746	* CC
+0.16337	* Supply * CC
-0.10665	* Supply2

H.4 ANOVA AND MODEL EQUATION – RESPONSE 10 - HS – CONWIP – Period 2

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	3.923E-003	1	3.923E-003			
Model	0.032	4	7.907E-003	68.30	< 0.0001	significant
A-Supply	*0.018*	*1*	*0.018*	*156.55*	*< 0.0001*	
B-CC	*0.013*	*1*	*0.013*	*113.17*	*< 0.0001*	
A^2	*5.853E-004*	*1*	*5.853E-004*	*5.06*	*0.0593*	
B^2	*9.594E-004*	*1*	*9.594E-004*	*8.29*	*0.0237*	
Residual	8.104E-004	7	1.158E-004			
Lack of Fit	*8.104E-004*	*3*	*2.701E-004*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.036	12				

R-Squared	0.9750
Adj R-Squared	0.9607
Pred R-Squared	0.7651
Adeq Precision	27.569

SupplyAcc =
-0.36488
+0.043113 * Supply
+0.013617 * CC
-3.95157E-004 * Supply2
-2.16091E-004 * CC2

H.5 ANOVA AND MODEL EQUATION – RESPONSES 7,11,9 - HS – CONWIP – Period 3

ANOVA TABLE

Response 7 Stage2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	3.90	1	3.90			
Model	871.52	5	174.30	359.97	< 0.0001	significant
A-Supply	*166.86*	*1*	*166.86*	*344.60*	*< 0.0001*	
B-CC	*606.92*	*1*	*606.92*	*1253.39*	*< 0.0001*	
AB	*73.36*	*1*	*73.36*	*151.51*	*< 0.0001*	
A^2	*0.45*	*1*	*0.45*	*0.93*	*0.3716*	
B^2	*9.76*	*1*	*9.76*	*20.16*	*0.0042*	
Residual	2.91	6	0.48			
Lack of Fit	*2.91*	*2*	*1.45*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	878.33	12				

FINAL EQUATION ACTUAL FACTORS

R-Squared 0.9967
Adj R-Squared 0.9939
Pred R-Squared 0.9412
Adeq Precision 59.264

Stage2_Mean =
-15.08035
+0.83058 * Supply
-2.35499 * CC
+0.067121 * Supply * CC
-0.010973 * $Supply^2$
-0.021794 * CC^2

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	5.262E-003	1	5.262E-003			
Model	0.043	4	0.011	131.58	< 0.0001	significant
A-Supply	*0.011*	*1*	*0.011*	*134.33*	*< 0.0001*	
B-CC	*0.032*	*1*	*0.032*	*391.68*	*< 0.0001*	
A^2	*2.419E-004*	*1*	*2.419E-004*	*2.97*	*0.1286*	
B^2	*3.492E-003*	*1*	*3.492E-003*	*42.83*	*0.0003*	
Residual	5.706E-004	7	8.152E-005			
Lack of Fit	*5.706E-004*	*3*	*1.902E-004*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.049	12				

R-Squared 0.9869
Adj R-Squared 0.9794
Pred R-Squared 0.8732
Adeq Precision 37.241

SLA =
-0.92093
+0.038643 * Supply
+0.024199 * CC
-2.54059E-004 * $Supply^2$
-4.12242E-004 * CC^2

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	0.61	1	0.61			
Model	3387.31	3	1129.10	1007.87	< 0.0001	significant
A-Supply	*77.33*	*1*	*77.33*	*69.03*	*< 0.0001*	
B-CC	*3275.84*	*1*	*3275.84*	*2924.12*	*< 0.0001*	
AB	*33.86*	*1*	*33.86*	*30.23*	*0.0006*	
Residual	8.96	8	1.12			
Lack of Fit	*8.96*	*4*	*2.24*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	3396.88	12				

R-Squared 0.9974
Adj R-Squared 0.9964
Pred R-Squared 0.9740
Adeq Precision 79.426

Stage2_Max =
+32.55164
-0.39312 * Supply
-0.49876 * CC
+0.045600 * Supply * CC

H.6 ANOVA AND MODEL EQUATION – RESPONSES 10 - HS – CONWIP – Period 3

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	1.651E-003	1	1.651E-003			
Model	0.046	3	0.015	249.69	< 0.0001	significant
A-Supply	*0.012*	*1*	*0.012*	*199.61*	*< 0.0001*	
B-CC	*0.034*	*1*	*0.034*	*548.92*	*< 0.0001*	
B^2	*2.663E-003*	*1*	*2.663E-003*	*43.47*	*0.0002*	
Residual	4.902E-004	8	6.127E-005			
Lack of Fit	*4.902E-004*	*4*	*1.225E-004*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.048	12				

R-Squared	0.9894
Adj R-Squared	0.9855
Pred R-Squared	0.9053
Adeq Precision	48.775

SupplyAcc =
+1.02967
-6.31898E-003 * Supply
+0.021805 * CC
-3.46323E-004 * CC2

H.7 ANOVA AND MODEL EQUATION – RESPONSE 11 - MS – CONWIP – Periods 1,2 and 3

Response 11 SLA – Period 1

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	0.021	1	0.021			
Model	0.097	2	0.049	19.98	0.0005	significant
A-Supply	*0.066*	*1*	*0.066*	*27.20*	*0.0006*	
B-CC	*0.031*	*1*	*0.031*	*12.75*	*0.0060*	
Residual	0.022	9	2.436E-003			
Lack of Fit	*0.022*	*5*	*4.385E-003*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.14	12				

R-Squared	0.8162
Adj R-Squared	0.7753
Pred R-Squared	0.2122
Adeq Precision	13.518

SLA =
-1.02992
+0.029438 * Supply
+0.020128 * CC

Response 11 SLA – Period 2

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	7.088E-003	1	7.088E-003			
Model	0.060	2	0.030	58.42	< 0.0001	significant
A-Supply	*0.039*	*1*	*0.039*	*75.26*	*< 0.0001*	
B-CC	*0.021*	*1*	*0.021*	*41.57*	*0.0001*	
Residual	4.614E-003	9	5.127E-004			
Lack of Fit	*4.614E-003*	*5*	*9.229E-004*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.072	12				

R-Squared	0.9285
Adj R-Squared	0.9126
Pred R-Squared	0.7726
Adeq Precision	22.261

SLA =
-0.66196
+0.022463 * Supply
+0.016672 * CC

Response 11 SLA – Period 3

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Block	4.058E-003	1	4.058E-003			
Model	0.026	2	0.013	62.10	< 0.0001	significant
A-Supply	*5.067E-003*	*1*	*5.067E-003*	*24.56*	*0.0008*	
B-CC	*0.021*	*1*	*0.021*	*99.64*	*< 0.0001*	
Residual	1.857E-003	9	2.063E-004			
Lack of Fit	*1.857E-003*	*5*	*3.714E-004*			
Pure Error	*0.000*	*4*	*0.000*			
Cor Total	0.032	12				

R-Squared	0.9324
Adj R-Squared	0.9174
Pred R-Squared	0.8379
Adeq Precision	23.145

SLA =
+0.036789
+8.14044E-003 * Supply
+0.016373 * CC

H.8 ANOVA AND MODEL EQUATION – RESPONSES 7, 11 - HS – KCS – Period 1

ANOVA TABLE

Response 7 Stage2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	901.50	7	128.79	102.76	< 0.0001	significant
A-Supply	*185.26*	*1*	*185.26*	*147.82*	*< 0.0001*	
B-K1	*31.10*	*1*	*31.10*	*24.82*	*< 0.0001*	
C-K2	*448.06*	*1*	*448.06*	*357.51*	*< 0.0001*	
D-K3	*120.44*	*1*	*120.44*	*96.10*	*< 0.0001*	
AC	*27.66*	*1*	*27.66*	*22.07*	*0.0001*	
CD	*8.45*	*1*	*8.45*	*6.74*	*0.0165*	
D^2	*80.54*	*1*	*80.54*	*64.26*	*< 0.0001*	
Residual	27.57	22	1.25			
Lack of Fit	*27.57*	*17*	*1.62*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	929.07	29				

FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9703
Adj R-Squared	0.9609
Pred R-Squared	0.9339
Adeq Precision	37.704

Stage2_Mean =

+47.98211	
-0.73865	* Supply
+0.45096	* K1
-4.10118	* K2
-10.70909	* K3
+0.10309	* Supply * K2
-0.38039	* K2 * K3
+2.92128	* K32

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.19	9	0.021	289.63	< 0.0001	significant
A-Supply	*0.012*	*1*	*0.012*	*170.69*	*< 0.0001*	
B-K1	*4.793E-004*	*1*	*4.793E-004*	*6.59*	*0.0184*	
C-K2	*9.735E-004*	*1*	*9.735E-004*	*13.38*	*0.0016*	
D-K3	*0.11*	*1*	*0.11*	*1523.38*	*< 0.0001*	
AD	*1.065E-003*	*1*	*1.065E-003*	*14.65*	*0.0011*	
A^2	*9.320E-004*	*1*	*9.320E-004*	*12.81*	*0.0019*	
B^2	*3.646E-004*	*1*	*3.646E-004*	*5.01*	*0.0367*	
C^2	*5.163E-004*	*1*	*5.163E-004*	*7.10*	*0.0149*	
D^2	*0.063*	*1*	*0.063*	*872.15*	*< 0.0001*	
Residual	1.455E-003	20	7.274E-005			
Lack of Fit	*1.455E-003*	*15*	*9.698E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.19	29				

significant

R-Squared	0.9924
Adj R-Squared	0.9890
Pred R-Squared	0.9709
Adeq Precision	52.095

SLA =

-0.88977	
+0.029295	* Supply
+0.016073	* K1
+0.019544	* K2
+0.31215	* K3
+2.13461E-003	* Supply * K3
-2.28369E-004	* Supply2
-5.72100E-004	* K12
-6.80841E-004	* K22
-0.084010	* K32

H.9 ANOVA AND MODEL EQUATION – RESPONSES 9, 10 - HS – KCS – Period 1

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	873.72	9	97.08	56.05	< 0.0001
A-Supply	*57.99*	*1*	*57.99*	*33.48*	*< 0.0001*
B-K1	*24.14*	*1*	*24.14*	*13.94*	*0.0013*
C-K2	*644.45*	*1*	*644.45*	*372.09*	*< 0.0001*
D-K3	*47.12*	*1*	*47.12*	*27.21*	*< 0.0001*
AB	*14.33*	*1*	*14.33*	*8.27*	*0.0093*
AC	*23.28*	*1*	*23.28*	*13.44*	*0.0015*
CD	*14.14*	*1*	*14.14*	*8.16*	*0.0097*
A^2	*20.70*	*1*	*20.70*	*11.95*	*0.0025*
B^2	*32.76*	*1*	*32.76*	*18.91*	*0.0003*
Residual	34.64	20	1.73		
Lack of Fit	*34.64*	*15*	*2.31*		
Pure Error	*0.000*	*5*	*0.000*		
Cor Total	908.36	29			

R-Squared	0.9619
Adj R-Squared	0.9447
Pred R-Squared	0.9043
Adeq Precision	29.063

Stage2_Max =

-47.22636
+2.49514 * Supply
-0.16221 * K1
-2.97407 * K2
+4.29997 * K3
+0.074193 * Supply * K1
+0.094579 * Supply * K2
-0.49216 * K2 * K3
-0.033422 * Supply2
-0.16840 * K12

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.090	9	0.010	122.03	< 0.0001	significant
A-Supply	*0.049*	*1*	*0.049*	*600.94*	*< 0.0001*	
B-K1	*2.557E-003*	*1*	*2.557E-003*	*31.20*	*< 0.0001*	
C-K2	*2.433E-003*	*1*	*2.433E-003*	*29.69*	*< 0.0001*	
D-K3	*0.021*	*1*	*0.021*	*260.67*	*< 0.0001*	
AD	*9.727E-004*	*1*	*9.727E-004*	*11.87*	*0.0026*	
A^2	*1.273E-003*	*1*	*1.273E-003*	*15.53*	*0.0008*	
B^2	*6.641E-004*	*1*	*6.641E-004*	*8.10*	*0.0100*	
C^2	*3.982E-004*	*1*	*3.982E-004*	*4.86*	*0.0394*	
D^2	*0.013*	*1*	*0.013*	*158.59*	*< 0.0001*	
Residual	1.639E-003	20	8.195E-005			
Lack of Fit	*1.639E-003*	*15*	*1.093E-004*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.092	29				

R-Squared	0.9821
Adj R-Squared	0.9741
Pred R-Squared	0.9341
Adeq Precision	45.167

SupplyAccuracy =

+0.13621
+0.020977 * Supply
+0.023393 * K1
+0.018936 * K2
+0.071057 * K3
+2.03977E-003 * Supply * K3
-2.66848E-004 * $Supply^2$
-7.72174E-004 * $K1^2$
-5.97884E-004 * $K2^2$
-0.038026 * $K3^2$

H.10 ANOVA AND MODEL EQUATION – RESPONSES 7, 11 - HS – KCS – Period 2

ANOVA TABLE

Response 7 Stage2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	834.45	8	104.31	75.06	< 0.0001	significant
A-Supply	*158.35*	*1*	*158.35*	*113.95*	*< 0.0001*	
B-K1	*59.51*	*1*	*59.51*	*42.82*	*< 0.0001*	
C-K2	*401.69*	*1*	*401.69*	*289.06*	*< 0.0001*	
D-K3	*98.59*	*1*	*98.59*	*70.95*	*< 0.0001*	
AC	*32.89*	*1*	*32.89*	*23.67*	*< 0.0001*	
A^2	*9.70*	*1*	*9.70*	*6.98*	*0.0152*	
B^2	*8.01*	*1*	*8.01*	*5.76*	*0.0257*	
D^2	*55.51*	*1*	*55.51*	*39.95*	*< 0.0001*	
Residual	29.18	21	1.39			
Lack of Fit	*29.18*	*16*	*1.82*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	863.63	29				

FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9662
Adj R-Squared	0.9533
Pred R-Squared	0.9054
Adeq Precision	31.828

Stage2_Mean =

-43.97733	
+2.06838	* Supply
+2.72158	* K1
-5.60624	* K2
-13.20623	* K3
+0.11242	* Supply * K2
-0.023063	* Supply2
-0.083912	* K12
+2.45967	* K32

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.19	10	0.019	286.17	< 0.0001	significant
A-Supply	*5.038E-003*	*1*	*5.038E-003*	*76.21*	*< 0.0001*	
B-K1	*1.822E-003*	*1*	*1.822E-003*	*27.56*	*< 0.0001*	
C-K2	*1.501E-003*	*1*	*1.501E-003*	*22.70*	*0.0001*	
D-K3	*0.12*	*1*	*0.12*	*1764.73*	*< 0.0001*	
AD	*3.689E-004*	*1*	*3.689E-004*	*5.58*	*0.0290*	
BD	*3.031E-004*	*1*	*3.031E-004*	*4.59*	*0.0454*	
A^2	*4.929E-004*	*1*	*4.929E-004*	*7.46*	*0.0133*	
B^2	*8.285E-004*	*1*	*8.285E-004*	*12.53*	*0.0022*	
C^2	*4.024E-004*	*1*	*4.024E-004*	*6.09*	*0.0233*	
D^2	*0.063*	*1*	*0.063*	*954.06*	*< 0.0001*	
Residual	1.256E-003	19	6.611E-005			
Lack of Fit	*1.256E-003*	*14*	*8.972E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.19	29				

FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9934
Adj R-Squared	0.9899
Pred R-Squared	0.9796
Adeq Precision	48.378

SLA =

-0.66087	
+0.021532	* Supply
+0.020136	* K1
+0.018158	* K2
+0.34143	* K3
+1.25621E-003	* Supply * K3
+2.27887E-003	* K1 * K3
-1.66073E-004	* Supply2
-8.62453E-004	* K12
-6.01028E-004	* K22
-0.083767	* K32

H.11 ANOVA AND MODEL EQUATION – RESPONSES 9, 10 - HS – KCS – Period 2

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1033.64	10	103.36	52.21	< 0.0001	significant
A-Supply	*95.37*	*1*	*95.37*	*48.17*	*< 0.0001*	
B-K1	*77.32*	*1*	*77.32*	*39.05*	*< 0.0001*	
C-K2	*650.04*	*1*	*650.04*	*328.32*	*< 0.0001*	
D-K3	*44.28*	*1*	*44.28*	*22.36*	*0.0001*	
AB	*17.89*	*1*	*17.89*	*9.04*	*0.0073*	
AC	*55.35*	*1*	*55.35*	*27.96*	*< 0.0001*	
AD	*13.21*	*1*	*13.21*	*6.67*	*0.0182*	
CD	*17.10*	*1*	*17.10*	*8.64*	*0.0084*	
B^2	*17.99*	*1*	*17.99*	*9.09*	*0.0071*	
D^2	*38.47*	*1*	*38.47*	*19.43*	*0.0003*	
Residual	37.62	19	1.98			
Lack of Fit	*37.62*	*14*	*2.69*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	1071.25	29				

R-Squared	0.9649
Adj R-Squared	0.9464
Pred R-Squared	0.8892
Adeq Precision	29.797

Stage2_Max =
+174.01725
-2.97362 * Supply
-1.49944 * K1
-6.15535 * K2
-19.00675 * K3
+0.082916 * Supply * K1
+0.14584 * Supply * K2
+0.23773 * Supply * K3
-0.54124 * K2 * K3
-0.12479 * $K1^2$
+2.03143 * $K3^2$

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.093	7	0.013	115.88	< 0.0001	significant
A-Supply	*0.053*	*1*	*0.053*	*461.48*	*< 0.0001*	
B-K1	*4.374E-003*	*1*	*4.374E-003*	*38.21*	*< 0.0001*	
C-K2	*2.343E-003*	*1*	*2.343E-003*	*20.47*	*0.0002*	
D-K3	*0.021*	*1*	*0.021*	*183.99*	*< 0.0001*	
AD	*5.391E-004*	*1*	*5.391E-004*	*4.71*	*0.0411*	
A^2	*5.057E-004*	*1*	*5.057E-004*	*4.42*	*0.0472*	
D^2	*0.012*	*1*	*0.012*	*101.35*	*< 0.0001*	
Residual	2.518E-003	22	1.145E-004			
Lack of Fit	*2.518E-003*	*17*	*1.481E-004*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.095	29				

R-Squared	0.9736
Adj R-Squared	0.9652
Pred R-Squared	0.9311
Adeq Precision	44.468

SupplyAccuracy =
+0.70292
+8.70312E-003 * Supply
+5.34806E-003 * K1
+3.91405E-003 * K2
+0.092533 * K3
+1.51847E-003 * Supply * K3
-1.65191E-004 * $Supply^2$
-0.035279 * $K3^2$

H.12 ANOVA AND MODEL EQUATION – RESPONSES 7, 11, 9 - HS – KCS – Period 3

ANOVA TABLE

Response 7 Stage2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	607.86	8	75.98	88.50	< 0.0001	significant
A-Supply	*56.36*	*1*	*56.36*	*65.64*	*< 0.0001*	
B-K1	*79.35*	*1*	*79.35*	*92.42*	*< 0.0001*	
C-K2	*314.63*	*1*	*314.63*	*366.47*	*< 0.0001*	
D-K3	*76.83*	*1*	*76.83*	*89.49*	*< 0.0001*	
AC	*16.29*	*1*	*16.29*	*18.98*	*0.0005*	
BC	*11.10*	*1*	*11.10*	*12.93*	*0.0024*	
CD	*9.53*	*1*	*9.53*	*11.10*	*0.0042*	
D^2	*43.79*	*1*	*43.79*	*51.00*	*< 0.0001*	
Residual	13.74	16	0.86			
Cor Total	621.60	24				

FINAL EQUATION ACTUAL FACTORS

R-Squared 0.9779
Adj R-Squared 0.9669
Pred R-Squared 0.9299
Adeq Precision 32.142

Stage2_Mean =
+56.62137
-0.68577 * Supply
-0.91341 * K1
-4.42144 * K2
-7.21721 * K3
+0.079126 * Supply * K2
+0.13070 * K1 * K2
-0.40401 * K2 * K3
+2.31369 * K32

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.14	6	0.024	86.73	< 0.0001	significant
A-Supply	*0.018*	*1*	*0.018*	*64.39*	*< 0.0001*	
B-K1	*0.028*	*1*	*0.028*	*99.95*	*< 0.0001*	
C-K2	*7.149E-003*	*1*	*7.149E-003*	*25.79*	*< 0.0001*	
D-K3	*0.068*	*1*	*0.068*	*245.85*	*< 0.0001*	
BD	*1.079E-003*	*1*	*1.079E-003*	*3.89*	*0.0641*	
D^2	*0.022*	*1*	*0.022*	*80.52*	*< 0.0001*	
Residual	4.990E-003	18	2.772E-004			
Cor Total	0.15	24				

R-Squared 0.9666
Adj R-Squared 0.9554
Pred R-Squared 0.9378
Adeq Precision 29.552

SLA =
-0.091597
+5.39780E-003 * Supply
+4.25989E-003 * K1
+6.83710E-003 * K2
+0.24029 * K3
+4.29887E-003 * K1 * K3
-0.052241 * K32

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	944.63	6	157.44	38.66	< 0.0001	significant
A-Supply	*32.11*	*1*	*32.11*	*7.89*	*0.0116*	
B-K1	*123.84*	*1*	*123.84*	*30.41*	*< 0.0001*	
C-K2	*687.51*	*1*	*687.51*	*168.83*	*< 0.0001*	
D-K3	*55.69*	*1*	*55.69*	*13.67*	*0.0016*	
CD	*17.51*	*1*	*17.51*	*4.30*	*0.0527*	
B^2	*27.97*	*1*	*27.97*	*6.87*	*0.0173*	
Residual	73.30	18	4.07			
Cor Total	1017.93	24				

R-Squared 0.9280
Adj R-Squared 0.9040
Pred R-Squared 0.8525
Adeq Precision 23.145

Stage2_Max =
-49.82158
+0.22895 * Supply
+5.05248 * K1
+3.29248 * K2
+4.83413 * K3
-0.54779 * K2 * K3
-0.16610 * $K1^2$

H.13 ANOVA AND MODEL EQUATION – RESPONSES 10 - HS – KCS – Period 3

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.076	6	0.013	149.26	< 0.0001	significant
A-Supply	*0.034*	*1*	*0.034*	*407.21*	*< 0.0001*	
B-K1	*0.024*	*1*	*0.024*	*284.98*	*< 0.0001*	
C-K2	*9.846E-003*	*1*	*9.846E-003*	*116.22*	*< 0.0001*	
D-K3	*5.716E-003*	*1*	*5.716E-003*	*67.48*	*< 0.0001*	
B^2	*4.062E-004*	*1*	*4.062E-004*	*4.79*	*0.0420*	
D^2	*1.579E-003*	*1*	*1.579E-003*	*18.64*	*0.0004*	
Residual	1.525E-003	18	8.471E-005			
Cor Total	0.077	24				

R-Squared	0.9803
Adj R-Squared	0.9737
Pred R-Squared	0.9628
Adeq Precision	40.437

SupplyAccuracy =
+0.89974
-7.50397E-003 * Supply
+0.029060 * K1
+8.02344E-003 * K2
+0.082378 * K3
-6.59840E-004 * $K1^2$
-0.014482 * $K3^2$

H.14 ANOVA AND MODEL EQUATION – RESPONSE 11 – MS – KCS – Periods 1, 2 and 3

ANOVA TABLE

Response 11 SLA – Period 1

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.059	3	0.020	13.57	< 0.0001	significant
A-Supply	*0.054*	*1*	*0.054*	*37.02*	*< 0.0001*	
B-K1	*2.541E-004*	*1*	*2.541E-004*	*0.17*	*0.6798*	
AB	*5.121E-003*	*1*	*5.121E-003*	*3.51*	*0.0722*	
Residual	0.038	26	1.458E-003			
Lack of Fit	*0.028*	*21*	*1.315E-003*	*0.64*	*0.7875*	*not significant*
Pure Error	*0.010*	*5*	*2.061E-003*			
Cor Total	0.097	29				

METRICS AND FINAL EQUATION ACTUAL FACTORS

R-Squared	0.6102
Adj R-Squared	0.5653
Pred R-Squared	0.3671
Adeq Precision	14.753

SLA =
-1.98705
+0.053881 * Supply
+0.13909 * K1
-2.80749E-003 * Supply * K1

Response 11 SLA – Period 2

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.073	5	0.015	195.00	< 0.0001	significant
A-Supply	*0.057*	*1*	*0.057*	*753.75*	*< 0.0001*	
D-K3	*9.343E-003*	*1*	*9.343E-003*	*124.25*	*< 0.0001*	
AD	*9.242E-004*	*1*	*9.242E-004*	*12.29*	*0.0018*	
A^2	*3.235E-004*	*1*	*3.235E-004*	*4.30*	*0.0490*	
D^2	*5.666E-003*	*1*	*5.666E-003*	*75.36*	*< 0.0001*	
Residual	1.805E-003	24	7.519E-005			
Lack of Fit	*1.805E-003*	*19*	*9.498E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.075	29				

R-Squared	0.9760
Adj R-Squared	0.9710
Pred R-Squared	0.9277
Adeq Precision	49.834

SLA =
+1.29328
-0.042186 * Supply
-0.067367 * K3
+3.97935E-003 * Supply * K3
+5.29201E-004 * $Supply^2$
-0.024655 * $K3^2$

Response 11 SLA – Period 3

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.074	13	5.722E-003	296.76	< 0.0001	significant
A-Supply	*0.026*	*1*	*0.026*	*1366.58*	*< 0.0001*	
B-K1	*9.910E-003*	*1*	*9.910E-003*	*513.99*	*< 0.0001*	
C-K2	*5.384E-004*	*1*	*5.384E-004*	*27.92*	*< 0.0001*	
D-K3	*0.024*	*1*	*0.024*	*1255.61*	*< 0.0001*	
AB	*2.062E-004*	*1*	*2.062E-004*	*10.70*	*0.0048*	
AC	*1.045E-004*	*1*	*1.045E-004*	*5.42*	*0.0333*	
AD	*5.850E-004*	*1*	*5.850E-004*	*30.34*	*< 0.0001*	
BD	*1.291E-004*	*1*	*1.291E-004*	*6.70*	*0.0198*	
CD	*8.645E-005*	*1*	*8.645E-005*	*4.48*	*0.0502*	
A^2	*1.347E-003*	*1*	*1.347E-003*	*69.89*	*< 0.0001*	
B^2	*8.707E-004*	*1*	*8.707E-004*	*45.16*	*< 0.0001*	
C^2	*1.423E-004*	*1*	*1.423E-004*	*7.38*	*0.0153*	
D^2	*0.012*	*1*	*0.012*	*602.01*	*< 0.0001*	
Residual	3.085E-004	16	1.928E-005			
Lack of Fit	*3.085E-004*	*11*	*2.804E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.075	29				

R-Squared	0.9959
Adj R-Squared	0.9925
Pred R-Squared	0.9784
Adeq Precision	64.119

SLA =
-2.34810
+0.10428 * Supply
-1.19758E-003 * K1
-6.64043E-003 * K2
+0.034111 * K3
+5.63368E-004 * Supply * K1
+4.01109E-004 * Supply * K2
+3.16578E-003 * Supply * K3
+1.48736E-003 * K1 * K3
-1.21701E-003 * K2 * K3
-1.09987E-003 * $Supply^2$
-8.84167E-004 * $K1^2$
-3.57374E-004 * $K2^2$
-0.035935 * $K3^2$

H.15 ANOVA AND MODEL EQUATION – RESPONSES 7, 11 – HS – CONWIP/KCS – Period 1

ANOVA TABLE

Response 7 Stage2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1098.15	14	78.44	97.78	< 0.0001	significant
A-Supply	*212.37*	*1*	*212.37*	*264.75*	*< 0.0001*	
B-K1	*30.30*	*1*	*30.30*	*37.77*	*< 0.0001*	
C-K2	*356.36*	*1*	*356.36*	*444.24*	*< 0.0001*	
D-K3	*168.39*	*1*	*168.39*	*209.92*	*< 0.0001*	
E-CC	*93.60*	*1*	*93.60*	*116.68*	*< 0.0001*	
AB	*3.61*	*1*	*3.61*	*4.50*	*0.0421*	
AC	*21.17*	*1*	*21.17*	*26.39*	*< 0.0001*	
CD	*5.50*	*1*	*5.50*	*6.85*	*0.0136*	
CE	*19.02*	*1*	*19.02*	*23.71*	*< 0.0001*	
A^2	*2.97*	*1*	*2.97*	*3.71*	*0.0634*	
B^2	*8.78*	*1*	*8.78*	*10.94*	*0.0024*	
C^2	*13.92*	*1*	*13.92*	*17.35*	*0.0002*	
D^2	*83.08*	*1*	*83.08*	*103.57*	*< 0.0001*	
E^2	*30.96*	*1*	*30.96*	*38.59*	*< 0.0001*	
Residual	24.87	31	0.80			
Lack of Fit	*24.87*	*26*	*0.96*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	1123.02	45				

FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9779
Adj R-Squared	0.9679
Pred R-Squared	0.9347
Adeq Precision	38.102

Stage2_Mean =

+3.60652
+0.38713 * Supply
-0.040299 * K1
-2.86797 * K2
-10.72978 * K3
+0.58739 * CC
+0.037227 * Supply * K1
+0.090185 * Supply * K2
-0.30689 * K2 * K3
+0.085483 * K2 * CC
-0.011432 * $Supply^2$
-0.078694 * $K1^2$
-0.099086 * $K2^2$
+2.69485 * $K3^2$
-0.036892 * CC^2

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.25	12	0.021	300.35	< 0.0001	significant
A-Supply	*0.014*	*1*	*0.014*	*198.97*	*< 0.0001*	
B-K1	*1.758E-003*	*1*	*1.758E-003*	*25.50*	*< 0.0001*	
C-K2	*4.723E-004*	*1*	*4.723E-004*	*6.85*	*0.0133*	
D-K3	*0.14*	*1*	*0.14*	*2058.12*	*< 0.0001*	
E-CC	*3.676E-003*	*1*	*3.676E-003*	*53.31*	*< 0.0001*	
AD	*8.127E-004*	*1*	*8.127E-004*	*11.79*	*0.0016*	
DE	*2.576E-004*	*1*	*2.576E-004*	*3.74*	*0.0619*	
A^2	*1.786E-003*	*1*	*1.786E-003*	*25.90*	*< 0.0001*	
B^2	*1.056E-003*	*1*	*1.056E-003*	*15.32*	*0.0004*	
C^2	*4.976E-004*	*1*	*4.976E-004*	*7.22*	*0.0112*	
D^2	*0.081*	*1*	*0.081*	*1173.32*	*< 0.0001*	
E^2	*2.343E-003*	*1*	*2.343E-003*	*33.98*	*< 0.0001*	
Residual	2.276E-003	33	6.896E-005			
Lack of Fit	*2.276E-003*	*28*	*8.127E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.25	45				

R-Squared	0.9909
Adj R-Squared	0.9876
Pred R-Squared	0.9785
Adeq Precision	55.936

SLA =

-1.24566
+0.036135 * Supply
+0.024518 * K1
+0.016334 * K2
+0.30937 * K3
+0.011336 * CC
+1.86444E-003 * Supply * K3
+1.04971E-003 * K3 * CC
-2.80207E-004 * $Supply^2$
-8.63256E-004 * $K1^2$
-5.92495E-004 * $K2^2$
-0.084100 * $K3^2$
-3.20950E-004 * CC^2

H.16 ANOVA AND MODEL EQUATION – RESPONSES 9, 10 - HS – CONWIP/KCS – Period 1

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1001.38	10	100.14	50.11	< 0.0001	significant
A-Supply	*90.73*	*1*	*90.73*	*45.40*	*< 0.0001*	
C-K2	*639.71*	*1*	*639.71*	*320.10*	*< 0.0001*	
D-K3	*27.75*	*1*	*27.75*	*13.88*	*0.0007*	
E-CC	*92.59*	*1*	*92.59*	*46.33*	*< 0.0001*	
CD	*9.09*	*1*	*9.09*	*4.55*	*0.0400*	
CE	*17.10*	*1*	*17.10*	*8.56*	*0.0060*	
A^2	*30.36*	*1*	*30.36*	*15.19*	*0.0004*	
C^2	*9.50*	*1*	*9.50*	*4.75*	*0.0361*	
D^2	*12.43*	*1*	*12.43*	*6.22*	*0.0175*	
E^2	*68.75*	*1*	*68.75*	*34.40*	*< 0.0001*	
Residual	69.95	35	2.00			
Lack of Fit	*69.95*	*30*	*2.33*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	1071.33	45				

R-Squared	0.9347
Adj R-Squared	0.9161
Pred R-Squared	0.8326
Adeq Precision	30.080

Stage2_Max =
-168.72556
+4.85258 * Supply
+3.13720 * K2
-0.58938 * K3
+1.21236 * CC
-0.39464 * K2 * K3
+0.081054 * K2 * CC
-0.035151 * $Supply^2$
-0.078748 * $K2^2$
+1.00273 * $K3^2$
-0.052894 * CC^2

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.25	12	0.021	300.35	< 0.0001	significant
A-Supply	*0.014*	*1*	*0.014*	*198.97*	*< 0.0001*	
B-K1	*1.758E-003*	*1*	*1.758E-003*	*25.50*	*< 0.0001*	
C-K2	*4.723E-004*	*1*	*4.723E-004*	*6.85*	*0.0133*	
D-K3	*0.14*	*1*	*0.14*	*2058.12*	*< 0.0001*	
E-CC	*3.676E-003*	*1*	*3.676E-003*	*53.31*	*< 0.0001*	
AD	*8.127E-004*	*1*	*8.127E-004*	*11.79*	*0.0016*	
DE	*2.576E-004*	*1*	*2.576E-004*	*3.74*	*0.0619*	
A^2	*1.786E-003*	*1*	*1.786E-003*	*25.90*	*< 0.0001*	
B^2	*1.056E-003*	*1*	*1.056E-003*	*15.32*	*0.0004*	
C^2	*4.976E-004*	*1*	*4.976E-004*	*7.22*	*0.0112*	
D^2	*0.081*	*1*	*0.081*	*1173.32*	*< 0.0001*	
E^2	*2.343E-003*	*1*	*2.343E-003*	*33.98*	*< 0.0001*	
Residual	2.276E-003	33	6.896E-005			
Lack of Fit	*2.276E-003*	*28*	*8.127E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.25	45				

R-Squared	0.9909
Adj R-Squared	0.9876
Pred R-Squared	0.9785
Adeq Precision	55.936

SLA =
-1.24566
+0.036135 * Supply
+0.024518 * K1
+0.016334 * K2
+0.30937 * K3
+0.011336 * CC
+1.86444E-003 * Supply * K3
+1.04971E-003 * K3 * CC
-2.80207E-004 * $Supply^2$
-8.63256E-004 * $K1^2$
-5.92495E-004 * $K2^2$
-0.084100 * $K3^2$
-3.20950E-004 * CC^2

H.17 ANOVA AND MODEL EQUATION – RESPONSES 7, 11 - HS – CONWIP/KCS – Period 2

ANOVA TABLE

Response 7 Stage2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	861.38	14	61.53	86.35	< 0.0001	significant
A-Supply	*156.06*	*1*	*156.06*	*219.03*	*< 0.0001*	
B-K1	*51.45*	*1*	*51.45*	*72.21*	*< 0.0001*	
C-K2	*328.89*	*1*	*328.89*	*461.59*	*< 0.0001*	
D-K3	*116.13*	*1*	*116.13*	*162.99*	*< 0.0001*	
E-CC	*45.03*	*1*	*45.03*	*63.19*	*< 0.0001*	
AC	*24.54*	*1*	*24.54*	*34.44*	*< 0.0001*	
BE	*5.71*	*1*	*5.71*	*8.02*	*0.0081*	
CD	*4.02*	*1*	*4.02*	*5.65*	*0.0239*	
CE	*14.34*	*1*	*14.34*	*20.13*	*< 0.0001*	
A^2	*6.49*	*1*	*6.49*	*9.11*	*0.0050*	
B^2	*5.76*	*1*	*5.76*	*8.09*	*0.0078*	
C^2	*2.59*	*1*	*2.59*	*3.63*	*0.0660*	
D^2	*53.56*	*1*	*53.56*	*75.17*	*< 0.0001*	
E^2	*16.84*	*1*	*16.84*	*23.63*	*< 0.0001*	
Residual	22.09	31	0.71			
Lack of Fit	*22.09*	*26*	*0.85*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	883.47	45				

FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9750
Adj R-Squared	0.9637
Pred R-Squared	0.9268
Adeq Precision	37.027

Stage2_Mean =

-19.37822
+1.39565 * Supply
+1.25956 * K1
-4.66810 * K2
-8.49723 * K3
-0.30712 * CC
+0.097106 * Supply * K2
+0.046848 * K1 * CC
-0.26254 * K2 * K3
+0.074237 * K2 * CC
-0.016897 * $Supply^2$
-0.063750 * $K1^2$
-0.042722 * $K2^2$
+2.16382 * $K3^2$
-0.027210 * CC^2

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.24	12	0.020	208.58	< 0.0001	significant
A-Supply	*0.012*	*1*	*0.012*	*122.21*	*< 0.0001*	
B-K1	*4.331E-003*	*1*	*4.331E-003*	*44.55*	*< 0.0001*	
C-K2	*1.269E-003*	*1*	*1.269E-003*	*13.05*	*0.0010*	
D-K3	*0.14*	*1*	*0.14*	*1410.42*	*< 0.0001*	
E-CC	*1.574E-003*	*1*	*1.574E-003*	*16.19*	*0.0003*	
AD	*7.242E-004*	*1*	*7.242E-004*	*7.45*	*0.0101*	
BD	*3.402E-004*	*1*	*3.402E-004*	*3.50*	*0.0703*	
BE	*4.641E-004*	*1*	*4.641E-004*	*4.77*	*0.0361*	
CE	*4.268E-004*	*1*	*4.268E-004*	*4.39*	*0.0439*	
A^2	*4.581E-004*	*1*	*4.581E-004*	*4.71*	*0.0372*	
D^2	*0.084*	*1*	*0.084*	*862.77*	*< 0.0001*	
E^2	*7.158E-004*	*1*	*7.158E-004*	*7.36*	*0.0105*	
Residual	3.208E-003	33	9.722E-005			
Lack of Fit	*3.208E-003*	*28*	*1.146E-004*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.25	45				

R-Squared	0.9870
Adj R-Squared	0.9823
Pred R-Squared	0.9726
Adeq Precision	46.207

SLA =

-0.17456
+0.017195 * Supply
-8.09719E-003 * K1
-4.73602E-003 * K2
+0.28760 * K3
-2.99883E-003 * CC
+1.76004E-003 * Supply * K3
+2.41422E-003 * K1 * K3
+4.22265E-004 * K1 * CC
+4.04947E-004 * K2 * CC
-1.33373E-004 * $Supply^2$
-0.080468 * $K3^2$
-1.66711E-004 * CC^2

H.18 ANOVA AND MODEL EQUATION – RESPONSES 9, 10 - HS – CONWIP/KCS – Period 2

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	1200.14	14	85.72	43.10	< 0.0001	significant
A-Supply	*152.28*	*1*	*152.28*	*76.56*	*< 0.0001*	
B-K1	*85.84*	*1*	*85.84*	*43.16*	*< 0.0001*	
C-K2	*686.57*	*1*	*686.57*	*345.20*	*< 0.0001*	
D-K3	*62.65*	*1*	*62.65*	*31.50*	*< 0.0001*	
E-CC	*25.73*	*1*	*25.73*	*12.94*	*0.0011*	
AB	*15.41*	*1*	*15.41*	*7.75*	*0.0091*	
AC	*53.73*	*1*	*53.73*	*27.01*	*< 0.0001*	
AD	*6.60*	*1*	*6.60*	*3.32*	*0.0781*	
BC	*6.50*	*1*	*6.50*	*3.27*	*0.0803*	
BE	*11.36*	*1*	*11.36*	*5.71*	*0.0231*	
CD	*12.82*	*1*	*12.82*	*6.44*	*0.0164*	
A^2	*8.28*	*1*	*8.28*	*4.16*	*0.0499*	
C^2	*13.83*	*1*	*13.83*	*6.95*	*0.0130*	
D^2	*74.58*	*1*	*74.58*	*37.50*	*< 0.0001*	
Residual	61.66	31	1.99			
Lack of Fit	*61.66*	*26*	*2.37*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	1261.79	45				

R-Squared 0.9511
Adj R-Squared 0.9291
Pred R-Squared 0.8855
Adeq Precision 30.246

Stage2_Max =
+264.69933
-4.99111 * Supply
-4.22611 * K1
-7.46878 * K2
-17.06634 * K3
-0.64825 * CC
+0.076938 * Supply * K1
+0.14368 * Supply * K2
+0.16808 * Supply * K3
-0.10004 * K1 * K2
+0.066059 * K1 * CC
-0.46860 * K2 * K3
+0.017931 * $Supply^2$
+0.092815 * $K2^2$
+2.39941 * $K3^2$

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.24	12	0.020	208.58	< 0.0001	significant
A-Supply	*0.012*	*1*	*0.012*	*122.21*	*< 0.0001*	
B-K1	*4.331E-003*	*1*	*4.331E-003*	*44.55*	*< 0.0001*	
C-K2	*1.269E-003*	*1*	*1.269E-003*	*13.05*	*0.0010*	
D-K3	*0.14*	*1*	*0.14*	*1410.42*	*< 0.0001*	
E-CC	*1.574E-003*	*1*	*1.574E-003*	*16.19*	*0.0003*	
AD	*7.242E-004*	*1*	*7.242E-004*	*7.45*	*0.0101*	
BD	*3.402E-004*	*1*	*3.402E-004*	*3.50*	*0.0703*	
BE	*4.641E-004*	*1*	*4.641E-004*	*4.77*	*0.0361*	
CE	*4.268E-004*	*1*	*4.268E-004*	*4.39*	*0.0439*	
A^2	*4.581E-004*	*1*	*4.581E-004*	*4.71*	*0.0372*	
D^2	*0.084*	*1*	*0.084*	*862.77*	*< 0.0001*	
E^2	*7.158E-004*	*1*	*7.158E-004*	*7.36*	*0.0105*	
Residual	3.208E-003	33	9.722E-005			
Lack of Fit	*3.208E-003*	*28*	*1.146E-004*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.25	45				

R-Squared 0.9870
Adj R-Squared 0.9823
Pred R-Squared 0.9726
Adeq Precision 46.207

SLA =
-0.17456
+0.017195 * Supply
-8.09719E-003 * K1
-4.73602E-003 * K2
+0.28760 * K3
-2.99883E-003 * CC
+1.76004E-003 * Supply * K3
+2.41422E-003 * K1 * K3
+4.22265E-004 * K1 * CC
+4.04947E-004 * K2 * CC
-1.33373E-004 * $Supply^2$
-0.080468 * $K3^2$
-1.66711E-004 * CC^2

H.19 ANOVA AND MODEL EQUATION – RESPONSES 7, 11 - HS – CONWIP/KCS – Period 3

ANOVA TABLE

Response 7 Stage2_Mean

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	462.55	15	30.84	114.49	< 0.0001	significant
A-Supply	*44.98*	*1*	*44.98*	*167.00*	*< 0.0001*	
B-K1	*30.10*	*1*	*30.10*	*111.77*	*< 0.0001*	
C-K2	*216.76*	*1*	*216.76*	*804.82*	*< 0.0001*	
D-K3	*59.96*	*1*	*59.96*	*222.62*	*< 0.0001*	
E-CC	*27.79*	*1*	*27.79*	*103.19*	*< 0.0001*	
AC	*4.64*	*1*	*4.64*	*17.22*	*0.0003*	
BC	*1.42*	*1*	*1.42*	*5.26*	*0.0290*	
BE	*3.12*	*1*	*3.12*	*11.58*	*0.0019*	
CD	*2.04*	*1*	*2.04*	*7.59*	*0.0099*	
CE	*9.04*	*1*	*9.04*	*33.57*	*< 0.0001*	
A^2	*2.40*	*1*	*2.40*	*8.92*	*0.0056*	
B^2	*1.91*	*1*	*1.91*	*7.09*	*0.0123*	
C^2	*4.54*	*1*	*4.54*	*16.87*	*0.0003*	
D^2	*29.41*	*1*	*29.41*	*109.22*	*< 0.0001*	
E^2	*8.14*	*1*	*8.14*	*30.23*	*< 0.0001*	
Residual	8.08	30	0.27			
Lack of Fit	*8.08*	*25*	*0.32*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	470.63	45				

FINAL EQUATION ACTUAL FACTORS

R-Squared	0.9828
Adj R-Squared	0.9742
Pred R-Squared	0.9415
Adeq Precision	42.775

Stage2_Mean =

-16.12667
+1.02824 * Supply
+0.099958 * K1
-1.50263 * K2
-6.33284 * K3
-0.30937 * CC
+0.042211 * Supply * K2
+0.046688 * K1 * K2
+0.034620 * K1 * CC
-0.18715 * K2 * K3
+0.058937 * K2 * CC
-0.010276 * $Supply^2$
-0.036700 * $K1^2$
-0.056613 * $K2^2$
+1.60352 * $K3^2$
-0.018920 * CC^2

Response 11 SLA

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.18	13	0.014	185.74	< 0.0001	significant
A-Supply	*0.017*	*1*	*0.017*	*227.62*	*< 0.0001*	
B-K1	*0.013*	*1*	*0.013*	*171.16*	*< 0.0001*	
C-K2	*1.255E-003*	*1*	*1.255E-003*	*16.90*	*0.0003*	
D-K3	*0.086*	*1*	*0.086*	*1159.72*	*< 0.0001*	
E-CC	*9.779E-003*	*1*	*9.779E-003*	*131.68*	*< 0.0001*	
BC	*3.006E-004*	*1*	*3.006E-004*	*4.05*	*0.0527*	
BE	*9.162E-004*	*1*	*9.162E-004*	*12.34*	*0.0013*	
CE	*6.078E-004*	*1*	*6.078E-004*	*8.18*	*0.0074*	
A^2	*3.272E-003*	*1*	*3.272E-003*	*44.07*	*< 0.0001*	
B^2	*7.960E-004*	*1*	*7.960E-004*	*10.72*	*0.0025*	
C^2	*3.103E-004*	*1*	*3.103E-004*	*4.18*	*0.0493*	
D^2	*0.048*	*1*	*0.048*	*645.63*	*< 0.0001*	
E^2	*3.588E-003*	*1*	*3.588E-003*	*48.32*	*< 0.0001*	
Residual	2.376E-003	32	7.426E-005			
Lack of Fit	*2.376E-003*	*27*	*8.802E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.18	45				

R-Squared	0.9869
Adj R-Squared	0.9816
Pred R-Squared	0.9669
Adeq Precision	49.971

SLA =

-1.87681
+0.053316 * Supply
+0.024536 * K1
+0.014049 * K2
+0.34565 * K3
+4.18654E-003 * CC
-6.80146E-004 * K1 * K2
+5.93336E-004 * K1 * CC
+4.83271E-004 * K2 * CC
-3.79306E-004 * $Supply^2$
-7.49346E-004 * $K1^2$
-4.67826E-004 * $K2^2$
-0.064740 * $K3^2$
-3.97201E-004 * CC^2

H.20 ANOVA AND MODEL EQUATION – RESPONSES 9, 10 - HS – CONWIP/KCS – Period 3

Response 9 StageB2_Max

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	769.74	11	69.98	42.65	< 0.0001	significant
A-Supply	*7.63*	*1*	*7.63*	*4.65*	*0.0382*	
B-K1	*68.31*	*1*	*68.31*	*41.63*	*< 0.0001*	
C-K2	*543.36*	*1*	*543.36*	*331.14*	*< 0.0001*	
D-K3	*21.86*	*1*	*21.86*	*13.32*	*0.0009*	
E-CC	*50.80*	*1*	*50.80*	*30.96*	*< 0.0001*	
AE	*6.84*	*1*	*6.84*	*4.17*	*0.0490*	
BE	*6.18*	*1*	*6.18*	*3.76*	*0.0607*	
CE	*9.06*	*1*	*9.06*	*5.52*	*0.0247*	
B^2	*12.38*	*1*	*12.38*	*7.55*	*0.0095*	
D^2	*6.49*	*1*	*6.49*	*3.96*	*0.0548*	
E^2	*32.87*	*1*	*32.87*	*20.03*	*< 0.0001*	
Residual	55.79	34	1.64			
Lack of Fit	*55.79*	*29*	*1.92*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	825.53	45				

R-Squared 0.9324
Adj R-Squared 0.9106
Pred R-Squared 0.8645
Adeq Precision 25.709

Stage2_Max =
+34.10905
-0.36064 * Supply
+1.90496 * K1
+0.57887 * K2
-4.12233 * K3
-1.46784 * CC
+0.025612 * Supply * CC
+0.048711 * K1 * CC
+0.059002 * K2 * CC
-0.087836 * $K1^2$
+0.70795 * $K3^2$
-0.035722 * CC^2

Response 10 Supply Accuracy

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.078	12	6.487E-003	129.97	< 0.0001	significant
A-Supply	*0.042*	*1*	*0.042*	*835.70*	*< 0.0001*	
B-K1	*7.550E-003*	*1*	*7.550E-003*	*151.28*	*< 0.0001*	
C-K2	*1.886E-003*	*1*	*1.886E-003*	*37.78*	*< 0.0001*	
D-K3	*7.555E-003*	*1*	*7.555E-003*	*151.37*	*< 0.0001*	
E-CC	*0.012*	*1*	*0.012*	*237.93*	*< 0.0001*	
BC	*4.256E-004*	*1*	*4.256E-004*	*8.53*	*0.0063*	
BE	*7.486E-004*	*1*	*7.486E-004*	*15.00*	*0.0005*	
CE	*7.291E-004*	*1*	*7.291E-004*	*14.61*	*0.0006*	
A^2	*1.779E-004*	*1*	*1.779E-004*	*3.56*	*0.0679*	
B^2	*3.224E-004*	*1*	*3.224E-004*	*6.46*	*0.0159*	
D^2	*4.322E-003*	*1*	*4.322E-003*	*86.59*	*< 0.0001*	
E^2	*2.023E-003*	*1*	*2.023E-003*	*40.54*	*< 0.0001*	
Residual	1.647E-003	33	4.991E-005			
Lack of Fit	*1.647E-003*	*28*	*5.882E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.079	45				

R-Squared 0.9793
Adj R-Squared 0.9717
Pred R-Squared 0.9509
Adeq Precision 42.903

SupplyAccuracy =
+0.63243
+3.79336E-003 * Supply
+0.018095 * K1
+3.70684E-003 * K2
+0.10035 * K3
+7.39452E-004 * CC
-8.09304E-004 * K1 * K2
+5.36324E-004 * K1 * CC
+5.29284E-004 * K2 * CC
-8.50844E-005 * $Supply^2$
-4.58786E-004 * $K1^2$
-0.018700 * $K3^2$
-2.86939E-004 * CC^2

H.21 ANOVA AND MODEL EQUATION – RESPONSE 11 - MS – CONWIP/KCS – Periods 1 AND 2

ANOVA TABLE

Response 11 SLA – Period 1

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.13	8	0.016	272.82	< 0.0001	significant
A-Supply	*0.073*	*1*	*0.073*	*1239.64*	*< 0.0001*	
B-K1	*6.949E-004*	*1*	*6.949E-004*	*11.80*	*0.0015*	
D-K3	*0.033*	*1*	*0.033*	*555.25*	*< 0.0001*	
E-CC	*1.668E-004*	*1*	*1.668E-004*	*2.83*	*0.1008*	
AD	*2.199E-003*	*1*	*2.199E-003*	*37.33*	*< 0.0001*	
AE	*1.537E-004*	*1*	*1.537E-004*	*2.61*	*0.1147*	
B^2	*2.009E-004*	*1*	*2.009E-004*	*3.41*	*0.0728*	
D^2	*0.020*	*1*	*0.020*	*332.29*	*< 0.0001*	
Residual	2.179E-003	37	5.890E-005			
Lack of Fit	*2.179E-003*	*32*	*6.810E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.13	45				

METRICS AND FINAL EQUATION ACTUAL FACTORS

R-Squared 0.9833
Adj R-Squared 0.9797
Pred R-Squared 0.9598
Adeq Precision 66.435

SLA =
+0.28304
+1.44888E-003 * Supply
+0.010551 * K1
-0.10086 * K3
-0.011700 * CC
+6.13737E-003 * Supply * K3
+2.43040E-004 * Supply * CC
-3.48191E-004 * $K1^2$
-0.038260 * $K3^2$

Response 11 SLA – Period 2

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.093	9	0.010	215.88	< 0.0001	significant
A-Supply	*0.069*	*1*	*0.069*	*1436.85*	*< 0.0001*	
B-K1	*1.141E-003*	*1*	*1.141E-003*	*23.84*	*< 0.0001*	
C-K2	*1.343E-004*	*1*	*1.343E-004*	*2.80*	*0.1027*	
D-K3	*0.013*	*1*	*0.013*	*272.52*	*< 0.0001*	
E-CC	*1.333E-004*	*1*	*1.333E-004*	*2.78*	*0.1039*	
AD	*8.098E-004*	*1*	*8.098E-004*	*16.91*	*0.0002*	
A^2	*2.532E-004*	*1*	*2.532E-004*	*5.29*	*0.0274*	
B^2	*2.439E-004*	*1*	*2.439E-004*	*5.09*	*0.0302*	
D^2	*7.909E-003*	*1*	*7.909E-003*	*165.18*	*< 0.0001*	
Residual	1.724E-003	36	4.788E-005			
Lack of Fit	*1.724E-003*	*31*	*5.560E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.095	45				

R-Squared 0.9818
Adj R-Squared 0.9773
Pred R-Squared 0.9501
Adeq Precision 58.352

SLA =
+0.86886
-0.029320 * Supply
+0.012112 * K1
+8.11460E-004 * K2
-0.053799 * K3
+4.03966E-004 * CC
+3.72491E-003 * Supply * K3
+3.97163E-004 * $Supply^2$
-3.89829E-004 * $K1^2$
-0.024710 * $K3^2$

H.22 ANOVA AND MODEL EQUATION – RESPONSE 11 - MS – CONWIP/KCS – Period 3

Response 11 SLA – Period 3

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	
Model	0.11	13	8.332E-003	170.37	< 0.0001	significant
A-Supply	*0.035*	*1*	*0.035*	*722.93*	*< 0.0001*	
B-K1	*7.344E-003*	*1*	*7.344E-003*	*150.17*	*< 0.0001*	
D-K3	*0.034*	*1*	*0.034*	*696.96*	*< 0.0001*	
E-CC	*5.623E-003*	*1*	*5.623E-003*	*114.98*	*< 0.0001*	
AB	*2.062E-004*	*1*	*2.062E-004*	*4.22*	*0.0483*	
AD	*1.191E-003*	*1*	*1.191E-003*	*24.36*	*< 0.0001*	
AE	*1.227E-003*	*1*	*1.227E-003*	*25.08*	*< 0.0001*	
BD	*1.537E-004*	*1*	*1.537E-004*	*3.14*	*0.0858*	
BE	*4.270E-004*	*1*	*4.270E-004*	*8.73*	*0.0058*	
A^2	*3.785E-003*	*1*	*3.785E-003*	*77.39*	*< 0.0001*	
B^2	*1.655E-003*	*1*	*1.655E-003*	*33.83*	*< 0.0001*	
D^2	*0.022*	*1*	*0.022*	*442.26*	*< 0.0001*	
E^2	*2.275E-003*	*1*	*2.275E-003*	*46.51*	*< 0.0001*	
Residual	1.565E-003	32	4.891E-005			
Lack of Fit	*1.565E-003*	*27*	*5.796E-005*			
Pure Error	*0.000*	*5*	*0.000*			
Cor Total	0.11	45				

R-Squared	0.9858
Adj R-Squared	0.9800
Pred R-Squared	0.9716
Adeq Precision	49.646

SLA =

-2.98384
+0.14141 * Supply
-6.88331E-003 * K1
-0.023985 * K3
-0.025901 * CC
+5.63307E-004 * Supply * K1
+4.51773E-003 * Supply * K3
+6.86525E-004 * Supply * CC
+1.62281E-003 * K1 * K3
+4.05044E-004 * K1 * CC
-1.57209E-003 * $Supply^2$
-1.03942E-003 * $K1^2$
-0.041834 * $K3^2$
-3.04251E-004 * CC^2

APPENDIX I – CONWIP

I.1 CONWIP – Summary - High Season Raw Material – Supply Periods 1,2 and 3

Factor	*Name*	*Units*	*Type*	*Minimum*	*Maximum*	*Coded*	*Values*	*Mean*	*Std. Dev.*
A	Supply – Stage 0	Lots	Numeric	57.14	71.43	-1.000=57.14	1.000=71.43	64.29	5.05
B	CC – Stage 1	Lots	Numeric	10.71	32.14	*-1.000=10.71*	*1.000=28.57*	*19.91*	*6.79*

Response	*Name*	*Units*	*Obs*	*Minimum*	*Maximum*	*Mean*	*Std. Dev.*	*Ratio*	*Period*
R4	StageB1_Mean	%	13	5.34	8.35	6.73	0.94	1.56	
R6	StageB1_Max	%	13	38.53	48.79	44.18	2.85	1.27	
R7	StageB2_Mean	%	13	9.92	51.11	24.52	11.05	5.15	
R9	StageB2_Max	%	13	30.55	85.52	54.42	14.71	2.80	1
R10	SupplyAccuracy		13	0.83	1.00	0.94	0.05	1.21	
R11	SLA		13	0.80	0.90	0.86	0.03	1.13	
R13	Stage2 Utilisation		13	0.55	0.65	0.60	0.03	1.19	
R4	StageB1_Mean	%	13	4.70	9.37	6.83	1.42	1.99	
R6	StageB1_Max	%	13	37.12	79.08	61.43	14.48	2.13	
R7	StageB2_Mean	%	13	9.94	51.95	24.70	11.76	5.22	
R9	StageB2_Max	%	13	31.05	84.88	52.21	16.65	2.73	2
R10	SupplyAccuracy		13	0.81	1.00	0.94	0.06	1.23	
R11	SLA		13	0.76	0.88	0.86	0.04	1.17	
R13	Stage2 Utilisation		13	0.54	0.66	0.61	0.03	1.20	
R4	StageB1_Mean	%	13	5.72	14.00	9.26	2.46	2.45	
R6	StageB1_Max	%	13	48.97	89.69	74.33	12.70	1.83	
R7	StageB2_Mean	%	13	9.70	41.24	22.01	8.56	4.25	
R9	StageB2_Max	%	13	32.23	85.14	55.45	16.82	2.64	3
R10	SupplyAccuracy		13	0.77	1.00	0.91	0.06	1.30	
R11	SLA		13	0.68	0.89	0.81	0.06	1.31	
R13	Stage2 Utilisation		13	0.50	0.65	0.58	0.04	1.30	

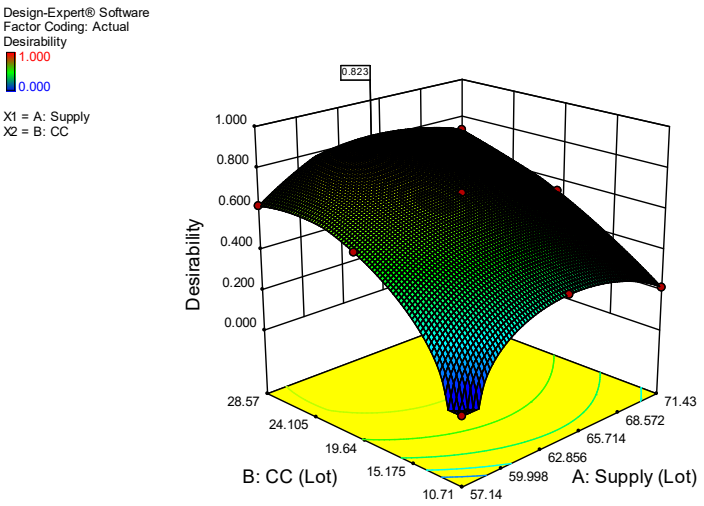
I.2 CONWIP – RSM Optimisation (SLA - StageB2_Mean) – High Season

is in range	is in range	none	minimize	none	none	maximize		
A:Supply	B:CC	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Period
69.33	14.03	44.09	22.15	46.96	0.87	0.87	0.70	1
71.43	10.71	42.67	12.50	34.93	0.82	0.86	0.86	2
69.24	16.11	72.03	20.98	48.16	0.85	0.82	0.65	3

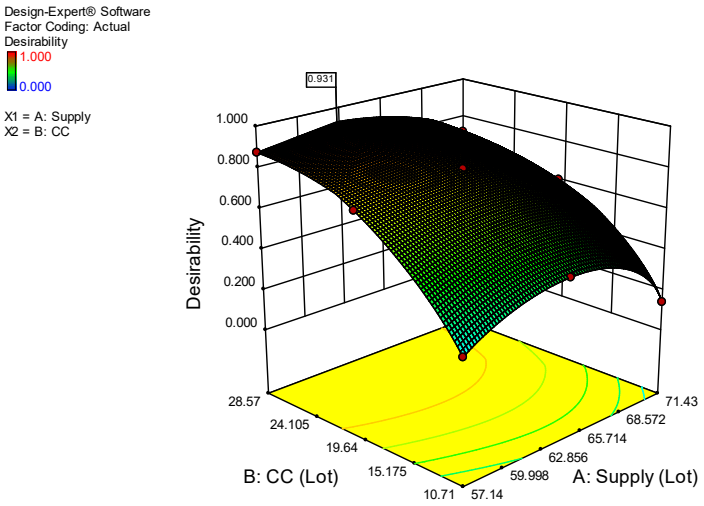
I.3 CONWIP – RSM Optimisation – SLA and Supply Accuracy – High Season

is in range	is in range	None	none	none	maximize	maximize		
A:Supply	B:CC	StageB1_Max %	StageB2_Mean%	StageB2_Max%	SupplyAccuracy	SLA	Desirability	Period
64.68	28.57	45.21	33.39	69.16	0.97	0.88	0.82	1
62.30	28.57	67.35	29.23	62.68	1.00	0.87	0.93	2
64.17	28.57	82.75	30.70	76.68	0.96	0.87	0.87	3

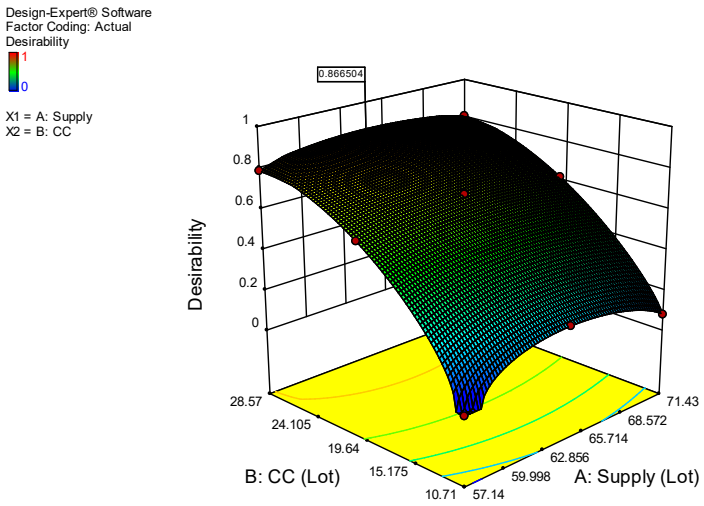
I.4 CONWIP – Desirability Function RSM – CONWIP - High Season – Period 1



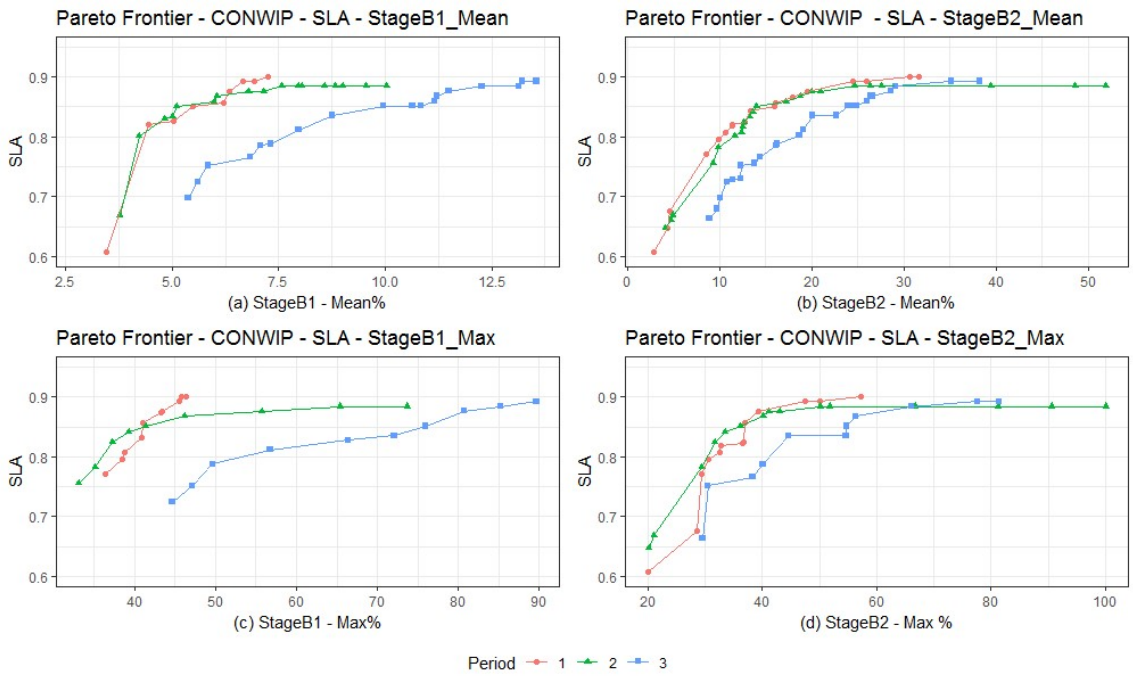
I.5 CONWIP – Desirability Function RSM – CONWIP - High Season – Period 2



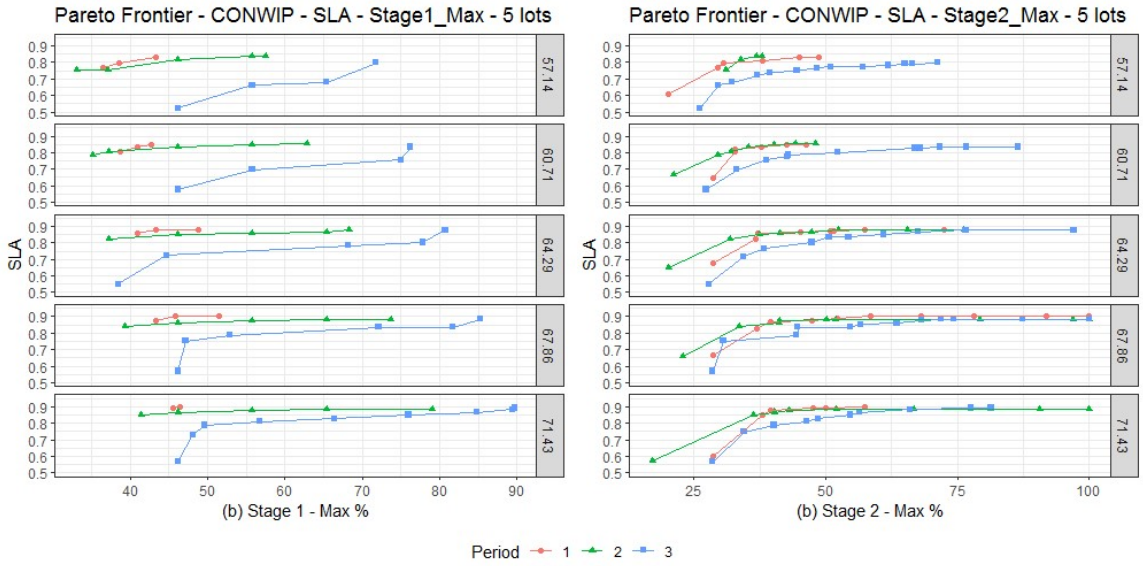
I.6 CONWIP – Desirability Function RSM – CONWIP - High Season – Period 3



I.7 CONWIP – Pareto Frontier – Simulated results - High Season



I.8 CONWIP –Pareto Frontier – Simulated results – High Season – 5 Lot-sizes



I.9 CONWIP – Summary - Medium Season Raw Material – Supply Periods 1,2 and 3

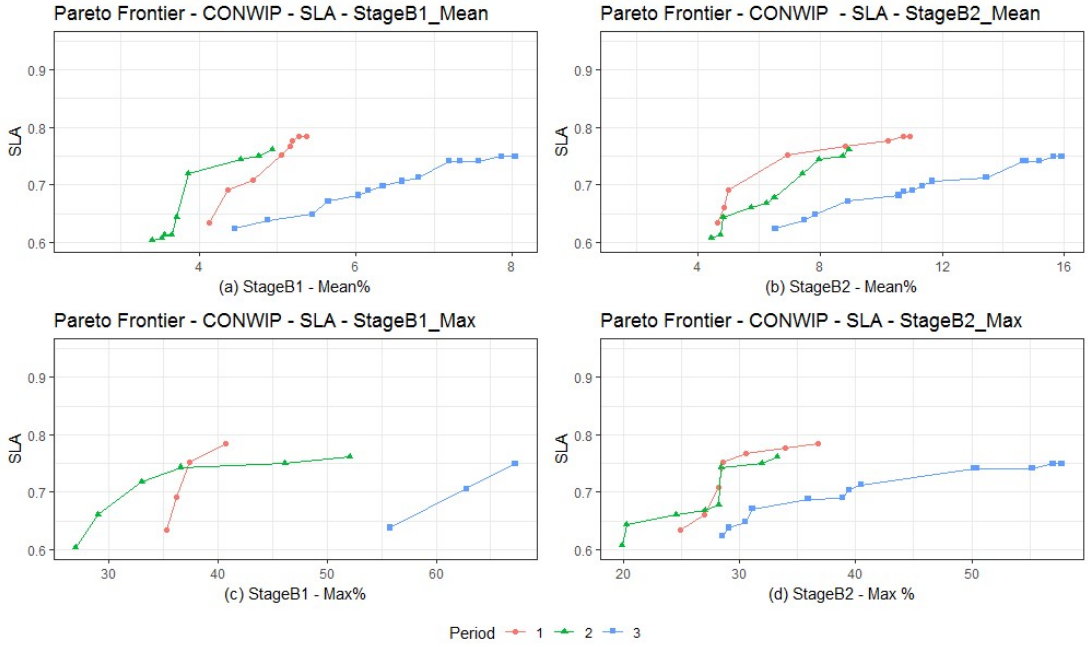
Factor	Name	Units	Type	Minimum	Maximum	*Coded*	*Values*	*Mean*	*Std. Dev.*
A	Supply – Stage 0	Lots	Numeric	46.43	53.57	-1.000=46.43	1.000=53.57	50.00	2.52
B	CC – Stage 1	Lots	Numeric	7.14	14.29	*-1.000=7.14*	*1.000=14.29*	*10.72*	*2.53*

Response	*Name*	*Units*	*Obs*	*Minimum*	*Maximum*	*Mean*	*Std. Dev.*	*Ratio*	*Period*
R4	StageB1_Mean	%	13	2.42	5.28	4.46	0.70	2.18	
R6	StageB1_Max	%	13	31.31	40.66	37.30	2.44	1.30	
R7	StageB2_Mean	%	13	1.51	10.74	6.34	2.22	7.10	
R9	StageB2_Max	%	13	17.56	36.78	27.68	4.20	2.09	1
R10	SupplyAccuracy		13	0.58	1.00	0.95	0.12	1.74	
R11	SLA		13	0.34	0.78	0.67	0.11	2.28	
R13	Stage2 Utilisation		13	0.29	0.54	0.48	0.06	1.86	
R4	StageB1_Mean	%	13	2.62	4.93	3.91	0.55	1.88	
R6	StageB1_Max	%	13	26.89	52.10	37.13	6.74	1.94	
R7	StageB2_Mean	%	13	2.48	8.95	5.84	1.63	3.61	
R9	StageB2_Max	%	13	19.58	33.27	25.48	4.06	1.70	2
R10	SupplyAccuracy		13	0.75	1.00	0.96	0.07	1.33	
R11	SLA		13	0.44	0.76	0.65	0.08	1.72	
R13	Stage2 Utilisation		13	0.35	0.54	0.48	0.05	1.53	
R4	StageB1_Mean	%	13	3.56	6.31	5.13	0.84	1.77	
R6	StageB1_Max	%	13	46.15	67.27	58.80	7.59	1.46	
R7	StageB2_Mean	%	13	4.45	10.75	7.55	2.02	2.41	
R9	StageB2_Max	%	13	22.83	38.57	30.47	4.50	1.69	3
R10	SupplyAccuracy		13	0.77	0.99	0.92	0.06	1.28	
R11	SLA		13	0.53	0.69	0.63	0.05	1.31	
R13	Stage2 Utilisation		13	0.40	0.50	0.46	0.03	1.26	

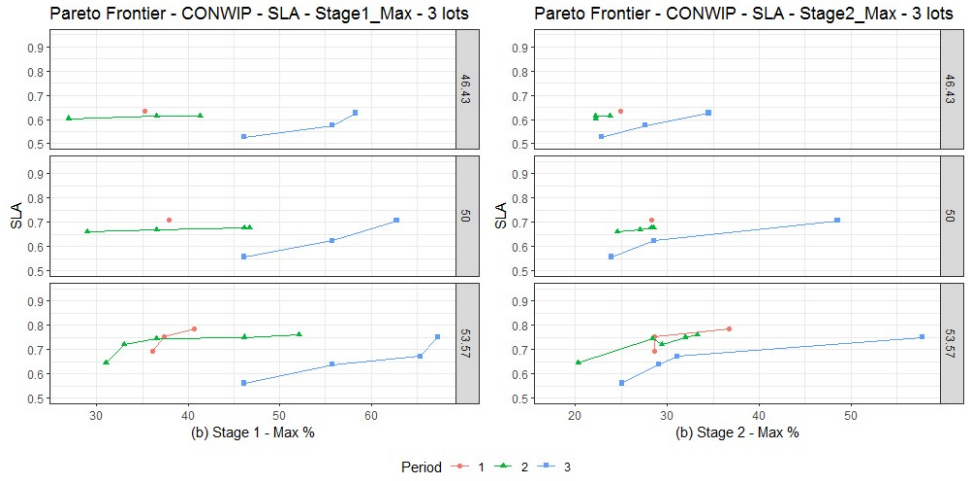
I.10 CONWIP – RSM Optimisation (SLA) – Medium Season

is in range	is in range	None	none	none	none	maximize		
A:Supply	B:CC	StageB1_Max %	StageB2_Mean%	StageB2_Max%	SupplyAccuracy	SLA	Desirability	Period
52.30	14.07	39.89	9.32	33.17	1.00	0.79	1.00	1
53.57	14.29	48.69	8.72	34.37	1.00	0.78	1.00	2
53.57	14.29	67.70	11.45	36.98	1.00	0.71	1.00	3

I.11 CONWIP –Pareto Frontier – Simulated results – Medium Seasons



I.12 CONWIP –Pareto Frontier – Simulated results – Medium Seasons – Lot Sizes



APPENDIX J – HKCS – Hybrid CONWIP/KCS

J.1 CONWIP/KCS – Summary - High Season Raw Material – Supply Periods 1,2 and 3

Factor	Name	Units	Type	Minimum	Maximum	*Coded*	*Values*	*Mean*	*Std. Dev.*
A	Supply – Stage 0	Lots	Numeric	57.14	71.43	-1.000=57.14	1.000=71.43	64.29	4.26
B	K1 – Stage 1	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.13
C	K2 – Stage 2	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.13
D	K3 – Stage 3	Lots	Numeric	1.07	3.21	-1.000=1.07	1.000=3.21	2.14	0.64
E	CC – Stage 1	Lots	Numeric	10.71	25.00	*-1.000=10.71*	*1.000=25*	*17.86*	*4.26*

Response	*Name*	*Units*	*Obs*	*Minimum*	*Maximum*	*Mean*	*Std. Dev.*	*Ratio*	*Period*
R4	StageB1_Mean	%	46	4.99	28.23	13.99	6.26	5.66	
R6	StageB1_Max	%	46	40.99	86.54	55.75	10.74	2.76	
R7	StageB2_Mean	%	46	10.10	30.50	17.90	5.00	2.11	
R9	StageB2_Max	%	46	30.55	51.97	39.01	4.88	1.70	1
R10	SupplyAccuracy		46	0.77	1.00	0.91	0.05	1.99	
R11	SLA		46	0.66	0.90	0.83	0.07	1.70	
R13	Stage2 Utilisation		46	0.54	0.63	0.59	0.03	1.29	
R4	StageB1_Mean	%	46	5.06	27.89	13.15	6.34	5.51	
R6	StageB1_Max	%	46	37.23	86.54	56.70	11.44	2.46	
R7	StageB2_Mean	%	46	9.63	27.92	16.48	4.43	2.32	
R9	StageB2_Max	%	46	27.01	52.36	37.82	5.30	1.94	2
R10	SupplyAccuracy		46	0.78	1.00	0.91	0.05	1.89	
R11	SLA		46	0.66	0.88	0.81	0.07	1.94	
R13	Stage2 Utilisation		46	0.53	0.62	0.58	0.02	1.29	
R4	StageB1_Mean	%	46	6.08	27.26	14.39	5.27	4.48	
R6	StageB1_Max	%	46	48.08	86.54	63.66	10.31	2.16	
R7	StageB2_Mean	%	46	9.21	22.99	14.42	3.23	1.80	3
R9	StageB2_Max	%	46	29.50	46.21	37.77	4.28	1.57	
R10	SupplyAccuracy		46	0.78	0.95	0.87	0.04	1.75	
R11	SLA		46	0.61	0.88	0.76	0.06	1.57	
R13	Stage2 Utilisation		46	0.50	0.59	0.55	0.01	1.22	

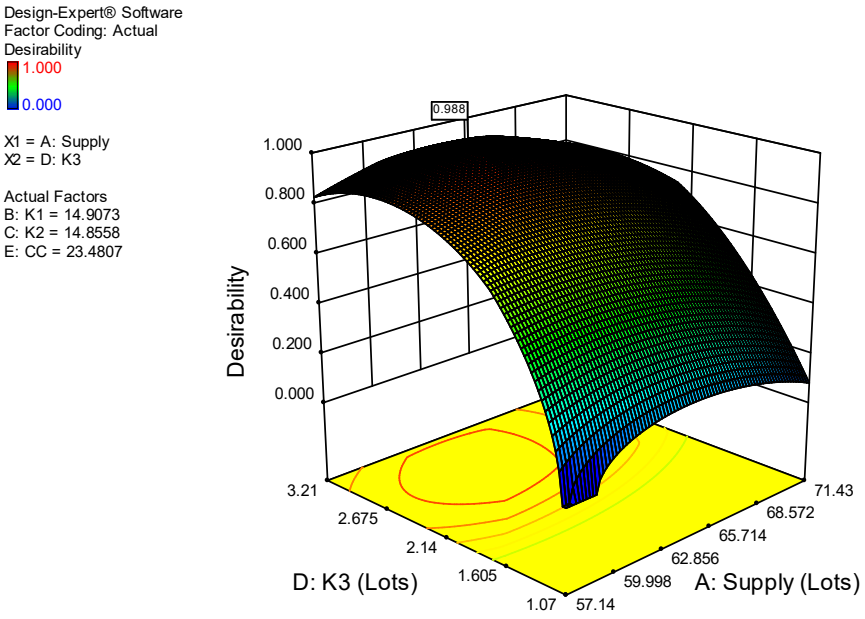
J.2 CONWIP/KCS – RSM Optimisation (SLA – StageB2_Mean) – High Season

is in range	is in range	is in range	is in range	is in range	None	minimize	none	none	maximize		
A:Supply	B:K1	C:K2	D:K3	E:CC	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Per
70.12	10.44	8.94	2.75	24.57	58.67	10.03	32.38	0.86	0.90	1.00	1
71.43	12.48	8.93	2.67	24.90	74.55	9.76	33.53	0.86	0.88	0.99	2
71.43	16.06	8.93	2.66	25.00	89.73	10.274	34.97	0.87	0.87	0.95	3

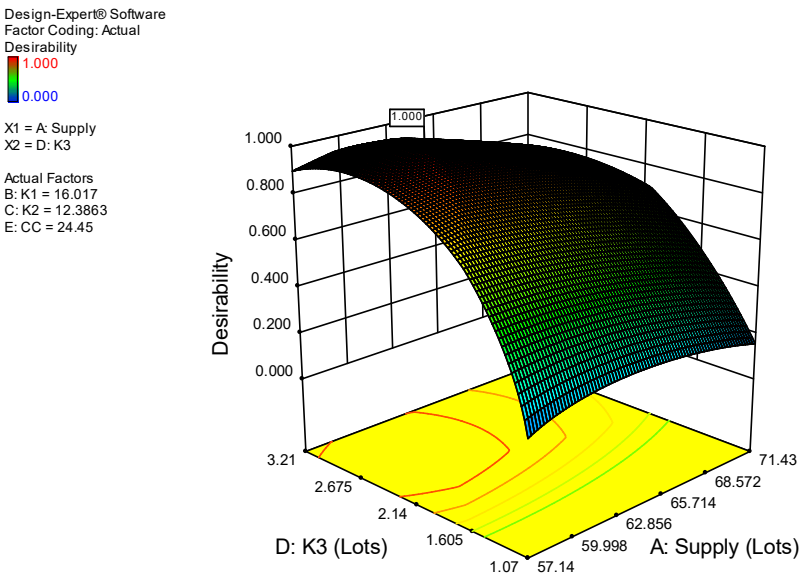
J.3 CONWIP/KCS – RSM Optimisation (SLA – Supply Accuracy) – High Season

is in range	is in range	is in range	is in range	is in range	None	None	None	maximize	maximize		
A:Supply	B:K1	C:K2	D:K3	E:CC	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Per
62.31	14.91	14.85	2.68	23.48	69.41	20.48	43.87	1.00	0.90	0.99	1
60.60	16.03	12.41	2.71	24.23	80.88	16.61	38.00	1.00	0.89	1.00	2
63.43	16.06	14.452	2.78	21.71	86.53	18.78	44.02	0.95	0.87	1.00	3

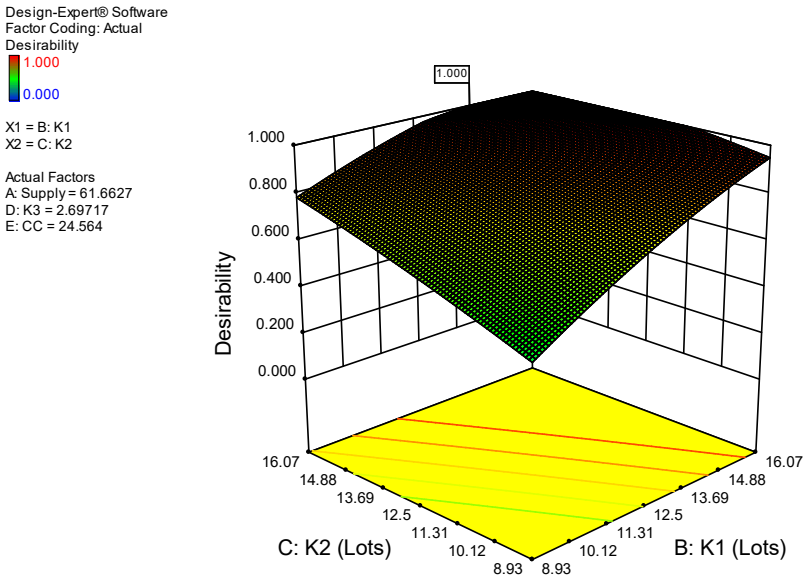
J.4 CONWIP/KCS – Desirability Function RSM – CONWIP/KCS - High Season – Period 1



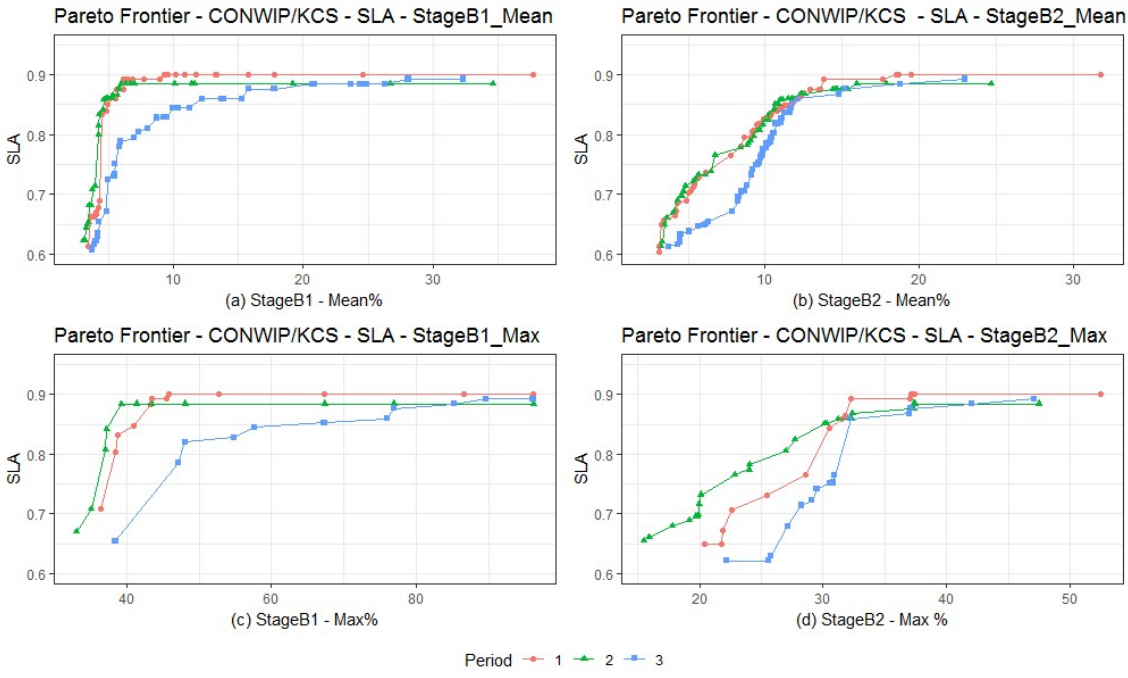
J.5 CONWIP/KCS – Desirability Function RSM – CONWIP/KCS - High Season – Period 2



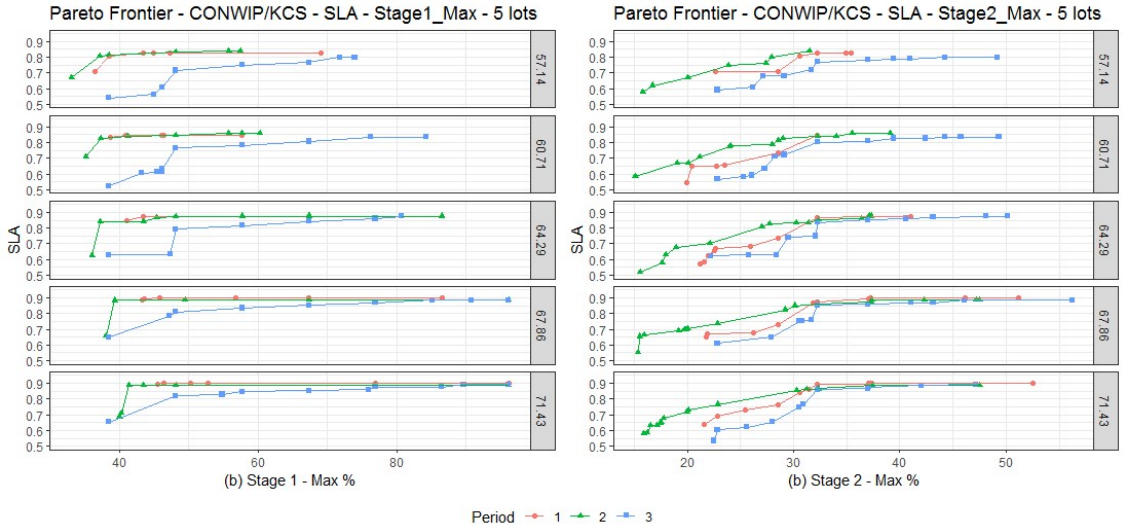
J.6 CONWIP/KCS – Desirability Function RSM – CONWIP/KCS - High Season – Period 3



J.7 CONWIP/KCS –Pareto Frontier - High Season Raw Material – Supply Periods 1,2 and 3



J.8 CONWIP/KCS –Pareto Frontier – Simulated results – High Season – 5 Lot-sizes



J.9 CONWIP/KCS - RSM - Summary - Medium Season Raw Material – Supply Periods 1,2 and 3

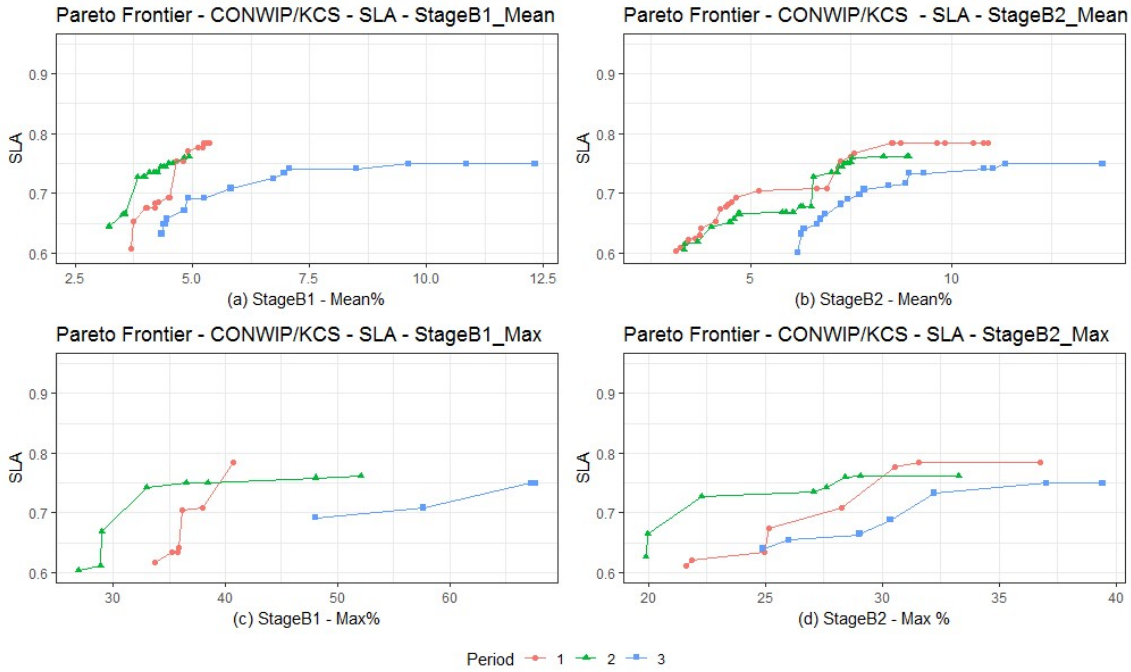
Factor	Name	Units	Type	*Minimum*	*Maximum*	*Coded*	*Values*	*Mean*	*Std. Dev.*
A	Supply – Stage 0	Lots	Numeric	46.43	53.57	-1.000=46.43	1.000=53.57	50.00	2.13
B	K1 – Stage 1	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.13
C	K2 – Stage 2	Lots	Numeric	8.93	16.07	-1.000=8.93	1.000=16.07	12.50	2.13
D	K3 – Stage 3	Lots	Numeric	1.07	3.21	-1.000=1.07	1.000=3.21	2.14	0.64
E	CC – Stage 1	Lots	Numeric	10.71	25	*-1.000=10.71*	*1.000=25*	*17.86*	*4.26*

Response	*Name*	*Units*	*Obs*	*Minimum*	*Maximum*	*Mean*	*Std. Dev.*	*Ratio*	*Period*
R4	StageB1_Mean	%	46	4.06	11.73	5.34	1.55	2.89	
R6	StageB1_Max	%	46	35.24	67.31	40.28	7.01	2.00	
R7	StageB2_Mean	%	46	4.80	17.63	8.30	3.14	1.91	
R9	StageB2_Max	%	46	24.94	39.56	29.45	3.54	1.59	1
R10	SupplyAccuracy		46	0.96	1.00	1.00	0.01	2.05	
R11	SLA		46	0.59	0.78	0.69	0.05	1.59	
R13	Stage2 Utilisation		46	0.46	0.54	0.50	0.02	1.04	
R4	StageB1_Mean	%	46	3.27	9.45	4.43	1.19	2.89	
R6	StageB1_Max	%	46	26.89	52.53	38.77	5.92	2.04	
R7	StageB2_Mean	%	46	4.33	17.80	7.28	2.76	1.95	
R9	StageB2_Max	%	46	21.41	35.87	27.59	3.66	1.68	2
R10	SupplyAccuracy		46	0.97	1.00	0.99	0.01	1.96	
R11	SLA		46	0.57	0.76	0.66	0.05	1.68	
R13	Stage2 Utilisation		46	0.46	0.54	0.50	0.02	1.03	
R4	StageB1_Mean	%	46	4.29	14.66	7.96	2.68	3.41	
R6	StageB1_Max	%	46	48.08	67.31	60.34	6.24	2.11	
R7	StageB2_Mean	%	46	6.32	15.41	9.46	2.32	1.40	3
R9	StageB2_Max	%	46	24.91	45.15	34.66	3.88	1.81	
R10	SupplyAccuracy		46	0.90	1.00	0.97	0.03	1.77	
R11	SLA		46	0.55	0.73	0.65	0.05	1.81	
R13	Stage2 Utilisation		46	0.44	0.52	0.48	0.02	1.11	

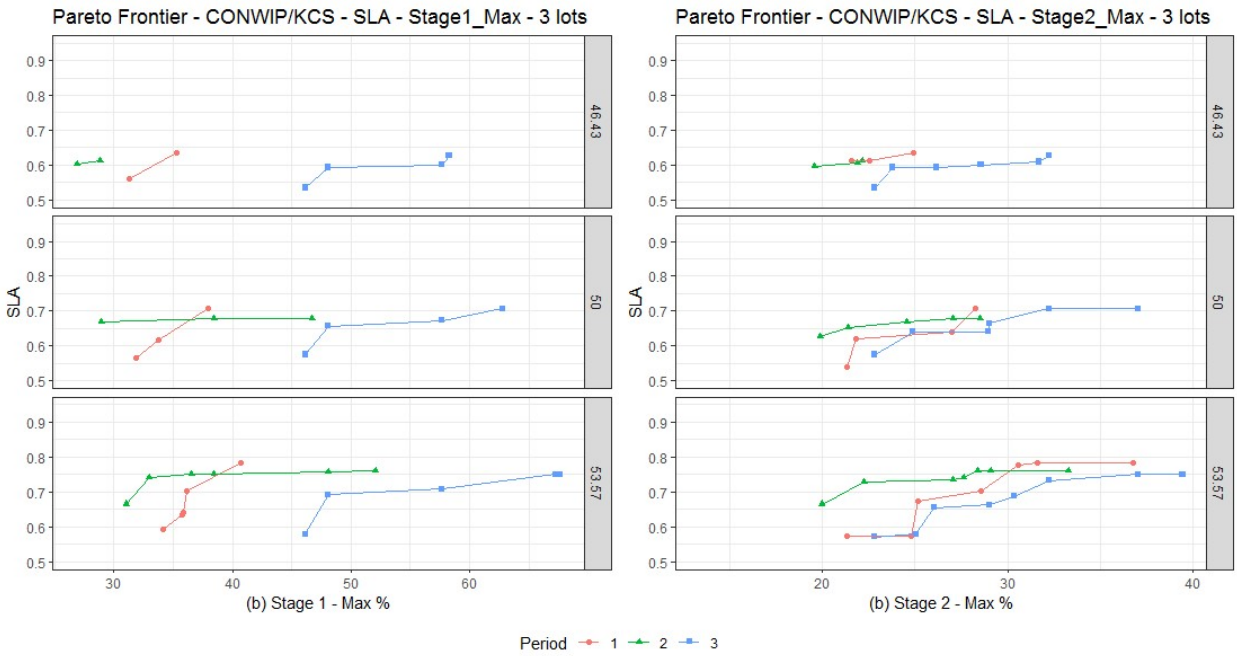
J.10 CONWIP/KCS – RSM Optimisation – SLA – Medium Season

is in range	is in range	is in range	is in range	is in range	None	None	None	None	maximize		
A:Supply	B:K1	C:K2	D:K3	E:CC	StageB1_Max %	StageB2_Mean %	StageB2_Max %	Supply Accuracy	SLA	Desirability	Per
53.402	13.727	12.912	2.322	22.781	41.181	10.038	31.570	1.005	0.789	1.000	1
53.423	14.708	15.089	2.852	19.454	43.405	7.371	31.977	0.999	0.763	1.000	2
51.363	14.979	15.570	2.821	22.727	66.368	11.386	42.023	1.003	0.745	1.000	3

J.11 CONWIP/KCS - Pareto Frontier – Non-dominant results for CONWIP/KCS – Medium Season



J.12 CONWIP/KCS - Pareto Frontier – Non-dominant results for CONWIP/KCS – Medium Season – 3 Lot-sizes



APPENDIX K – Adaptive Recommendation Algorithm

K.1 KCS - Results Simulated – SLA Cumulative Curve

Period	Stage0_Mean	Stage0_Sum	StageB1_Mean	StageB1_Max	StageB2_Mean	StageB2_Max	SupplyAccuracy	Stage2Rate	Stage2Util	SLA	Lot	KCS1	KCS2	KCS3	Inter	Cum_SLA	Type
1	2.381	285.714	6.124	52.824	8.540	34.969	1.000	1.000	0.557	0.783	57.14	14.29	16.07	3.21	0	0.78327	KCS
2	2.381	285.714	7.066	48.098	8.319	32.002	1.000	1.000	0.557	0.774	57.14	14.29	16.07	3.21	0	1.55728	KCS
3	2.364	283.702	8.787	71.753	11.874	37.835	0.993	1.000	0.553	0.778	57.14	14.29	16.07	3.21	0	2.3349	KCS
4	2.381	285.714	6.957	52.824	8.410	35.837	1.000	1.000	0.557	0.787	57.14	14.29	16.07	3.21	0	3.12205	KCS
5	2.381	285.714	6.854	49.613	8.772	37.513	1.000	1.000	0.557	0.770	57.14	14.29	16.07	3.21	0	3.89195	KCS
6	2.381	285.714	6.824	57.345	9.603	37.909	1.000	1.000	0.557	0.796	57.14	14.29	16.07	3.21	0	4.68787	KCS
7	2.381	285.714	6.330	53.582	8.446	37.513	1.000	1.000	0.557	0.769	57.14	14.29	16.07	3.21	0	5.45715	KCS
8	2.381	285.714	7.134	58.683	9.987	37.909	1.000	1.000	0.557	0.781	57.14	14.29	16.07	3.21	0	6.23766	KCS
9	2.381	285.714	6.682	49.809	8.642	34.591	1.000	1.000	0.557	0.778	57.14	14.29	16.07	3.21	0	7.01549	KCS
10	2.381	285.714	7.817	50.076	8.790	37.513	1.000	1.000	0.557	0.775	57.14	14.29	16.07	3.21	0	7.79013	KCS
11	2.381	285.714	7.142	55.854	11.216	36.420	1.000	1.000	0.557	0.775	57.14	14.29	16.07	3.21	0	8.56533	KCS
12	2.381	285.714	8.895	59.872	11.054	41.931	1.000	1.000	0.557	0.785	57.14	14.29	16.07	3.21	0	9.35054	KCS
1	2.53	303.571	7.336	57.868	11.959	37.513	1.000	1.000	0.592	0.848	60.71	14.29	16.07	3.21	0	10.19856	KCS
2	2.53	303.571	8.373	52.846	11.674	36.010	1.000	1.000	0.592	0.838	60.71	14.29	16.07	3.21	0	11.03689	KCS
3	2.498	299.722	10.575	76.238	14.733	37.909	0.987	1.000	0.585	0.826	60.71	14.29	16.07	3.21	0	11.86315	KCS
4	2.53	303.571	8.354	57.868	10.701	37.909	1.000	1.000	0.592	0.832	60.71	14.29	16.07	3.21	0	12.69519	KCS
5	2.53	303.571	8.213	52.714	12.354	37.513	1.000	1.000	0.592	0.843	60.71	14.29	16.07	3.21	0	13.5383	KCS
6	2.529	303.526	8.394	60.929	14.307	37.909	1.000	1.000	0.592	0.844	60.71	14.29	16.07	3.21	0	14.3821	KCS
7	2.53	303.571	7.734	56.931	10.834	37.908	1.000	1.000	0.592	0.826	60.71	14.29	16.07	3.21	0	15.20854	KCS
8	2.53	303.571	8.532	62.351	14.947	37.909	1.000	1.000	0.592	0.833	60.71	14.29	16.07	3.21	0	16.04122	KCS
9	2.53	303.571	7.818	52.922	11.654	37.513	1.000	1.000	0.592	0.835	60.71	14.29	16.07	3.21	0	16.87588	KCS
10	2.529	303.494	9.132	54.948	11.200	37.908	1.000	1.000	0.592	0.824	60.71	14.29	16.07	3.21	0	17.70014	KCS
11	2.53	303.571	8.586	61.088	15.148	37.908	1.000	1.000	0.592	0.832	60.71	14.29	16.07	3.21	0	18.53196	KCS
12	2.517	302.061	10.546	65.357	13.922	41.959	0.995	1.000	0.589	0.833	60.71	14.29	16.07	3.21	0	19.36534	KCS
1	2.679	321.429	8.875	62.912	20.639	37.909	1.000	1.000	0.627	0.884	64.29	14.29	16.07	3.21	0	20.24955	KCS
2	2.671	320.574	9.894	57.595	16.802	39.355	0.997	1.000	0.625	0.885	64.29	14.29	16.07	3.21	0	21.13477	KCS
3	2.602	312.200	12.115	76.923	17.540	37.909	0.971	1.000	0.609	0.857	64.29	14.29	16.07	3.21	0	21.99173	KCS
4	2.679	321.429	9.948	62.912	15.230	37.909	1.000	1.000	0.627	0.891	64.29	14.29	16.07	3.21	0	22.88299	KCS
5	2.679	321.429	9.756	55.815	17.214	37.862	1.000	1.000	0.627	0.887	64.29	14.29	16.07	3.21	0	23.76993	KCS
6	2.671	320.540	10.069	64.514	21.184	37.909	0.997	1.000	0.625	0.875	64.29	14.29	16.07	3.21	0	24.64484	KCS
7	2.679	321.429	9.352	60.280	16.239	37.909	1.000	1.000	0.627	0.886	64.29	14.29	16.07	3.21	0	25.53077	KCS
8	2.675	320.986	10.612	66.019	22.233	37.909	0.999	1.000	0.626	0.873	64.29	14.29	16.07	3.21	0	26.40385	KCS
9	2.679	321.429	9.699	56.035	20.588	41.950	1.000	1.000	0.627	0.889	64.29	14.29	16.07	3.21	0	27.29239	KCS
10	2.668	320.202	10.511	59.821	15.024	38.063	0.996	1.000	0.625	0.890	64.29	14.29	16.07	3.21	0	28.18196	KCS
11	2.67	320.393	10.802	66.321	21.027	38.881	0.997	1.000	0.625	0.887	64.29	14.29	16.07	3.21	0	29.06852	KCS
12	2.623	314.739	12.877	76.923	19.108	41.961	0.979	1.000	0.614	0.888	64.29	14.29	16.07	3.21	0	29.95617	KCS
1	2.752	330.205	20.601	76.923	30.011	41.954	0.973	1.000	0.644	0.900	67.86	14.29	16.07	3.21	0	30.85617	KCS
2	2.742	328.986	15.458	76.923	26.968	41.961	0.970	1.000	0.642	0.900	67.86	14.29	16.07	3.21	0	31.75617	KCS
3	2.682	321.855	13.769	76.923	20.332	37.909	0.949	1.000	0.628	0.884	67.86	14.29	16.07	3.21	0	32.63997	KCS
4	2.783	334.018	19.680	76.923	28.477	41.961	0.984	0.989	0.645	0.900	67.86	14.29	16.07	3.21	0	33.53997	KCS
5	2.744	329.302	20.992	76.923	28.407	41.961	0.971	1.000	0.642	0.900	67.86	14.29	16.07	3.21	0	34.43997	KCS
6	2.779	333.494	18.244	72.390	28.262	41.847	0.983	0.991	0.645	0.900	67.86	14.29	16.07	3.21	0	35.33997	KCS
7	2.782	333.852	19.992	76.923	28.737	41.961	0.984	0.987	0.643	0.895	67.86	14.29	16.07	3.21	0	36.23451	KCS
8	2.761	331.349	16.333	76.923	28.435	41.724	0.977	0.997	0.645	0.900	67.86	14.29	16.07	3.21	0	37.13451	KCS
9	2.769	332.241	19.972	76.923	29.370	41.961	0.979	0.995	0.645	0.900	67.86	14.29	16.07	3.21	0	38.03451	KCS
10	2.763	331.572	17.532	67.183	27.213	41.961	0.977	0.997	0.645	0.900	67.86	14.29	16.07	3.21	0	38.93451	KCS
11	2.703	324.352	19.304	76.923	28.682	41.961	0.956	1.000	0.633	0.900	67.86	14.29	16.07	3.21	0	39.83451	KCS
12	2.651	318.105	16.642	76.923	25.934	41.961	0.938	1.000	0.620	0.900	67.86	14.29	16.07	3.21	0	40.73451	KCS
1	2.76	331.221	30.905	76.923	33.182	41.961	0.927	0.998	0.645	0.900	71.43	14.29	16.07	3.21	0	41.63451	KCS
2	2.749	329.938	22.749	76.923	30.528	41.961	0.924	1.000	0.644	0.900	71.43	14.29	16.07	3.21	0	42.53451	KCS
3	2.723	326.755	16.210	76.923	23.987	41.750	0.915	1.000	0.637	0.891	71.43	14.29	16.07	3.21	0	43.42582	KCS
4	2.788	334.590	27.839	76.923	31.817	41.961	0.937	0.988	0.645	0.900	71.43	14.29	16.07	3.21	0	44.32582	KCS
5	2.752	330.271	28.957	76.923	31.491	41.961	0.925	1.000	0.644	0.900	71.43	14.29	16.07	3.21	0	45.22582	KCS
6	2.784	334.138	24.181	76.923	30.950	41.961	0.936	0.989	0.645	0.900	71.43	14.29	16.07	3.21	0	46.12582	KCS
7	2.79	334.812	26.780	76.923	31.144	41.961	0.937	0.985	0.643	0.896	71.43	14.29	16.07	3.21	0	47.02172	KCS
8	2.768	332.193	22.686	76.923	31.396	41.956	0.930	0.995	0.645	0.900	71.43	14.29	16.07	3.21	0	47.92172	KCS
9	2.778	333.364	25.877	76.923	31.917	41.961	0.933	0.991	0.645	0.900	71.43	14.29	16.07	3.21	0	48.82172	KCS
10	2.77	332.388	24.239	76.923	30.279	41.961	0.931	0.994	0.645	0.900	71.43	14.29	16.07	3.21	0	49.72172	KCS
11	2.709	325.060	26.429	76.923	31.259	41.961	0.910	1.000	0.634	0.900	71.43	14.29	16.07	3.21	0	50.62172	KCS
12	2.654	318.485	21.265	76.923	29.015	41.961	0.892	1.000	0.621	0.900	71.43	14.29	16.07	3.21	0	51.52172	KCS

K.2 Adaptive Pull-Type - Results Simulated – SLA Cumulative Curve

Period	Stage0_Mean	Stage0_Sum	StageB1_Mean	StageB1_Max	StageB2_Mean	StageB2_Max	SupplyAccuracy	Stage2Rate	Stage2Util	SLA	Lot	KCS1	KCS2	KCS3	Inter	Cum_SLA	Type
1	2.371	284.502	11.970	56.975	9.336	27.518	0.996	0.995	0.594	0.789	57.14	11	11	2.68	11	0.78928	PT-Adapt
2	2.373	284.724	10.113	71.882	10.733	32.786	0.997	0.998	0.596	0.779	57.14	15	15	2.68	15	1.56839	PT-Adapt
3	2.369	284.232	15.090	72.560	12.469	40.538	0.995	0.999	0.596	0.770	57.14	18	17	2.68	18	2.33856	PT-Adapt
4	2.381	285.714	10.049	58.548	10.034	37.441	1.000	0.998	0.598	0.772	57.14	17	16	2.68	17	3.11049	PT-Adapt
5	2.381	285.714	10.260	46.206	11.066	31.931	1.000	1.000	0.599	0.782	57.14	15	14	2.68	15	3.89204	PT-Adapt
6	2.363	283.533	11.437	52.181	9.711	30.207	0.992	1.000	0.595	0.767	57.14	12	12	2.68	12	4.65888	PT-Adapt
7	2.369	284.338	10.097	62.994	11.661	32.044	0.995	0.998	0.596	0.765	57.14	14	14	2.68	14	5.42387	PT-Adapt
8	2.376	285.158	12.109	67.102	11.162	33.847	0.998	0.999	0.598	0.773	57.14	16	16	2.68	16	6.19663	PT-Adapt
9	2.361	283.366	11.049	50.118	9.145	25.885	0.992	1.000	0.595	0.762	57.14	11	11	2.68	11	6.95885	PT-Adapt
10	2.380	285.544	10.956	52.885	10.880	34.821	0.999	1.000	0.599	0.773	57.14	15	15	2.68	15	7.73184	PT-Adapt
11	2.370	284.398	12.402	68.598	10.938	30.207	0.995	0.998	0.596	0.769	57.14	13	12	2.68	13	8.50086	PT-Adapt
12	2.380	285.658	12.482	60.438	13.187	36.092	1.000	0.998	0.598	0.778	57.14	14	14	2.68	14	9.27905	PT-Adapt
1	2.530	303.571	14.716	58.616	12.087	27.518	1.000	0.999	0.637	0.838	60.71	12	11	2.68	12	10.11667	PT-Adapt
2	2.530	303.571	12.129	79.049	13.591	40.312	1.000	0.999	0.637	0.840	60.71	18	17	2.68	18	10.95698	PT-Adapt
3	2.460	295.217	16.876	79.427	14.273	37.707	0.972	0.998	0.618	0.805	60.71	16	16	2.68	16	11.76207	PT-Adapt
4	2.525	303.006	10.193	52.885	12.800	34.778	0.998	1.000	0.636	0.832	60.71	15	15	2.68	15	12.59412	PT-Adapt
5	2.530	303.571	11.854	50.836	15.089	32.044	1.000	0.999	0.636	0.832	60.71	15	14	2.68	15	13.42616	PT-Adapt
6	2.522	302.681	13.563	56.027	13.255	31.168	0.997	0.995	0.632	0.831	60.71	14	13	2.68	14	14.25693	PT-Adapt
7	2.506	300.764	11.959	64.077	13.786	31.168	0.991	0.999	0.631	0.802	60.71	13	13	2.68	13	15.05904	PT-Adapt
8	2.530	303.571	14.746	67.750	14.609	37.706	1.000	0.998	0.636	0.827	60.71	17	16	2.68	17	15.88577	PT-Adapt
9	2.530	303.571	12.942	49.641	13.834	33.018	1.000	0.999	0.637	0.820	60.71	15	14	2.68	15	16.70604	PT-Adapt
10	2.530	303.571	13.021	56.558	13.631	35.877	1.000	0.998	0.636	0.831	60.71	15	14	2.68	15	17.53718	PT-Adapt
11	2.530	303.571	12.468	67.871	15.477	37.707	1.000	1.000	0.637	0.823	60.71	17	16	2.68	17	18.36038	PT-Adapt
12	2.530	303.571	13.028	58.115	17.377	44.536	1.000	0.998	0.636	0.838	60.71	18	17	2.68	18	19.19796	PT-Adapt
1	2.648	317.754	18.006	70.000	15.463	30.347	0.989	0.999	0.666	0.878	64.29	13	12	2.68	13	20.07549	PT-Adapt
2	2.669	320.250	13.479	81.889	17.926	40.538	0.996	0.998	0.671	0.876	64.29	17	17	2.68	17	20.95145	PT-Adapt
3	2.651	318.110	19.801	78.217	22.560	46.200	0.990	0.996	0.665	0.875	64.29	20	19	2.68	20	21.82604	PT-Adapt
4	2.670	320.386	12.772	65.259	16.850	34.876	0.997	0.999	0.671	0.875	64.29	16	15	2.68	16	22.70072	PT-Adapt
5	2.679	321.429	12.141	51.140	23.268	43.878	1.000	0.999	0.674	0.879	64.29	19	18	2.68	19	23.5796	PT-Adapt
6	2.628	315.356	15.367	54.842	14.349	30.289	0.981	0.999	0.661	0.872	64.29	12	12	2.68	12	24.45166	PT-Adapt
7	2.679	321.429	13.182	69.486	24.902	51.697	1.000	0.997	0.672	0.863	64.29	22	21	2.68	22	25.31456	PT-Adapt
8	2.652	318.284	17.409	72.244	18.246	37.707	0.990	0.998	0.667	0.861	64.29	16	16	2.68	16	26.17553	PT-Adapt
9	2.679	321.429	17.373	64.243	18.958	36.097	1.000	0.998	0.674	0.880	64.29	15	14	2.68	15	27.0553	PT-Adapt
10	2.679	321.429	15.002	63.531	19.052	40.104	1.000	0.998	0.674	0.879	64.29	17	16	2.68	17	27.93466	PT-Adapt
11	2.661	319.315	17.125	80.769	19.736	38.205	0.993	0.998	0.669	0.875	64.29	15	15	2.68	15	28.80936	PT-Adapt
12	2.612	313.469	18.950	80.769	20.519	38.928	0.975	0.999	0.657	0.884	64.29	15	15	2.68	15	29.69306	PT-Adapt
1	2.715	325.774	21.995	70.000	19.223	33.266	0.960	0.997	0.682	0.898	67.86	13	13	2.68	13	30.59087	PT-Adapt
2	2.705	324.591	23.232	75.385	21.516	36.097	0.957	0.997	0.680	0.886	67.86	14	14	2.68	14	31.47699	PT-Adapt
3	2.742	329.071	26.522	82.328	26.618	46.895	0.970	0.999	0.690	0.892	67.86	18	18	2.68	18	32.36905	PT-Adapt
4	2.706	324.703	20.184	70.000	18.334	33.262	0.957	0.999	0.681	0.893	67.86	13	13	2.68	13	33.26225	PT-Adapt
5	2.642	317.098	23.841	70.000	18.291	30.435	0.935	0.999	0.665	0.880	67.86	13	12	2.68	13	34.14218	PT-Adapt
6	2.672	320.586	19.132	64.615	16.625	30.430	0.945	0.997	0.671	0.888	67.86	12	12	2.68	12	35.03063	PT-Adapt
7	2.656	318.706	22.554	64.615	15.603	27.603	0.939	0.998	0.667	0.880	67.86	12	11	2.68	12	35.91095	PT-Adapt
8	2.742	329.057	23.693	86.154	23.728	41.759	0.970	0.998	0.689	0.893	67.86	16	16	2.68	16	36.80444	PT-Adapt
9	2.761	331.315	27.162	86.154	26.922	41.759	0.977	0.995	0.692	0.894	67.86	16	16	2.68	16	37.69811	PT-Adapt
10	2.657	318.840	20.323	64.615	16.314	30.435	0.940	0.999	0.668	0.882	67.86	12	12	2.68	12	38.58027	PT-Adapt
11	2.697	323.677	24.224	80.769	22.137	36.096	0.954	0.999	0.679	0.895	67.86	15	14	2.68	15	39.47576	PT-Adapt
12	2.614	313.740	22.691	75.385	20.200	36.097	0.925	0.997	0.657	0.893	67.86	14	14	2.68	14	40.36905	PT-Adapt
1	2.703	324.313	23.173	64.615	16.382	27.603	0.908	0.998	0.679	0.903	71.43	12	11	2.68	12	41.27223	PT-Adapt
2	2.679	321.539	22.180	64.615	17.415	30.435	0.900	0.998	0.673	0.888	71.43	12	12	2.68	12	42.16017	PT-Adapt
3	2.821	338.501	34.254	100.000	29.803	47.417	0.948	0.983	0.699	0.907	71.43	19	18	2.68	19	43.06765	PT-Adapt
4	2.708	324.938	22.054	64.615	16.535	27.603	0.910	0.998	0.681	0.904	71.43	12	11	2.68	12	43.97123	PT-Adapt
5	2.636	316.322	24.656	64.615	16.582	27.603	0.886	0.999	0.663	0.884	71.43	12	11	2.68	12	44.855	PT-Adapt
6	2.674	320.833	19.447	59.231	15.129	27.603	0.898	0.998	0.672	0.894	71.43	11	11	2.68	11	45.7489	PT-Adapt
7	2.661	319.345	22.315	59.231	15.699	27.603	0.894	1.000	0.670	0.884	71.43	11	11	2.68	11	46.63302	PT-Adapt
8	2.747	329.584	29.955	80.769	24.909	38.928	0.923	0.999	0.691	0.903	71.43	15	15	2.68	15	47.53609	PT-Adapt
9	2.703	324.335	22.738	64.615	17.971	30.435	0.908	0.997	0.678	0.896	71.43	12	12	2.68	12	48.43258	PT-Adapt
10	2.693	323.184	23.715	64.615	17.798	30.435	0.905	0.999	0.678	0.891	71.43	12	12	2.68	12	49.32379	PT-Adapt
11	2.709	325.113	27.375	75.385	22.852	36.097	0.910	0.999	0.682	0.907	71.43	14	14	2.68	14	50.23042	PT-Adapt
12	2.638	316.544	25.699	75.385	19.631	33.266	0.886	1.000	0.664	0.894	71.43	14	13	2.68	14	51.12475	PT-Adapt

K.3 Example of the Structured Scheduling Algorithm for Medium Season

Equipment Set

	V1	V2	V3	V4
1	0	0	1	1
2	0	1	0	1
3	0	1	1	0
4	1	0	0	1
5	1	0	1	0
6	1	1	0	0
7	1	1	1	1

CIP Vector

	1:nhours	hourRUN	hourCIP	V4	V5	V6	V7	V8	V9	V10	V11	V12
1	1	4	14	0	1	1	1	1	1	1	1	1
2	2	4	14	0	0	1	1	1	1	1	1	1
3	3	4	14	0	0	0	1	1	1	1	1	1
4	4	4	14	0	0	0	0	1	1	1	1	1
5	5	4	14	0	0	0	0	0	1	1	1	1
6	6	4	14	0	0	0	0	0	0	1	1	1
7	7	4	14	0	0	0	0	0	0	0	1	1
8	8	4	14	0	0	0	0	0	0	0	0	1
9	9	4	14	0	0	0	0	0	0	0	0	0
10	10	4	14	0	0	0	0	0	0	0	0	0
11	11	4	14	0	0	0	0	0	0	0	0	0
12	12	4	14	0	0	0	0	0	0	0	0	0
13	13	4	14	0	0	0	0	0	0	0	0	0
14	14	4	14	0	0	0	0	0	0	0	0	0

Scheduling Plan - Hour

Supply	RealSupply	Difference	InitialTank	hour	comb	cip	run	start	C1	C2	C3
3.0355686	3.0355686	0	0.00000000	1	3	3	8	1	0	0.0000000	0.0000000
1.4012451	1.4012451	0	0.10896913	2	3	3	8	1	0	0.0000000	0.0000000
1.9006989	1.9006989	0	0.15927024	3	3	3	8	1	0	0.0000000	0.0000000
1.6100445	1.6100445	0	0.22750045	4	3	3	8	1	0	0.8035714	0.8035714
1.0377538	1.0377538	0	0.22760462	5	3	3	8	1	0	0.8035714	0.8035714
4.0088098	4.0088098	0	0.20716501	6	3	3	8	1	0	0.8035714	0.8035714
1.3540745	1.3540745	0	0.29337869	7	3	3	8	1	0	0.8035714	0.8035714
3.2103775	3.2103775	0	0.28429419	8	3	3	8	1	0	0.8035714	0.8035714
3.6584985	3.6584985	0	0.34184620	9	3	3	8	1	0	0.8035714	0.8035714
1.4567400	1.4567400	0	0.41548461	10	3	3	8	1	0	0.8035714	0.8035714
4.9647087	4.9647087	0	0.41008553	11	3	3	8	1	0	0.8035714	0.8035714
2.9453895	2.9453895	0	0.53061354	12	3	3	8	1	0	0.0000000	0.0000000
1.0779876	1.0779876	0	0.63634547	13	3	3	8	1	0	0.0000000	0.0000000
1.4192810	1.4192810	0	0.67504246	14	3	3	8	1	0	0.0000000	0.0000000

Scheduling Summary - Statistics

comb	cip	run	start	SupplyMean	SupplySD	SupplyPlanSum	SupplyActualSum	Stage1WIPMeanPerc	Stage1WIPS
3	3	8	1	2.261806	1.772284	108.5667	75.71429	82.14891	
3	3	8	6	2.261806	1.772284	108.5667	77.35138	81.36141	
3	3	8	7	2.261806	1.772284	108.5667	77.35138	80.36218	
3	3	8	8	2.261806	1.772284	108.5667	77.35138	78.76392	
3	3	8	9	2.261806	1.772284	108.5667	77.35138	77.36168	

K.4 Adaptive Pull-Type Interactions 12 periods

Period	Stage0_ Mean	Stage0_ SD	Stage0_ Sum	Real Supply	StageB1 _Max	StageB2 _Max	Supply Accuracy	Stage2 Util	SLA	Lot	Interacti ons
1	2.381	1.641	285.714	57.14	50.463	33.215	1.000	0.590	0.779	57.14	2
2	2.381	1.694	285.714	57.14	54.574	34.176	1.000	0.593	0.773	57.14	4
3	2.364	2.089	283.737	56.75	57.915	48.281	0.993	0.588	0.774	57.14	2
4	2.376	1.646	285.140	57.03	58.733	27.503	0.998	0.591	0.768	57.14	2
5	2.381	1.539	285.714	57.14	57.503	39.459	1.000	0.593	0.780	57.14	2
6	2.381	1.566	285.714	57.14	69.471	28.893	1.000	0.593	0.778	57.14	5
7	2.381	1.546	285.714	57.14	58.613	34.176	1.000	0.592	0.774	57.14	3
8	2.378	1.625	285.302	57.06	65.371	29.853	0.999	0.592	0.766	57.14	3
9	2.381	1.567	285.714	57.14	49.913	35.137	1.000	0.592	0.781	57.14	3
10	2.381	1.748	285.714	57.14	63.492	50.025	1.000	0.593	0.759	57.14	3
11	2.381	1.811	285.714	57.14	47.363	42.821	1.000	0.593	0.772	57.14	2
12	2.379	1.960	285.434	57.09	72.939	35.137	0.999	0.591	0.782	57.14	7
1	2.530	1.744	303.571	60.71	60.768	34.176	1.000	0.628	0.837	60.71	3
2	2.530	1.800	303.571	60.71	61.741	29.853	1.000	0.629	0.830	60.71	6
3	2.484	2.182	298.132	59.63	63.356	60.415	0.982	0.617	0.811	60.71	2
4	2.523	1.748	302.763	60.55	58.467	28.109	0.997	0.628	0.833	60.71	3
5	2.530	1.635	303.571	60.71	58.213	34.176	1.000	0.629	0.836	60.71	5
6	2.530	1.664	303.571	60.71	65.640	39.459	1.000	0.627	0.837	60.71	5
7	2.530	1.642	303.571	60.71	59.091	43.782	1.000	0.629	0.833	60.71	2
8	2.528	1.730	303.310	60.66	71.518	39.459	0.999	0.629	0.832	60.71	3
9	2.530	1.665	303.571	60.71	57.089	49.065	1.000	0.629	0.841	60.71	2
10	2.530	1.857	303.571	60.71	63.554	54.348	1.000	0.629	0.824	60.71	3
11	2.530	1.924	303.571	60.71	50.564	48.104	1.000	0.629	0.839	60.71	2
12	2.515	2.061	301.792	60.36	72.257	44.742	0.994	0.625	0.830	60.71	6
1	2.679	1.846	321.429	64.29	79.728	33.215	1.000	0.667	0.877	64.29	4
2	2.678	1.906	321.321	64.26	70.110	39.459	1.000	0.665	0.878	64.29	5
3	2.596	2.259	311.489	62.30	78.207	43.959	0.969	0.646	0.847	64.29	8
4	2.668	1.844	320.208	64.04	57.972	39.459	0.996	0.663	0.884	64.29	3
5	2.679	1.731	321.429	64.29	71.903	44.742	1.000	0.667	0.876	64.29	4
6	2.617	1.757	314.054	62.81	80.000	29.853	0.977	0.651	0.867	64.29	8
7	2.679	1.739	321.429	64.29	63.896	49.065	1.000	0.664	0.876	64.29	2
8	2.641	1.829	316.871	63.37	80.000	38.498	0.986	0.657	0.873	64.29	4
9	2.679	1.763	321.429	64.29	61.861	52.187	1.000	0.666	0.878	64.29	2
10	2.676	1.967	321.123	64.22	69.867	50.025	0.999	0.666	0.873	64.29	5
11	2.670	2.046	320.393	64.08	80.000	53.387	0.997	0.664	0.866	64.29	4
12	2.570	2.113	308.356	61.67	80.000	37.892	0.959	0.640	0.866	64.29	8
1	2.709	1.924	325.101	65.02	80.000	32.798	0.958	0.674	0.900	67.86	9
2	2.767	2.017	332.096	66.42	80.000	50.025	0.979	0.687	0.894	67.86	7
3	2.698	2.337	323.792	64.76	79.550	50.025	0.954	0.669	0.872	67.86	9
4	2.679	1.953	321.493	64.30	80.000	30.094	0.948	0.667	0.900	67.86	9
5	2.713	1.865	325.509	65.10	80.000	38.941	0.959	0.675	0.900	67.86	9
6	2.726	1.878	327.159	65.43	80.000	40.420	0.964	0.679	0.893	67.86	9
7	2.702	1.825	324.208	64.84	80.000	31.471	0.956	0.672	0.892	67.86	9
8	2.706	1.851	324.746	64.95	80.000	41.481	0.957	0.674	0.893	67.86	7
9	2.688	1.925	322.541	64.51	80.000	32.394	0.951	0.668	0.900	67.86	9
10	2.711	2.110	325.276	65.06	80.000	36.059	0.959	0.674	0.900	67.86	9
11	2.762	2.172	331.495	66.30	80.000	59.024	0.977	0.688	0.900	67.86	7
12	2.682	2.195	321.879	64.38	80.000	53.564	0.949	0.668	0.892	67.86	8
1	2.716	2.026	325.955	65.19	80.000	33.279	0.913	0.674	0.900	71.43	14
2	2.724	2.050	326.927	65.39	80.000	33.279	0.915	0.678	0.900	71.43	14
3	2.734	2.327	328.075	65.62	72.239	44.742	0.919	0.681	0.892	71.43	11
4	2.679	2.040	321.527	64.31	80.000	27.932	0.900	0.666	0.900	71.43	15
5	2.709	1.927	325.040	65.01	80.000	35.200	0.910	0.673	0.900	71.43	14
6	2.697	1.885	323.657	64.73	80.000	27.073	0.906	0.670	0.900	71.43	16
7	2.704	1.820	324.517	64.90	80.000	28.210	0.909	0.671	0.895	71.43	15
8	2.699	1.877	323.870	64.77	80.000	30.410	0.907	0.671	0.900	71.43	14
9	2.699	1.990	323.885	64.78	80.000	35.099	0.907	0.671	0.900	71.43	14
10	2.710	2.098	325.143	65.03	80.000	33.076	0.910	0.674	0.900	71.43	14
11	2.689	2.076	322.685	64.54	80.000	37.020	0.904	0.669	0.900	71.43	13
12	2.650	2.147	317.991	63.60	80.000	36.059	0.890	0.660	0.900	71.43	13

K.5 Function ScheduleStage

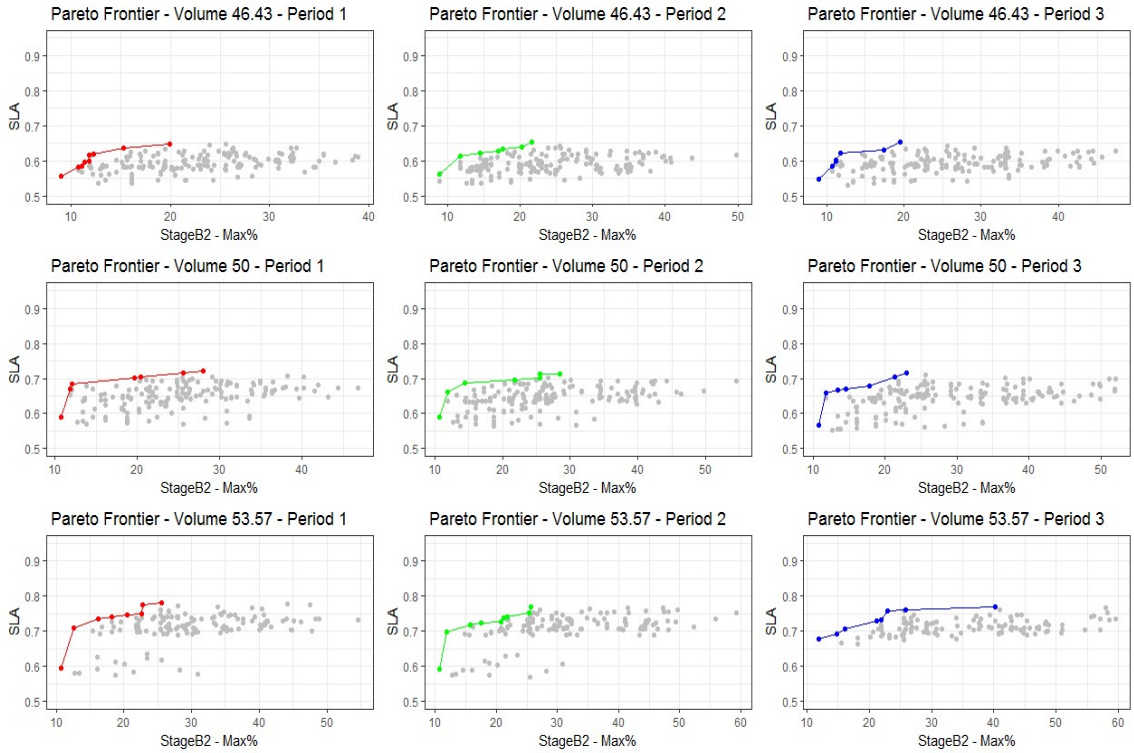
```
ScheduleStage = function(Stage, numequip,comb)  {


  # combination
  numcomb  = factorial(numequip) / ((factorial(numequip - comb)) * factorial(comb))
  equipvecaux  <<- as.data.frame(t(1:numequip))
  equipvecaux  <<- equipvecaux[-1,]
  equipvecaux[(1:(numcomb+1)),1:numequip] <<- 1


  ## first part - create a vector with  possible equipment combinations
  x = 0
  for (i in 1:(numequip-1))
    for (j in (i+1):numequip)
    {
      x = x + 1
      equipvecaux[x,c(i,j)] <<- 0
    }

  equipvecaux <<- as.matrix(equipvecaux)


  ## second part  - create a vectors for nhours * (maxcip - mincip) * (maxrun - minrun)
  for (maxrunaux in maxrunhours:minrunhours){

    data$hourRUN  <<- maxrunaux

    for (maxcipaux in mincip:maxcip) {

      data$hourCIP <<- maxcipaux

      for (startcip in col:(maxrunaux + col)) {

        data[c(startcip)]  <<- 1
        cipaux = 0
        runaux = 0

        for (i in 1:(nhours - startcip + col))
        {
          cipaux = cipaux + 1

          #the limits of cip times
          if (cipaux <= maxcipaux)
            data[i + startcip - col,startcip] <<- 0
          else {
            runaux = runaux + 1

            if (runaux >= maxrunaux) {
              cipaux = 0
              runaux = 0
            }
          } # else
        } # for hours
      } #for startcip
    #  CIPvectorAux <<- as.data.frame(data)
      CIPvector    <<- rbind(CIPvector,data) # add more observaions to the main vector
    } #for maxcipaux
    #pbar$step()
  } #for maxrunaux
  #
  CIPvector <<- as.matrix(CIPvector)
}
```

K.6 Function CalculateSchedule

```
CalculateSchedule = function()  {

colcapmat = 0
colrealmat = 0

for (combsep in 1:nrow(equipvecaux)) {

cipaux <<- 0
planAux[,6] <<- combsep

# from the maximum hours to the minimum hours
for (maxrunaux in maxrunhours:minrunhours){
planAux[,8]  <<- maxrunaux

for (maxcipaux in mincip:maxcip) {
planAux[,7]  <<- maxcipaux

for (startcip in 1:(maxrunhours +1)) {

silo1 <<- invlevel1
silo2 <<- invlevel2
rowaux <<- 0

if (((startcip <= (maxrunaux + 1))
&& (startcip >= (minrunhours + 1))) || startcip ==1) {

#  print(paste(startcip, maxcipaux,maxrunaux,cipaux))
colaux <<- 3 + startcip

lcipStop[1] <<- 0
lcipStop[2] <<- 0

for (h in 1:nhours){
planAux[h,4] <<- silo1
planAux[h,9] <<- startcip

rowaux <<- h + (nhours * cipaux)
realprocess2auxStage31 <<- 0
realprocess2auxStage32 <<- 0

realsepauxSkim <<- 0
realsepaux <<- 0

energyaux <<- 0

VerifyCipStages(h,cipstart31,cipstage31,1) #start 30 for 3 hours
VerifyCipStages(h,cipstart32,cipstage32,2) #start 70 for 10 hours

for (sep in 1:numseparators)   {
colcapmat  = colcapsep  + sep
colrealmat = colrealsep + sep

planAux[h,colcapmat] <<-  capsep[sep] *  equipvecaux[combsep,sep] * CIPvector[rowaux,colaux]

#  print(paste(h,colcapmat,silo1,realsepaux))

#testing inventory Silo1 > Separator Capacity
if (silo1 >= planAux[h,colcapmat])
realsepaux <<-  planAux[h,colcapmat]
else
realsepaux <<- silo1 * lpartial

#limiting the flow according to the next stage capacity
if (realsepaux >= (MaxCapStage2 - silo2))
realsepaux <<- (MaxCapStage2 - silo2)

realsepauxSkim = realsepaux *  (1 - PercCream)

# print(paste(realsepauxSkim, MaxCapStage2,silo2))

silo1 <<- silo1 - realsepaux
silo2 <<- silo2 + realsepauxSkim

planAux[h,colrealmat] <<- realsepaux
energyaux <<- energyaux + (planAux[h,colcapmat] >= 1)
} # for sep
```

```
planAux[h,colcapmat+1]  <<- sum(planAux[h,(colcapsep+1):(colcapsep+numseparators)])
planAux[h,colrealmat+1] <<- sum(planAux[h,(colrealsep+1):(colrealsep+numseparators)])

#original supply
realsepaux <<- planAux[h,1]

#limiting the flow according to the next stage capacity
if ( realsepaux >= (MaxCapStage1 - silo1))
realsepaux <<- (MaxCapStage1 - silo1)
silo1 <<- realsepaux + silo1

#saving the real separation
planAux[h,2] <<- realsepaux
planAux[h,3] <<- planAux[h,1] - realsepaux
#total real separated
planAux[h,colrealmat+2] <<-  silo1

#silo2 = silo2 + planAux[h,colcapmat+1]

#Stage 3.1 -
if (silo2 > TotalDownstreamRateStage1)
realprocess2auxStage31 <<- TotalDownstreamRateStage1 * (lcipStop[1] == 0)
else
realprocess2auxStage31 <<- silo2 * (lcipStop[1] == 0)

silo2 <<- silo2 - realprocess2auxStage31

#Stage 3.1 –
if (silo2 > TotalDownstreamRateStage2)
realprocess2auxStage32 <<- TotalDownstreamRateStage2 * (lcipStop[2] == 0)
else
realprocess2auxStage32 <<- silo2 * (lcipStop[2] == 0)

silo2 <<- silo2 - realprocess2auxStage32

#silo2
planAux[h,colrealmat+3] <<- silo2

# stage3.1
planAux[h,colrealmat+4] <<- realprocess2auxStage31

colrealmat
# stage3.2
planAux[h,colrealmat+5] <<- realprocess2auxStage32


#energy
planAux[h,colrealmat+6] <<- energyaux * (as.integer(!(h >= energymin && h <= energymax)) + 1)

planAux[h,colrealmat+7] <<-  lcipStop[1] #Stage3.1

planAux[h,colrealmat+8] <<-  lcipStop[2] #Stage3.2

} # for sep hours
planTotal <<- rbind(planTotal,planAux)
} # if start cip
} # for start cip
} #for max cip
} # for maxrunaux
} # for combsep
} # end function
```

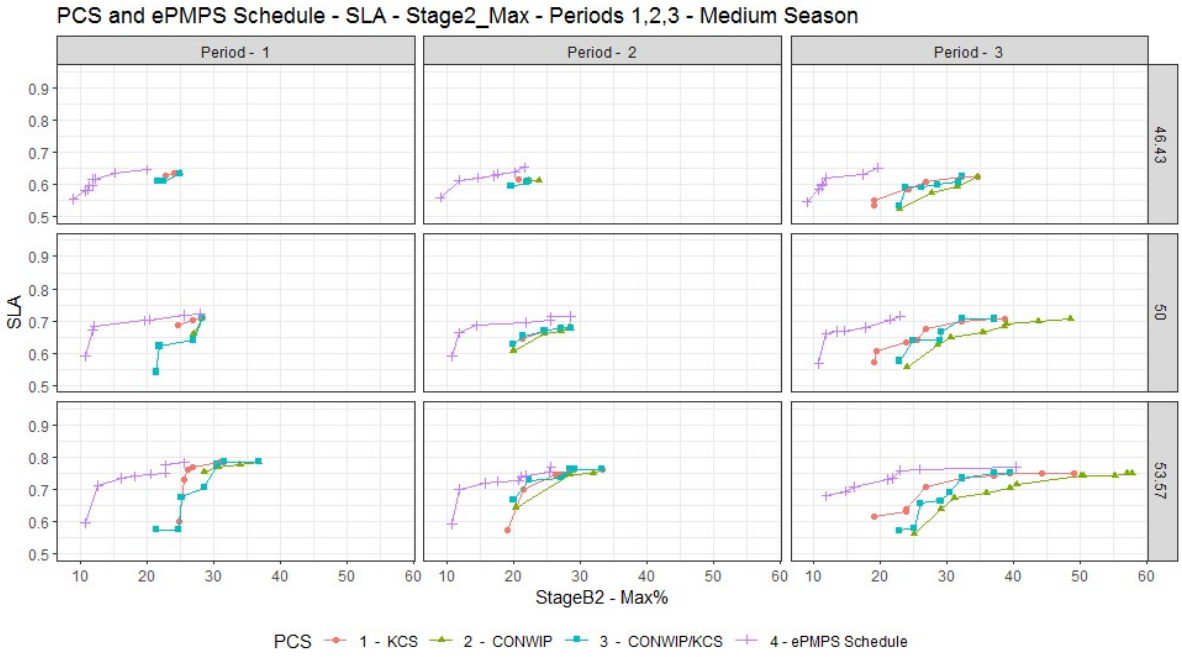
K.7 Pareto Frontier Medium Season – 3 Periods

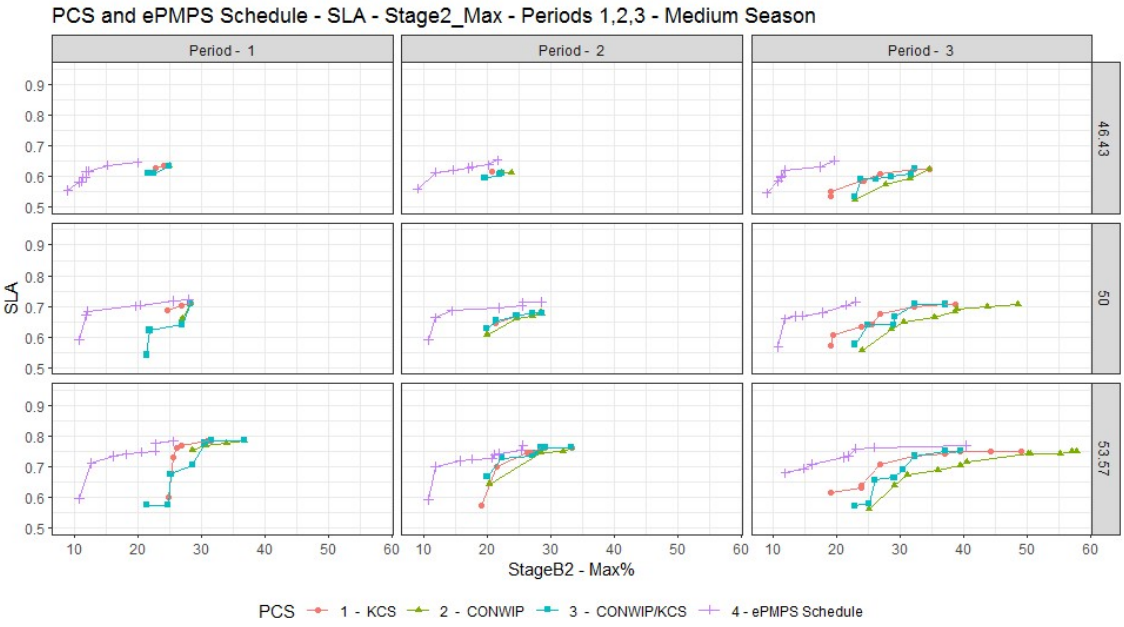


K.8 Example ePMPS Best Scheduling Period 1 – Medium Season

SupplyAll	RealSupplyAll	DifferenceAll	InitialTankAll	hour[...]	comb	dp	run	start	C1All	C2All	C3All	C4All	TotalCapacityAll	R1All	R2All	R3All	R4All	RealSeparatedAll	Silo1All	Silo2All	Stage31All	Stage32All	UtilisationAll	SupplyAccuracyAll	Stage1PercAll	Stage2PercAll
3.38	3.38	-	-	1	4	5	5	6	1.61	-	-	1.96	3.57	-	-	-	-	-	3.38	-	-	-	-	1.00	0.18	-
1.56	1.56	-	3.38	2	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.78	3.38	1.56	0.54	1.43	1.25	0.95	1.00	0.08	0.02
2.12	2.12	-	1.56	3	4	5	5	6	1.61	-	-	1.96	3.57	1.56	-	-	-	1.56	2.12	-	1.43	0.59	0.44	1.00	0.11	-
1.79	1.79	-	2.12	4	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.51	2.12	1.79	-	1.43	0.58	0.59	1.00	0.10	-
1.16	1.16	-	1.79	5	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.19	1.79	1.16	-	1.43	0.28	0.50	1.00	0.06	-
4.47	4.47	-	1.16	6	4	5	5	6	-	-	-	-	-	-	-	-	-	-	5.62	-	-	-	-	1.00	0.30	-
1.51	1.51	-	5.62	7	4	5	5	6	-	-	-	-	-	-	-	-	-	-	7.13	-	-	-	-	1.00	0.38	-
3.58	3.58	-	7.13	8	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	7.14	2.14	-	1.25	1.00	1.00	0.38	0.06
4.08	4.08	-	7.14	9	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	7.65	2.86	1.43	1.25	1.00	1.00	0.41	0.08
1.62	1.62	-	7.65	10	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.70	3.57	1.43	1.25	1.00	1.00	0.31	0.10
5.53	5.53	-	5.70	11	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	7.66	4.29	1.43	1.25	1.00	1.00	0.41	0.12
3.28	3.28	-	7.66	12	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	7.37	5.00	1.43	1.25	1.00	1.00	0.40	0.14
1.20	1.20	-	7.37	13	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.00	5.71	1.43	1.25	1.00	1.00	0.27	0.16
1.58	1.58	-	5.00	14	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.01	6.43	1.43	1.25	1.00	1.00	0.16	0.18
-	-	-	3.01	15	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.40	3.01	-	6.61	1.43	1.25	0.84	NaN	-	0.19
3.26	3.26	-	-	16	4	5	5	6	-	-	-	-	-	-	-	-	-	-	3.26	3.93	1.43	1.25	-	1.00	0.18	0.11
2.17	2.17	-	3.26	17	4	5	5	6	-	-	-	-	-	-	-	-	-	-	5.43	1.25	1.43	1.25	-	1.00	0.29	0.04
4.17	4.17	-	5.43	18	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	6.03	1.97	1.43	1.25	1.00	1.00	0.32	0.06
-	-	-	6.03	19	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	2.46	2.68	1.43	1.25	1.00	NaN	0.13	0.08
0.46	0.46	-	2.46	20	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.86	2.46	0.46	3.59	1.43	-	0.69	1.00	0.02	0.10
5.88	5.88	-	0.46	21	4	5	5	6	1.61	-	-	1.96	3.57	0.46	-	-	-	0.46	5.88	2.60	1.43	-	0.13	1.00	0.32	0.07
2.30	2.30	-	5.88	22	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	4.61	4.56	1.43	-	1.00	1.00	0.25	0.13
2.03	2.03	-	4.61	23	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.07	6.53	1.43	-	1.00	1.00	0.17	0.18
-	-	-	3.07	24	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.46	3.07	-	8.01	1.43	-	0.86	NaN	-	0.23
5.50	5.50	-	-	25	4	5	5	6	1.61	-	-	1.96	3.57	-	-	-	-	-	5.50	6.59	1.43	-	-	1.00	0.30	0.19
0.99	0.99	-	5.50	26	4	5	5	6	-	-	-	-	-	-	-	-	-	-	6.49	5.16	1.43	-	-	1.00	0.35	0.15
1.06	1.06	-	6.49	27	4	5	5	6	-	-	-	-	-	-	-	-	-	-	7.55	3.73	1.43	-	-	1.00	0.41	0.11
-	-	-	7.55	28	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.98	5.69	1.43	-	1.00	NaN	0.21	0.16
1.93	1.93	-	3.98	29	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	2.34	7.66	1.43	-	1.00	1.00	0.13	0.22
2.06	2.06	-	2.34	30	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.73	2.34	2.06	7.20	1.43	1.25	0.65	1.00	0.11	0.20
-	-	-	2.06	31	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.45	2.06	-	6.47	1.43	1.25	0.58	NaN	-	0.18
3.37	3.37	-	-	32	4	5	5	6	1.61	-	-	1.96	3.57	-	-	-	-	-	3.37	3.80	1.43	1.25	-	1.00	0.18	0.11
3.72	3.72	-	3.37	33	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.77	3.37	3.72	4.32	1.43	1.25	0.94	1.00	0.20	0.12
3.76	3.76	-	3.72	34	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.91	5.04	1.43	1.25	1.00	1.00	0.21	0.14
0.99	0.99	-	3.91	35	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	1.33	5.75	1.43	1.25	1.00	1.00	0.07	0.16
5.94	5.94	-	1.33	36	4	5	5	6	-	-	-	-	-	-	-	-	-	-	7.27	3.07	1.43	1.25	-	1.00	0.39	0.09
7.18	7.18	-	7.27	37	4	5	5	6	-	-	-	-	-	-	-	-	-	-	14.44	0.39	1.43	1.25	-	1.00	0.78	0.01
1.87	1.87	-	14.44	38	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	12.74	2.54	-	1.25	1.00	1.00	0.69	0.07
-	-	-	12.74	39	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	9.17	4.68	-	1.25	1.00	NaN	0.49	0.13
2.47	2.47	-	9.17	40	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	8.07	6.82	-	1.25	1.00	1.00	0.43	0.19
4.63	4.63	-	8.07	41	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	9.13	7.54	1.43	1.25	1.00	1.00	0.49	0.21
4.44	4.44	-	9.13	42	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	10.00	8.25	1.43	1.25	1.00	1.00	0.54	0.23
1.01	1.01	-	10.00	43	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	7.44	8.97	1.43	1.25	1.00	1.00	0.40	0.25
2.11	2.11	-	7.44	44	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.98	9.68	1.43	1.25	1.00	1.00	0.32	0.27
2.47	2.47	-	5.98	45	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	4.88	10.39	1.43	1.25	1.00	1.00	0.26	0.29
0.58	0.58	-	4.88	46	4	5	5	6	-	-	-	-	-	-	-	-	-	-	5.47	7.72	1.43	1.25	-	1.00	0.29	0.22
1.05	1.05	-	5.47	47	4	5	5	6	-	-	-	-	-	-	-	-	-	-	6.52	5.04	1.43	1.25	-	1.00	0.35	0.14
-	-	-	6.52	48	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	2.95	5.75	1.43	1.25	1.00	NaN	0.16	0.16
3.05	3.05	-	2.95	49	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.34	2.95	3.05	5.87	1.43	1.25	0.82	1.00	0.16	0.17
1.75	1.75	-	3.05	50	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.44	3.05	1.75	6.09	1.43	1.25	0.85	1.00	0.09	0.17
1.13	1.13	-	1.75	51	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.15	1.75	1.13	5.08	1.43	1.25	0.49	1.00	0.06	0.14
2.55	2.55	-	1.13	52	4	5	5	6	1.61	-	-	1.96	3.57	1.13	-	-	-	1.13	2.55	3.48	1.43	1.25	0.32	1.00	0.14	0.10
-	-	-	2.55	53	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.94	2.55	-	3.22	1.43	1.25	0.71	NaN	-	0.09
3.16	3.16	-	-	54	4	5	5	6	1.61	-	-	1.96	3.57	-	-	-	-	-	3.16	0.54	1.43	1.25	-	1.00	0.17	0.02
2.02	2.02	-	3.16	55	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.55	3.16	2.02	0.86	1.43	1.25	0.88	1.00	0.11	0.02
3.10	3.10	-	2.02	56	4	5	5	6	-	-	-	-	-	-	-	-	-	-	5.12	-	0.86	-	-	1.00	0.28	-
-	-	-	5.12	57	4	5	5	6	-	-	-	-	-	-	-	-	-	-	5.12	-	-	-	-	NaN	0.28	-
1.99	1.99	-	5.12	58	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.54	0.71	1.43	1.25	1.00	1.00	0.19	0.02
5.21	5.21	-	3.54	59	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.94	3.54	5.21	1.40	1.43	1.25	0.99	1.00	0.28	0.04
2.65	2.65	-	5.21	60	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	4.28	2.12	1.43	1.25	1.00	1.00	0.23	0.06
2.76	2.76	-	4.28	61	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.47	2.83	1.43	1.25	1.00	1.00	0.19	0.08
2.94	2.94	-	3.47	62	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.87	3.47	2.94	3.45	1.43	1.25	0.97	1.00	0.16	0.10
4.34	4.34	-	2.94	63	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.33	2.94	4.34	3.57	1.43	1.25	0.82	1.00	0.23	0.10
5.00	5.00	-	4.34	64	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.77	4.28	1.43	1.25	1.00	1.00	0.31	0.12
2.05	2.05	-	5.77	65	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	4.25	5.00	1.43	1.25	1.00	1.00	0.23	0.14
0.71	0.71	-	4.25	66	4	5	5	6	-	-	-	-	-	-	-	-	-	-	4.96	2.32	1.43	1.25	-	1.00	0.27	0.07
2.92	2.92	-	4.96	67	4	5	5	6	-	-	-	-	-	-	-	-	-	-	7.89	-	1.43	0.89	-	1.00	0.42	-
2.53	2.53	-	7.89	68	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	6.85	0.71	1.43	1.25	1.00	1.00	0.37	0.02
3.33	3.33	-	6.85	69	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	6.61	1.43	1.43	1.25	1.00	1.00	0.36	0.04
1.73	1.73	-	6.61	70	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	4.77	3.57	-	1.25	1.00	1.00	0.26	0.10
-	-	-	4.77	71	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	1.20	5.71	-	1.25	1.00	NaN	0.06	0.16
2.20	2.20	-	1.20	72	4	5	5	6	1.61	-	-	1.96	3.57	1.20	-	-	-	1.20	2.20	5.60	-	1.25	0.33	1.00	0.12	0.16
1.04	1.04	-	2.20	73	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.59	2.20	1.04	5.01	1.43	1.25	0.62	1.00	0.06	0.14
1.98	1.98	-	1.04	74	4	5	5	6	1.61	-	-	1.96	3.57	1.04	-	-	-	1.04	1.98	3.32	1.43	1.25	0.29	1.00	0.11	0.09
1.04	1.04	-	1.98	75	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.37	1.98	1.04	2.52	1.43	1.25	0.55	1.00	0.06	0.07
-	-	-	1.04	76	4	5	5	6	-	-	-	-	-	-	-	-	-	-	1.04	-	1.43	1.09	-	NaN	0.06	-
3.19	3.19	-	1.04	77	4	5	5	6	-	-	-	-	-	-	-	-	-	-	4.23	-	-	-	-	1.00	0.23	-
5.24	5.24	-	4.23	78	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.90	0.71	1.43	1.25	1.00	1.00	0.32	0.02
0.58	0.58	-	5.90	79	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	2.92	1.43	1.43	1.25	1.00	1.00	0.16	0.04
2.33	2.33	-	2.92	80	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.31	2.92	2.33	1.52	1.43	1.25	0.82	1.00	0.13	0.04
2.33	2.33	-	2.33	81	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.72	2.33	2.33	1.05	1.43	1.25	0.65	1.00	0.13	0.03
4.31	4.31	-	2.33	82	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.72	2.33	4.31	0.58	1.43	1.25	0.65	1.00	0.23	0.02
3.63	3.63	-	4.31	83	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	4.37	1.30	1.43	1.25	1.00	1.00	0.24	0.04
2.88	2.88	-	4.37	84	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.67	2.01	1.43	1.25	1.00	1.00	0.20	0.06
5.06	5.06	-	3.67	85	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.16	2.73	1.43	1.25	1.00	1.00	0.28	0.08
4.15	4.15	-	5.16	86	4	5	5	6	-	-	-	-	-	-	-	-	-	-	9.31	0.05	1.43	1.25	-	1.00	0.50	0.00
0.85	0.85	-	9.31	87	4	5	5	6	-	-	-	-	-	-	-	-	-	-	10.16	-	0.05	-	-	1.00	0.55	-
2.72	2.72	-	10.16	88	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	9.31	0.71	1.43	1.25	1.00	1.00	0.50	0.02
2.58	2.58	-	9.31	89	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	8.31	1.43	1.43	1.25	1.00	1.00	0.45	0.04
4.68	4.68	-	8.31	90	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	9.42	2.14	1.43	1.25	1.00	1.00	0.51	0.06
2.09	2.09	-	9.42	91	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	7.93	2.86	1.43	1.25	1.00	1.00	0.43	0.08
0.71	0.71	-	7.93	92	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.07	3.57	1.43	1.25	1.00	1.00	0.27	0.10
0.95	0.95	-	5.07	93	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	2.45	4.29	1.43	1.25	1.00	1.00	0.13	0.12
4.66	4.66	-	2.45	94	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.84	2.45	4.66	3.93	1.43	1.25	0.69	1.00	0.25	0.11
0.16	0.16	-	4.66	95	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	1.25	4.65	1.43	1.25	1.00	1.00	0.07	0.13
-	-	-	1.25	96	4	5	5	6	-	-	-	-	-	-	-	-	-	-	1.25	1.97	1.43	1.25	-	NaN	0.07	0.06
1.47	1.47	-	1.25	97	4	5	5	6	-	-	-	-	-	-	-	-	-	-	2.73	-	1.43	0.54	-	1.00	0.15	-
2.49	2.49	-	2.73	98	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.12	2.73	2.49	-	1.43	1.16	0.76	1.00	0.13	-
0.97	0.97	-	2.49	99	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.88	2.49	0.97	0.93	1.43	-	0.70	1.00	0.05	0.03
0.97	0.97	-	0.97	100	4	5	5	6	1.61	-	-	1.96	3.57	0.97	-	-	-	0.97	0.97	0.42	1.43	-	0.27	1.00	0.05	0.01
0.77	0.77	-	0.97	101	4	5	5	6	1.61	-	-	1.96	3.57	0.97	-	-	-	0.97	0.77	-	1.34	-	0.27	1.00	0.04	-
3.53	3.53	-	0.77	102	4	5	5	6	1.61	-	-	1.96	3.57	0.77	-	-	-	0.77	3.53	0.74	-	-	0.22	1.00	0.19	0.02
4.52	4.52	-	3.53	103	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.93	3.53	4.52	4.09	-	-	0.99	1.00	0.24	0.12
1.44	1.44	-	4.52	104	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	2.38	7.48	-	-	1.00	1.00	0.13	0.21
4.12	4.12	-	2.38	105	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	0.78	2.38	4.12	8.32	1.43	-	0.67	1.00	0.22	0.24
3.15	3.15	-	4.12	106	4	5	5	6	-	-	-	-	-	-	-	-	-	-	7.26	6.89	1.43	-	-	1.00	0.39	0.20
1.89	1.89	-	7.26	107	4	5	5	6	-	-	-	-	-	-	-	-	-	-	9.15	5.46	1.43	-	-	1.00	0.49	0.15
5.87	5.87	-	9.15	108	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	11.44	7.43	1.43	-	1.00	1.00	0.62	0.21
1.66	1.66	-	11.44	109	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	9.53	8.14	1.43	1.25	1.00	1.00	0.51	0.23
4.65	4.65	-	9.53	110	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	10.61	8.86	1.43	1.25	1.00	1.00	0.57	0.25
3.40	3.40	-	10.61	111	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	10.44	9.57	1.43	1.25	1.00	1.00	0.56	0.27
3.82	3.82	-	10.44	112	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	10.69	10.29	1.43	1.25	1.00	1.00	0.58	0.29
1.63	1.63	-	10.69	113	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	8.75	11.00	1.43	1.25	1.00	1.00	0.47	0.31
-	-	-	8.75	114	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	5.18	11.71	1.43	1.25	1.00	NaN	0.28	0.33
0.82	0.82	-	5.18	115	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	2.42	12.43	1.43	1.25	1.00	1.00	0.13	0.35
1.85	1.85	-	2.42	116	4	5	5	6	-	-	-	-	-	-	-	-	-	-	4.27	9.75	1.43	1.25	-	1.00	0.23	0.28
3.17	3.17	-	4.27	117	4	5	5	6	-	-	-	-	-	-	-	-	-	-	7.44	7.07	1.43	1.25	-	1.00	0.40	0.20
0.86	0.86	-	7.44	118	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	4.73	7.79	1.43	1.25	1.00	1.00	0.25	0.22
2.34	2.34	-	4.73	119	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.96	3.57	3.49	8.50	1.43	1.25	1.00	1.00	0.19	0.24
1.78	1.78	-	3.49	120	4	5	5	6	1.61	-	-	1.96	3.57	1.61	-	-	1.89	3.49	1.78	9.14	1.43	1.25	0.98	1.00	0.10	0.26

K.9 Pareto Frontier - ePMPS Best Scheduling Periods 1,2,3 – Medium Season




PCS and ePMPS Schedule - SLA - Stage2_Max - Periods 1,2,3 - Medium Season
Period - 1
Period - 2
Period - 3
46.43
50
53.57
SLA
StageB2 - Max%
PCS
1 - KCS
2 - CONWIP
3 - CONWIP/KCS
4 - ePMPS Schedule

APPENDIX L – List of Publications – Abstracts

L.1 C. Eccher, B. Minardi and J. Geraghty, "Application of Modelling and Simulation as the primary research methodology in Sustainable Supply Chain Management: an analysis of the literature," in 1st Conference of the EURO Working Group on Sustainable Supply Chains, 2016.

Application of Simulation Modelling as the Primary Research Methodology in Sustainable Supply Chain Management: An Analysis of Literature

Cristiani Eccher, Barbara Minardi- Kwiatkowska, John Geraghty (Dublin City University, Ireland)

The purpose of this literature review is to provide a deeper understanding the application of Simulation Modelling technology to issues in the Supply Chain Management. Simulation Modelling are widely applied in Industrial environments in order to evaluate performance, identify improvements, and establish the best results in Production Processes. Notwithstanding, Simulation Modelling are essential to support long term and short term decisions and understand the impact of the flow of material and information throughout the Supply Chain processes. Three questions are explored in this paper: RQ1. What Supply Chain Management research has been conduct using Simulation Modelling approaches? RQ2. What is the extent of the use of Simulation Modelling approaches in research on Sustainable Supply Chain and what is the potential for this technology?

RQ3. With respect to the question above, it was desired to determine the types of decision levels to which simulation technology has been applied i.e., Strategic, Tactical and Operational? A structured literature review was conducted to for the purpose of answering these questions and for the purpose of identifying what contributions have been made to Sustainable Supply Chain Management.

L.2 C. Eccher and J. Geraghty, “MODELLING & SIMULATION AS A STRATEGIC TOOL FOR DECISION-MAKING PROCESS IN THE DAIRY INDUSTRY,” in International Conference on Decision Making in Manufacturing and Services (DMMS 2017), 2017, pp. 97–107.C.

Modelling & Simulation as a Strategic Tool for Decision-Making Process in the Dairy Industry

Cristiani ECCHER[1], John GERAGHTY[2]

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Abstract: The Dairy Industry faces many challenges compared to other sectors. On the supply side due to the nature of the raw material shelf life, large inventories are not applied; during the manufacturing process the flow of production is continuous which is highly sensitive to any sort of unplanned disruption; and on the demand side, the market dictates the commodity prices. In response to the growth in competition, dairy organizations' strategy must incorporate technology into their daily processes in order to become more efficient, profitable and sustainable. To achieve desired levels of improvement, Modelling and Simulation has been increasing in popularity in the decision-making process. Using a Dairy company as a study case, this paper has highlighted the potential for Modelling and Simulation to be used as a powerful strategic tool.

Keywords: Modelling and Simulation, dairy, decision-making process

L.3 C. Eccher and J. Geraghty, “INDUSTRY 4 . 0 AND THE FUTURE FOR DAIRY SUPPLY CHAINS,” Int. J. Mech. Prod. Eng., vol. 8, no. 2, pp. 7–13, 2020.

DOIONLINE NO - IJMPE-IRAJ-DOI-16958

Publish In	International Journal of Mechanical and Production Engineering (IJMPE)-IJMPE
Issue	Volume-8,Issue-2 (Feb, 2020)
Paper Title	Industry 4.0 and the Future for Dairy Supply Chains
Author Name	Cristiani Eccher, John Geraghty
Affilition	Dublin City University, School of Mechanical and Manufacturing Engineering Glasnevin, Dublin 9, Dublin, Ireland Dairy Processing Technology Centre (DPTC), Ireland
Pages	7-13
Abstract	The Dairy Sector, one of the most significant segments in the Food Supply Chain, has benefited from sensor controlling equipment due to the fact that the high volumes of milk flow require precise temperature control, right levels of pressure, and transmitters sending signals to a central control in order to guarantee a reliable process. However, there is still a lack of communication between operational plant activities and the daily decision-making processes. In the context of Industry 4.0 where Cyber-Physical Systems (CPS) manage interconnected systems between equipment and software applications, the expansion of accurate data acquisition manufacturing activities would improve not only the inbound activities but also the entire Supply Chain reliability process since real-time information shared among companies reduces the uncertainty and unforeseen events therefore enhancing the quality of information for decision makers. Self-organising activities between chains is a promising area and could enhance the supply of raw material among manufacturers. This state-of-the-art technology is currently visible in high-level automated manufacturing products such as the automotive sector. Following a specific case study in the Dairy Sector, this paper presents a prototype for simulation model highlighting the benefits and important features in Industry 4.0 from the Dairy Supply Chain perspective. Keywords - Modelling and Simulation, Dairy Supply Chain, Industry 4.0

L.4 C. Eccher and J. Geraghty, “Incorporating sustainable criteria in a dynamic multi-objective recommendation planning tool for a continuous manufacturing process : A dairy case study,” J. Manuf. Syst., vol. 55, no. April, pp. 159–170, 2020. https://doi.org/10.1016/j.jmsy.2020.02.008. Impact Factor: 5.105.

Journal of Manufacturing Systems 55 (2020) 159–170

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journal homepage: www.elsevier.com/locate/jmansys

Incorporating sustainable criteria in a dynamic multi-objective recommendation planning tool for a continuous manufacturing process: A dairy case study

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ARTICLE INFO

Keywords:
Continuous manufacturing
Sustainability
Scheduling problems
Simulation
Multi-objective optimisation
Pareto frontier

ABSTRACT

The activity of scheduling the production plan with the aim of achieving an optimal criterion has been explored in literature for several manufacturing sectors, in particular when it comes to solving scheduling NP-complete problems. In Dairy Manufacturing, determining an optimum criterion for the scheduling process has numerous internal and external challenges due to the complexity of this environment.

The initial stages in the Dairy process are characterised by a continuous manufacturing environment and specific operational issues are observable: interruptions for the accomplishment of Cleaning-In-Place (CIP); a short raw material lifespan which demands a fast processing rate; and the stochastic raw material supply variation. By highlighting these three aspects, a critical trade-off emerges: CIP cycle-times heavily reduce the processing capacity, whereas the raw material processed requires an increase in available capacity due to the impact of seasonality, perishability and stochastic deliveries. Therefore, the scheduling plan must be dynamically readapted based on the current inventory, volume and frequency supplied, CIP cycle-times, maximum equipment running hours and downstream capacities.

The aim of this research is to develop an integrated approach for generating equipment schedules under supply uncertainty typically observed in the dairy sector where criteria of sustainability are effortlessly incorporated for an improved decision-making process. An efficient Multi-objective Algorithm (MOA) combining conflicting key performance metrics such as minimising Work-In-Process (WIP), maximising Service Level Agreement (SLA), Utilisation and Energy consumption is proposed.

The novelty consists of the ability to dynamically select trade-off criteria and visualise the optimum production plan according to the conditions defined by the decision-maker. The appropriate schedules are presented in a Pareto Frontier graph highlighting the entire non-dominance region according to the volume and frequency supplied. Even though sustainability metrics are usually ignored during production plan definitions, namely when a weak correlation between both environmental and profitable criteria is identified, the results demonstrate improved performance when both sustainable approaches are well explored.

L.5 C. Eccher and J. Geraghty, “Modelling & Simulation as a Strategic Tool for Decision-Making Process: A Dairy Case Study,” Int. J. Decis. Mak. Manuf. Serv., vol. 14, no. 1, 2020. https://doi.org/10.7494/dmms.2020.14.1.2785

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Vol. 14 • 2020 • No. 1 • pp. 5–22

Modelling & Simulation as a Strategic Tool for Decision-Making Processes: A Dairy Case Study

Cristiani Eccher*
John Geraghty**

Abstract. The dairy industry faces many challenges when compared to other sectors. On the supply side, due to the nature of the raw material, large inventories are not applied; during the manufacturing process, continuous production is highly sensitive to any sort of unplanned disruption; on the demand side, the market dictates the bulk powder commodity prices.
In response to the growth in competition, dairy organizations' strategy must incorporate technology into their daily processes in order to become more efficient, profitable and sustainable. To achieve desired levels of improvement, Modelling and Simulation (M&S) has been increasing in popularity in the decision-making process. Using a dairy company as a case study, this paper has highlighted the potential for M&S to be used as a powerful strategic tool for decision-making processes.

Keywords: modelling and simulation, dairy industry, decision-making processes, optimising, GAMS

Mathematics Subject Classification: 90B50, 93C95, 28A12

Submitted: February 2, 2018

Revised: August 28, 2018

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APPENDIX M – ePMPS User Guide

M.1 ePMPS – User Guid - Cover Page

Dairy Industrial Partner Logo

SIMULATION MODEL

User Guide

DPTC
DAIRY PROCESSING
TECHNOLOGY CENTRE

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	Simulation Model
Version 001 Version 002	Revision - 15/07/2019 Updated – 02/12/2019

1.0 Introduction

1.1 Description

The Framework ePMPS was developed according to the initial stages of a separation process in the Dairy Sector to support the planning process reproducing the same behaviour defined by the information structured in spreadsheets.

The Simulation Model main objectives are

- To provide a visual tool based on what-if scenarios, where supply, capacities and schedules can be changed, imported and compared
- Compare different scenarios simulated to provide better decisions regarding the current production flow
- Results calculated by the simulation are stored into an internal database and exported to a excel file for future download

1.2 Purpose

The purpose of this document is to describe the steps to operate the simulation model and how to visualise the results simulated.

2.0 Responsibility

The following is a summary of the roles and responsibilities of the functions involved in this model validation:

Lakeland

- Model validation and adjustment suggestions.

DPTC

- The DPTC team is responsible for the corrections required during the validation period.

	Simulation Model
Version 001 Version 002	Revision - 15/07/2019 Updated – 02/12/2019

3.0 Approvals

Department	Function	Name	Deliverables	Date
DPTC Team	Prepared By	Cristiani Eccher	First Version Release	15/07/2019
	Validated By		Validation in Progress	10/12/219

	Simulation Model
Version 001 Version 002	Revision - 15/07/2019 Updated – 02/12/2019

4.0 Process and Model Description

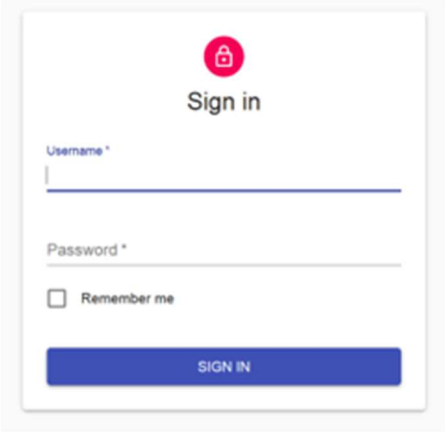
4.1 The Framework ePMPS

The model was developed in the ExtendSim® package and is available on Google WebService for the validation process where the company have total access without any licence costs involved.

4.2 User Authentication

Each user has different scenarios and will only have access to those scenarios created. This procedure guarantee data protection for all simulations performed on this environment.

For the purpose of this Manual the user was created.



	Simulation Model
Version 001 Version 002	Revision - 15/07/2019 Updated – 02/12/2019

4.3 The Interface

A web-based interface was developed in order to facilitate the input and simulation results. The tool can be accessed according to the address: https://linear-skill-260114.appspot.com/ Chrome, Firefox and Safari web browsers are recommended.

The screen is presented as shown in figure 4.1 – Simulation Interface.

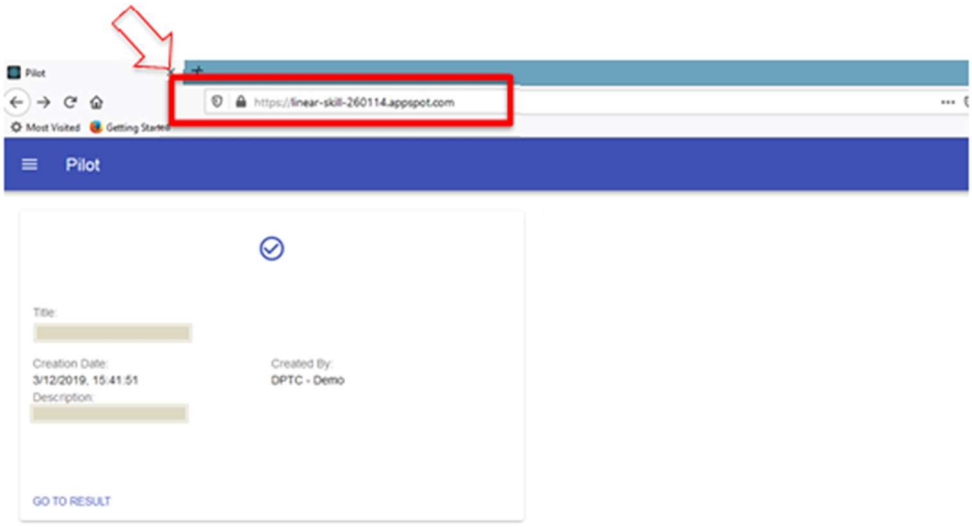


Figure 4.1 – Simulation Interface

4.4 Starting a Simulation

The ADD button (+ Symbol) starts a new simulation. The next figure demonstrates the Initial screen with 4 steps to finalise the simulation process.

- **Step1 – Introduce your simulation**: This step allows the user to inform a title and description for the simulation process as presented in figure 4.2 – Step 1 Simulation Process

	Simulation Model
Version 001 Version 002	Revision - 15/07/2019 Updated – 02/12/2019

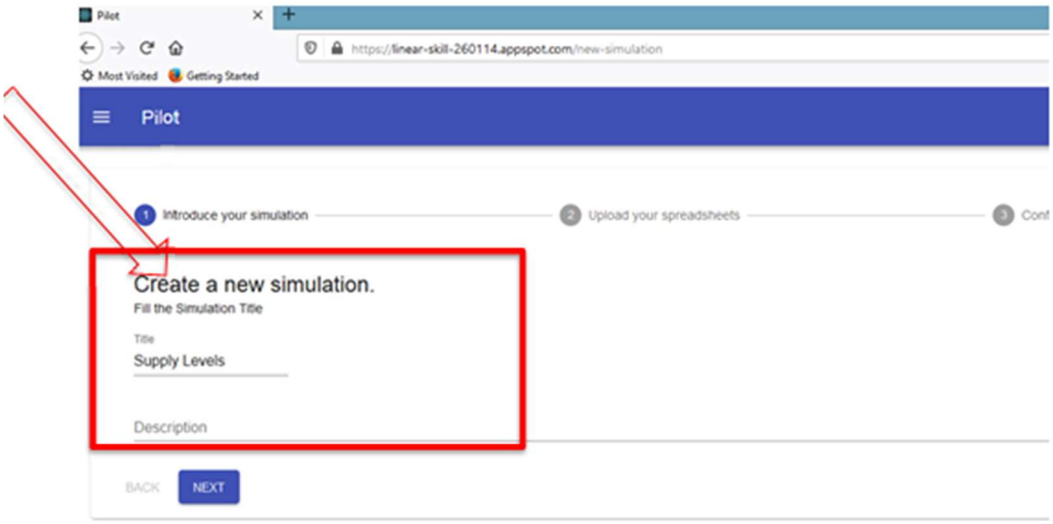


Figure 4.2 – Step 1 Simulation Process

- **Step2 – Uploading your spreadsheets:** In this step the input information is needed to be used by the model developed as presented in figure 4.3 – Step 2 Uploading the files. The complete map file is presented in Section 7 – Mapping the information for input.
  The ADD SPREADSHEETS button will present a screen to drag and drop or select the files as presented in figure 4.4 – Choosing the Files

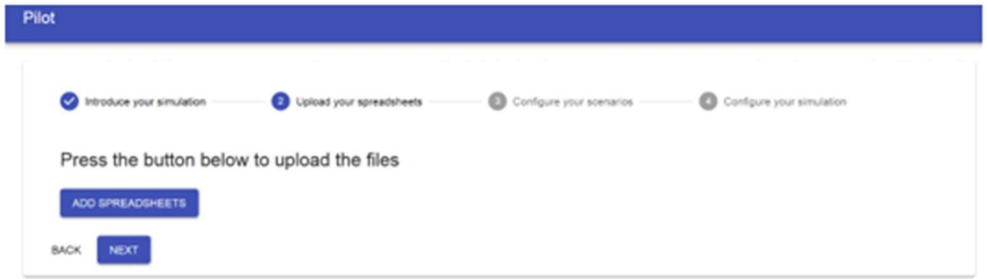


Figure 4.3 – Step 2 - Uploading the files

	Simulation Model
Version 001 Version 002	Revision - 15/07/2019 Updated – 02/12/2019

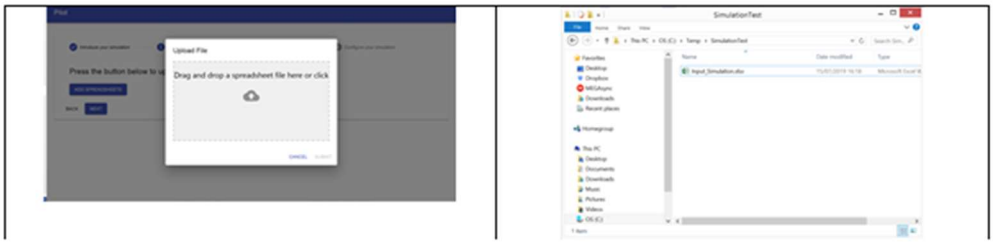


Figure 4.3 – Step 2 - Choosing the Files

The message "File *(file:name)* successfully added" will be presented if the file structure is compatible with the model.

- **Step3 – Configure your scenarios:** In this step basic information is required to create as many scenarios as needed. By changing schedules, capacities, supply volumes, different comparison is possible.
  In this specific case, three scenarios were created: one by planning the real volume and other by forecasting an increase of 10% of milk supply and 15% as presented in Figure 4.4.
  For all scenarios the separation and dryer schedules are the same.
- The First scenario is called "Supply" where the real supply hour is considered.
- The second scenario is called "Supply 10%" where the average milk supply was increased by 10%
- The third scenario is called "Supply 15%" where the average milk supply was increased by 15%

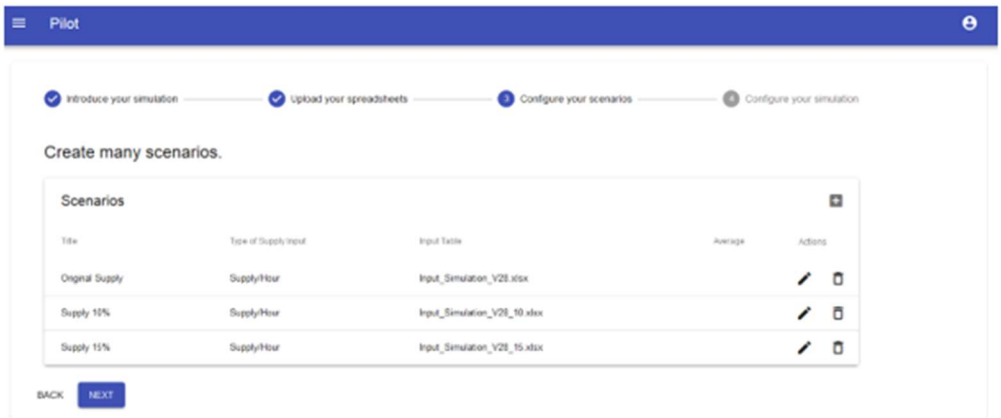


Figure 4.4 – Step 3 – Configuring the Scenarios

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- **Step4 – Configure your scenarios:** In this step, basic information is required to finalise the simulation such as: Simulation hours which corresponds how many hours the model should consider.

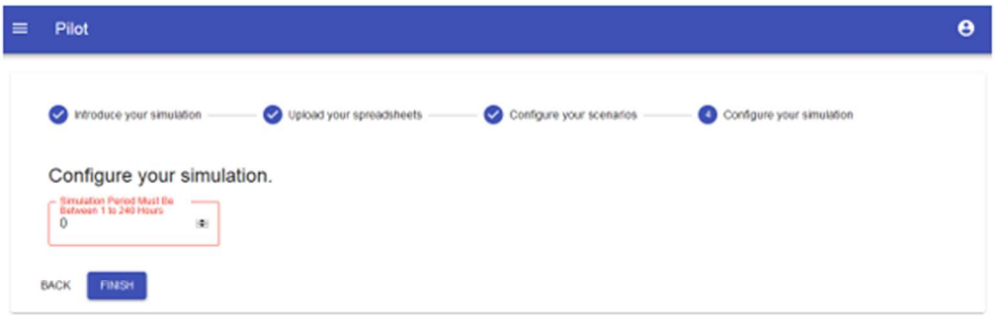

Figure 4.5 – Step 4 – Configuring the simulation

The FINISH button sends all the parameters collected to the simulation Framework according to Figure 4.6(a). The simulation is currently being processed and after pressing ***Back to Project List***, Figure 4.6(b) is presented. As the model is finalised the message "***The Simulation (title name) has finished***" as shown in Figure 4.6(c).

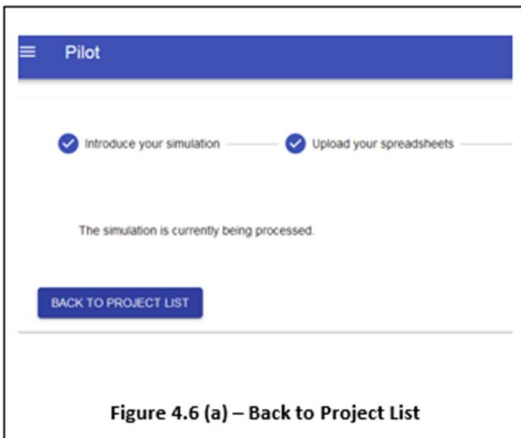

Figure 4.6 (a) – Back to Project List

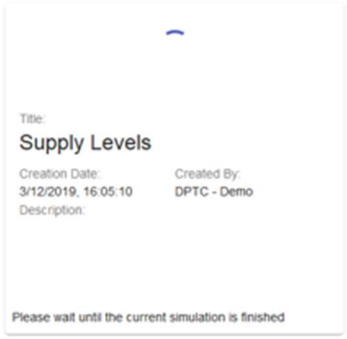

Figure 4.6 (b) - Processing the Simulation

Figure 4.6 (c) – Simulation.. [filename] has finished

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5.0 Analysing the Simulated Results

A dashboard is available for comparison after finishing the simulation. The Analytics data interface is presented according to figure 5.1 – Scenario Data Analysis. Through this page, the spreadsheet results are available for download.

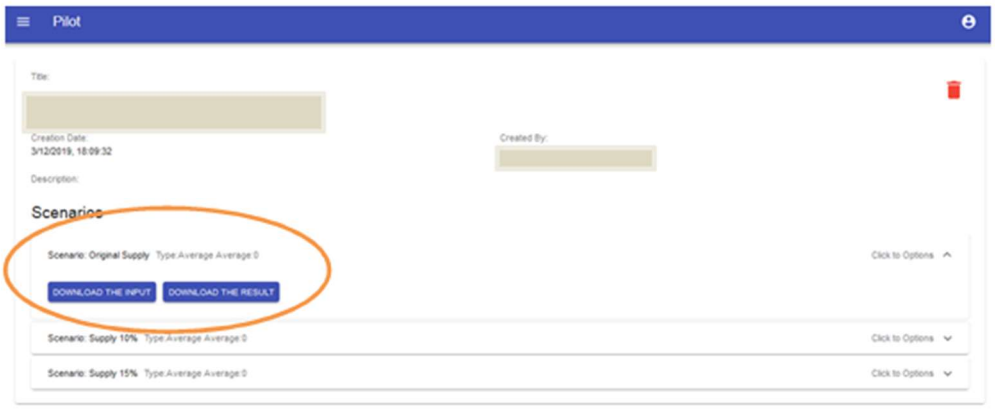

Figure 5.1 – Scenario Data Analysis

5.1 Totals

This folder presents the total volume processed at each stage in the production process according to the period selected. In this example 120 hours or 10 days were simulated as presented in Figure 5.2 no extra downstream was defined.

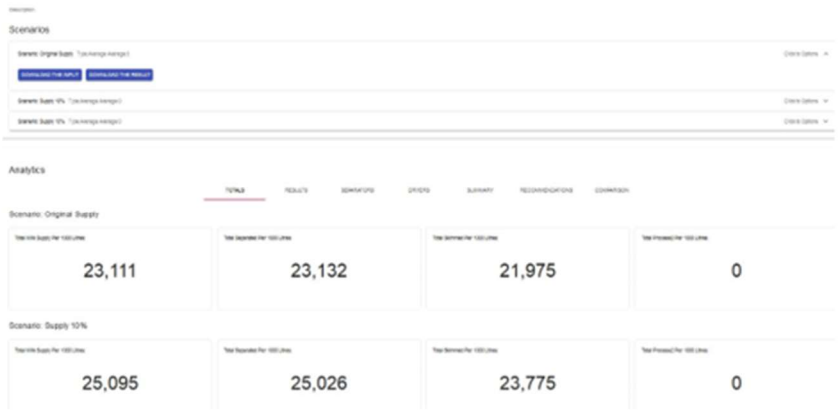

Figure 5.2 – Totals

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5.2 Results

This option presents the total processed by each stage throughout the period of time selected. The period selected in the filter options was **"All"** which provides all the period simulated.

In this example, it is possible to observe that given the schedules for Separators, Dryers capacities, the volume per hour was slightly increased at stage 1 – Total Raw Milk Silos as presented in Figure 5.3 – Results.

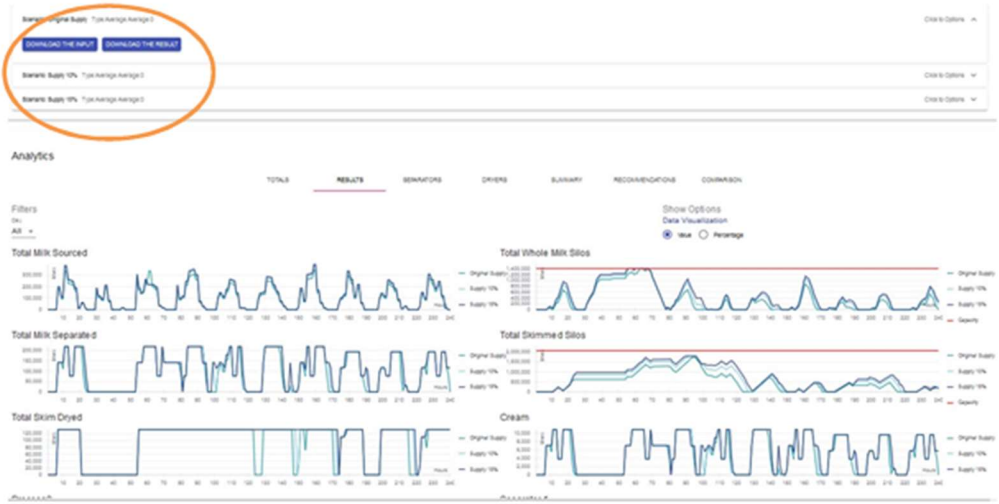

Figure 5.3 – Results

5.3 Separation

This option presents a schedule heat map for each separator according to the Day and Time simulated. The schedule is imported by the spreadsheet. It is possible to observe the grey slots represent the CIP/OFF time as presented in Figure 5.4 Separators.

The idea is just comparing how an extra volume would impact the production flow.

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Figure 5.4 – Separators - Schedule

At the bottom of the page a summary of machine utilisation times is presented as shown in Figure 5.5. Here it is possible to observe that the separator had a decrease in idle times (red slots) due to extra material being processed.

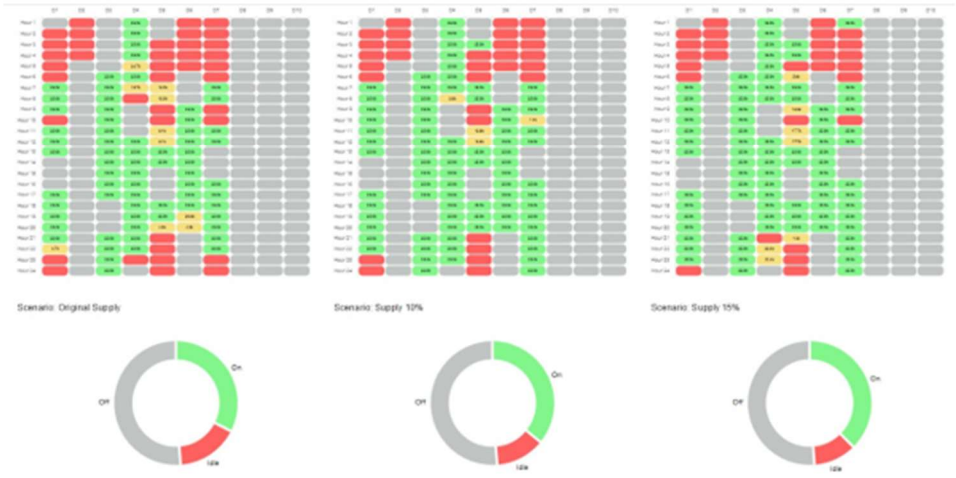

Figure 5.5 – Separators - Utilisation

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5.4 Dryers

This folder presents a heat map or schedule of each dryer according to the Day and Time simulated. The schedule is imported by the spreadsheet and the time scheduling for both scenarios (Real and Forecasted) is the same as shown in Figure 5.6 – Skim Milk Dryer – Schedule.

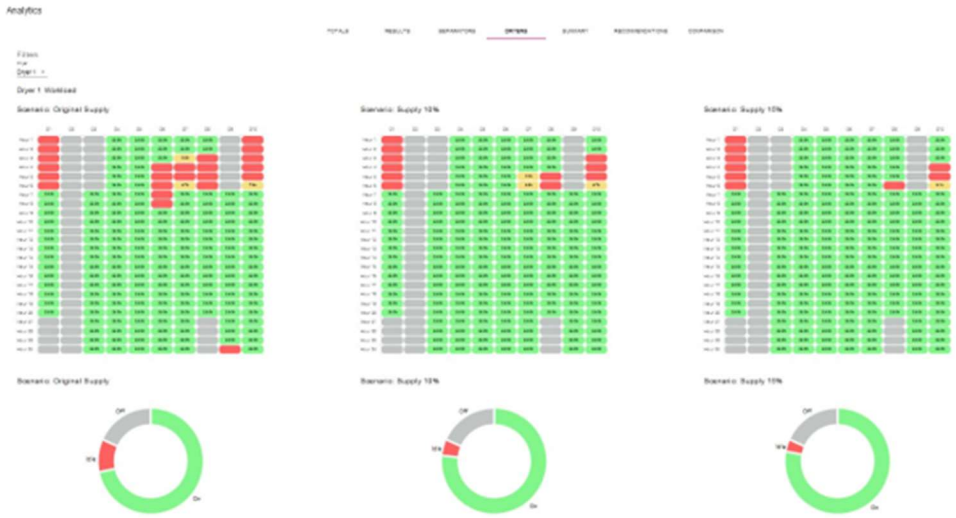

Figure 5.6– Skim Milk Dryer - Schedule

5.5 Summary

This page presents a summary of each stage in the production process comparing each scenario.

The first graph presented in Figure 5.7 shows the closing stock per day for each Silo.

In this example, it is possible to observe the inventory levels for Raw Milk Silos had increased compared to the "Average" scenario highlighting this increase would increase the silos.

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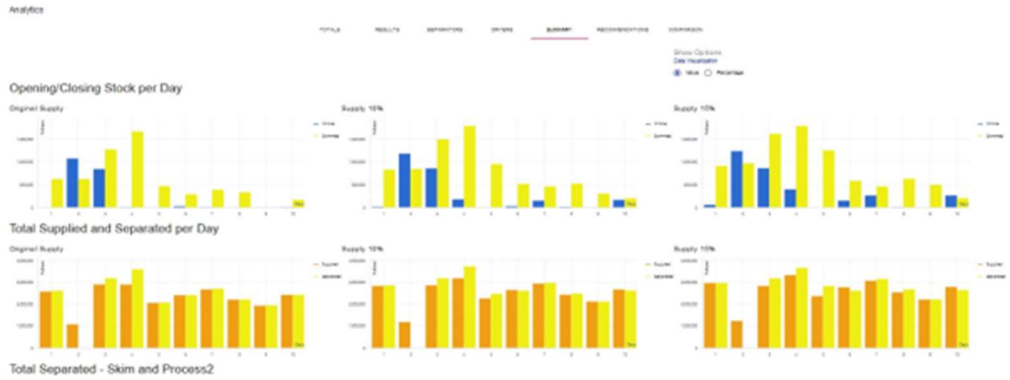

Figure 5.7 – Summary Graphs

5.6 Recommendations

The purpose of the Recommendation Page is select two objectives criteria for optimising the scheduling plan based on the simulation previously performed. The scenario simulated is available for selection and two Maximising/Minimising criteria can be combined. The range by running hours and CIP/OFF hours are available.

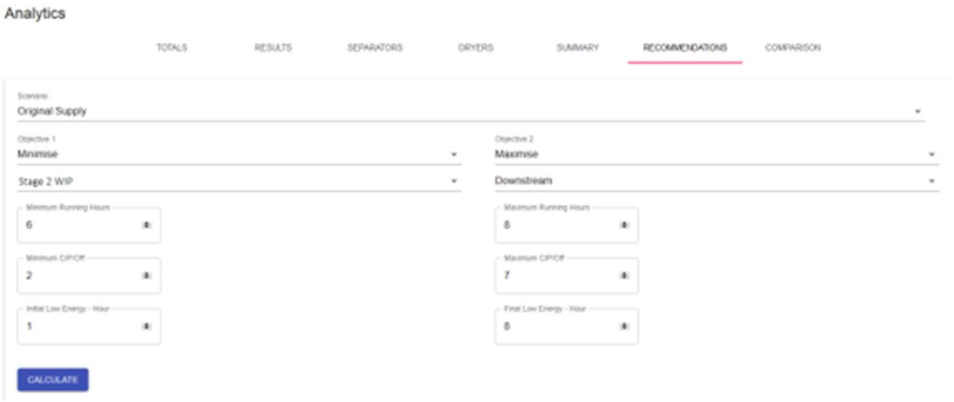

Figure 5.8 – Schedule Recommendation

After pressing **Calculate** button, a Pareto-Frontier graph is presented where it is possible to dynamically select the schedule according to the trade-off of both objectives. In Figure 5.9 the Stage 2 Wip was selected for Maximising as presented in X axis, while the downstream proportion is presented in the Y axis.

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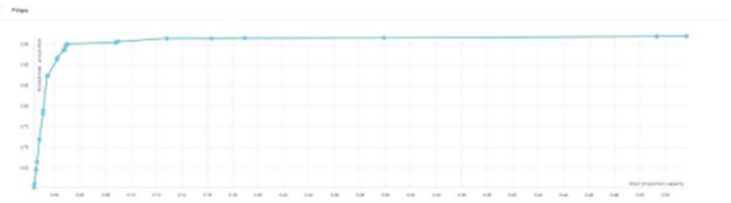

Figure 5.9 – Pareto Frontier – Maximising Downstream Flow and Minimising Stage2 WIP

All the schedules are available for verification/download. By selecting the best combination between the criteria defined, the plan is available for download as shown in Figure 5.10.

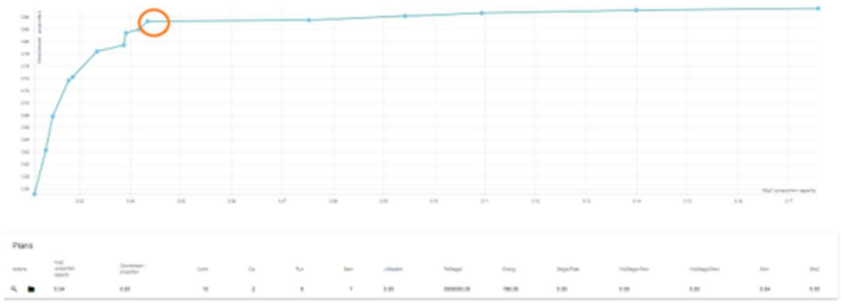

Figure 5.10 – Plan available for download

Figure 5.11 presents the plan recommended based on the criteria selected. The plan is available for download and be imported as a new simulation.

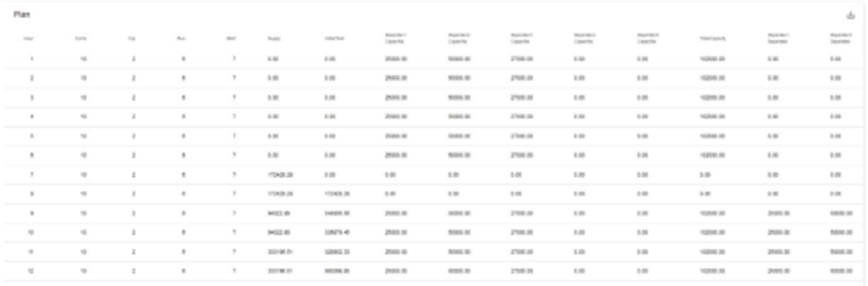

Figure 5.11 – Schedule Plan by hours

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5.7 Comparison

The purpose of this page is to present a summary of volumes processed comparing two different scenarios.

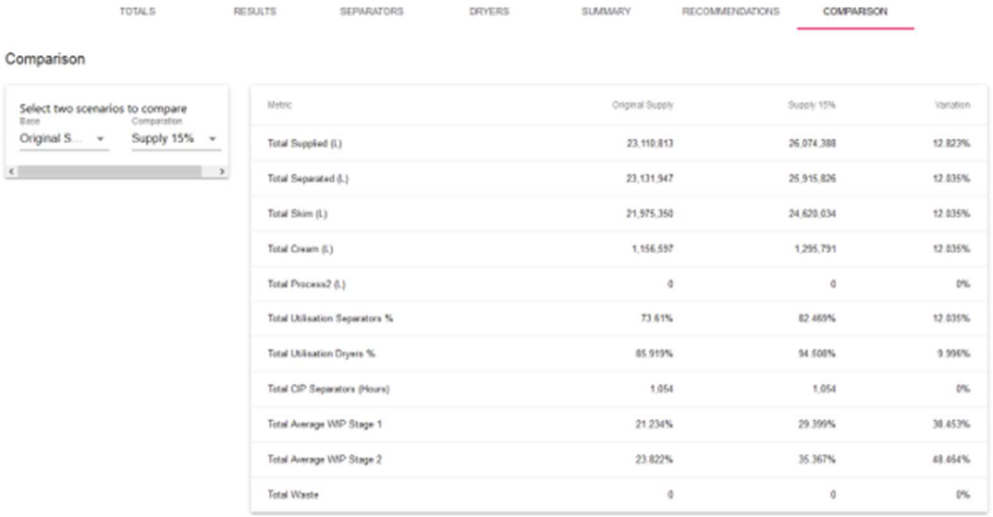

Figure 5.10 – Comparison between two scenarios

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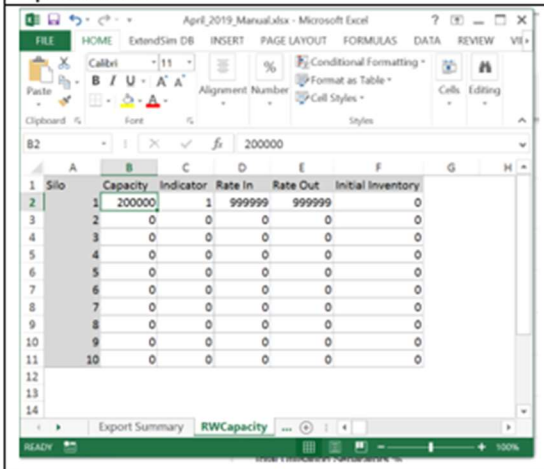
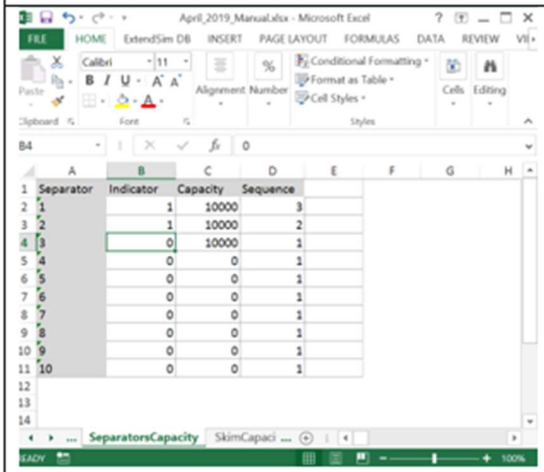
6.0 Mapping the Information

Some parameters are required during the input steps in the web page as presented in section 6, some parameters such as daily or hourly records are required to be imported by spreadsheets as explained in this section through table 6.1 – Spreadsheet Information

Table 6.1 – Spreadsheet information

Spreedsheet	Information
	RWCapacity • This spreadsheet is limited to 10 silos at any capacity. • The binary indicator (0/1) activates/deactivates an extra process flow • *Rate In* and *Rate Out* control the flow. • It is also possible to fill it up an initial inventory as presented in column F
	SeparatorsCapacity • This spreadsheet is limited to 10 separators • The binary indicator (0/1) activates/deactivates an extra process flow • The sequence defines the priority among separators

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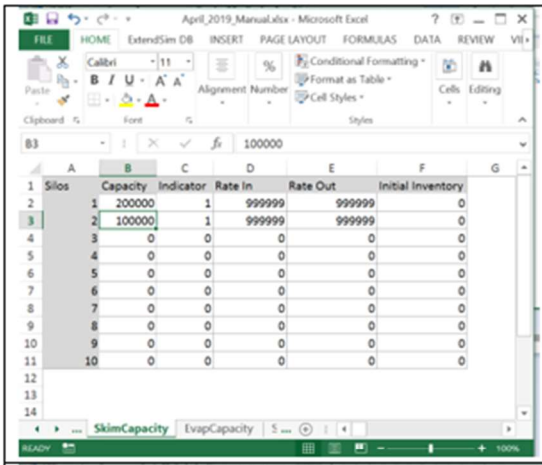
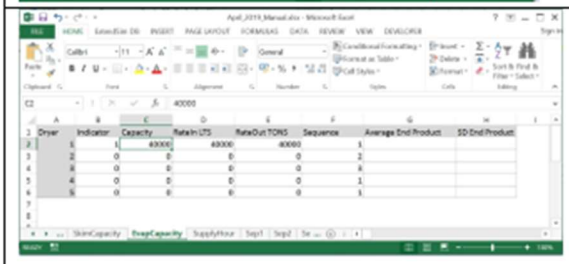
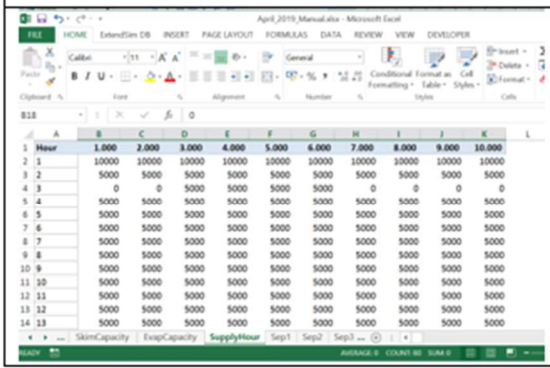
	SkimCapacity • This spreadsheet is limited to 10 silos • The binary indicator (0/1) activates/deactivates an extra process flow • *Rate In* and *Rate Out* control the flow. • It is also possible to fill it up an initial inventory as presented in column F
	EvapDryerCapacity • This spreadsheet is limited to 5 dryers • The binary indicator (0/1) activates/deactivates an extra process flow • The sequence defines the priority among dryers • Through the Average and SD is possible to incorporate some variability at the final production
	SupplyHour • This spreadsheet is limited to 10 days • The amount of milk received per hour should be fill up here

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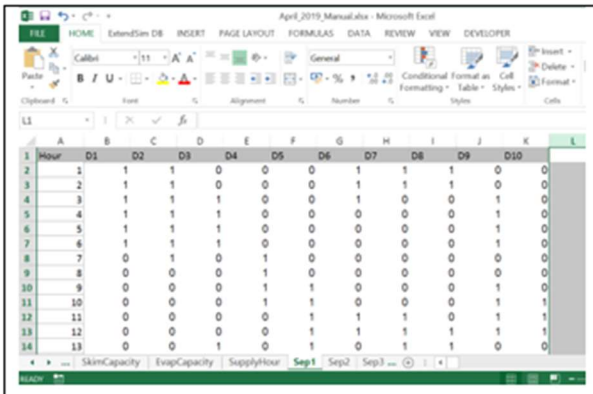
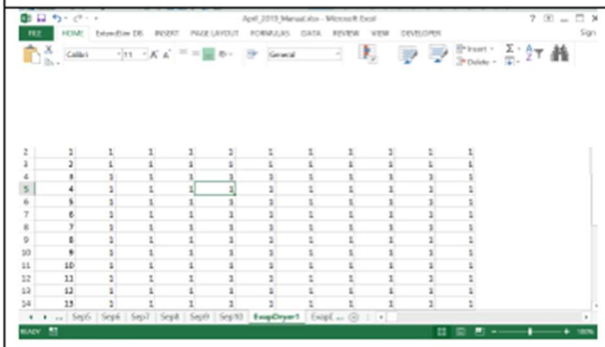
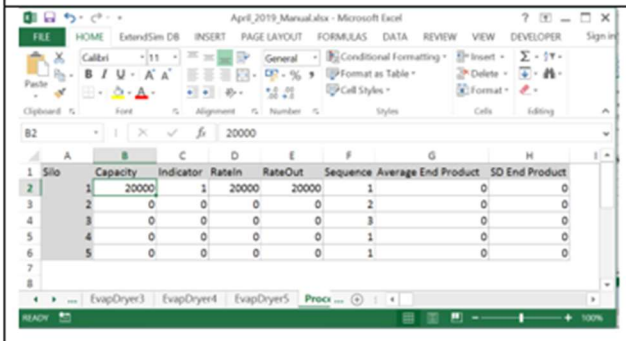
	Sep1, …. , Sep10 • Each spreadsheet stores the schedule for each separator. • The binary indicator (0/1) activates/deactivates an extra process flow • The separators will follow this schedule. If 3 separators are used, schedules for 3 separators (Sep1, Sep2, Sep3) are required.
	EvapDryer1, …. , EvapDryer5 • Each spreadsheet stores the schedule for each skim dryer. • The binary indicator (0/1) activates/deactivates an extra process flow • The dryers will follow this schedule. If 1 dryer is used, a schedule for only 1 dryer (EvapDryer1) is required.
	Process2Capacity • This spreadsheet is limited to 5 downstream processes • The binary indicator (0/1) activates/deactivates an extra process flow • Rate In and Rate Out control the flow • Through the Average and SD is possible to incorporate any variability at the final production

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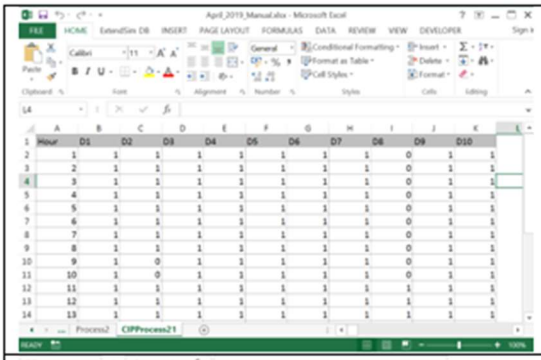
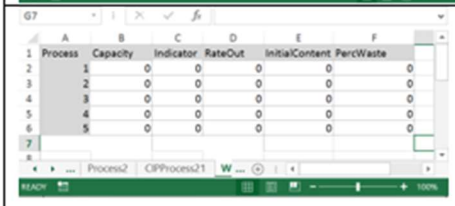
	CIPProcess2 • This spreadsheet stores the schedule for downstream processes • The binary indicator (0/1) activates/deactivates an extra process flow
	Waste • This spreadsheet stores the total waste produced by each downstream • The binary indicator (0/1) activates/deactivates an extra process flow • The Percentage of Waste produced by each downstream is imported and further analysed