A Centralized Model Predictive Control Framework for Just-In-Time Outbound Logistics under Information Asymmetries

A Case Study at Heineken

By

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Abstract

Recently, many companies have experienced the effects of the COVID-19 virus on the worldwide supply chain. These developments have put a massive strain on the container shipping industry; container shipping costs spiked due to a global shortage of empty shipping containers. The need for advanced integration and digitization of supply chain management along the chain has been fast-forwarded as companies are more than ever willing to invest in robust planning systems to minimize future inefficiencies in their logistic network. The recent developments in the global supply chain have also affected the logistic process for Heineken, the second-largest beer producer worldwide by volume. Specifically, the Heineken Brewery in Zoeterwoude, the largest brewery in Europe, exports over 70% of the produced volume to oversea customers. Due to the vast container shortages in recent years, Heineken could not ship products in containers to all oversea customers.

The long-term goal of Heineken is to be resilient to micro and macro supply chain uncertainties by enhancing its operational planning process regarding outbound logistics for export products. Despite efforts to optimize the process, the current system has proven insufficiently robust, especially concerning the container loading process of finished products at the brewery. This process is highly reliant on two physical characteristics - the availability of space in the finished goods warehouse and timely access to empty containers at the outbound docks to load palletized products. To facilitate a just-in-time (JIT) loading process, Heineken employs cross-docks at the end of the production lines, acting as a buffer for temporary storage to enable flexibility in the loading process; therefore, theoretically, the use of inventory space can be eliminated.

This study entails the development of a planning model utilizing Centralized Model Predictive Control (CMPC) to optimize the flow of physical goods throughout a network of supply chain nodes, utilizing a Mixed-Integer Linear Programming (MILP) approach to determine the optimal decision variables. Specifically, a Current State CMPC model was created to reflect the current outbound logistic network at Heineken Zoeterwoude, where information asymmetries are known to impact the accuracy of the outbound logistic planning tool. The Current State model was compared against a Future State model, where real-time data is available, thereby eliminating the aforementioned information asymmetries. By assessing four key performance indicators, it was found that the Future State model enables considerably better performance of the logistic network, even during peak production. Also, different planning horizons were considered, and it was concluded that longer horizons allow for better performance.

Contents

Acronyms

AI Artificial Intelligence. 91

APS Advanced Planning & Scheduling. 14

CCT Combined Cargo Terminals. 29

CMPC Centralized Model Predictive Control. 21

CSE Customer Service Export. 25

EDI Electronic Data Interchange. 3

ERP Enterprise Resource Planning. 13, 14

GCC Global Control Centre. 17

HNS Heineken Netherlands Supply. 3, 5, 25

HZW Heineken Zoeterwoude. 25

JIT Just-In-Time. 4

KPI Key Performance Indicator. 5

LDD Loading Due Date. 37

MILP Mixed-Integer Linear Programming. 19

MPC Model Predictive Control. 16

MTO Make-To-Order. 36

OpCo Operating Company. 26

PS Production Scheduling. 37

SCI Supply Chain Integration. 13

SCM Supply Chain Management. 3, 11

SKU Stock Keeping Unit. 5

UML Unified Modeling Language. 41

WMS Warehouse Management System. 38

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State of the Problem

1
Introduction

In today's globalized world, supply chain management (SCM) is the operations strategy for companies to be organizationally competitive. To achieve competitiveness, companies are extremely agile to improve the robustness of their supply chain system by being responsive to external events. This has intensified with the adoption of information systems, such as electronic data interchange (EDI) in the early 2000s. More recently, many companies have experienced the effects of the COVID-19 virus on the supply chain. These developments have put a massive strain on the industry; container shipping costs spiked due to a worldwide shortage of empty shipping containers. The need for advanced integration of SCM along the chain has been fast-forwarded as companies are more than ever willing to invest in robust planning systems to minimize future inefficiencies in their logistic network. Supply chain integration is the process that coordinates the products flow between supply chain partners, including transaction materials movements, procedures, and optimization processes by also considering the underlying information flow. Integration is regarded as an important step in the overall improvement of supply chains. Supply chain members are not very keen on interchanging data, but multiple studies pointed out the effectiveness of data sharing (Datta and Christopher, 2011 and Rossini and Portioli, 2018). Currently, business uncertainty in supply chain management has posed a considerable risk to the entire process flow. Supply chain risk management is important because of the cascading effects an incident might trigger in a logistic network.

1.1. Company Background

Heineken is the world's second-largest beer brewing company by produced volume. In 2021, a combined volume of 231 million hectoliters was produced. Heineken brand has word-wide coverage and a total of 300 brands are available in 190 countries across the world. Many of these countries have their production facility and produce products for the local market. Heineken Netherlands Supply (HNS) is a subsidiary of Heineken with three breweries (Den Bosch, Wijlre, and Zoeterwoude) in the Netherlands. The most volume produced by these breweries is bound for export. Part of the export is done by conventional semi-trucks across Europe, although the biggest amount is exported in shipping containers through the largest deep-sea ports of Europe. Major sales markets for HNS are the United States and African countries. For container transportation between the deep-sea ports and the breweries, Heineken relies on third-party transportation companies. These transportation companies work in close collaboration with Heineken and are dependent on data regarding production and logistics provided by Heineken.

The recent developments in the global supply chain have also affected the logistic process for Heineken. Due to the vast amount of container shortages, Heineken was not able to ship containers to all oversea customers. Furthermore, shipping carriers shifted from overcapacity to under-capacity on their ships and thus causing rising prices. These macro events cause uncertainties across all levels of the supply chain. First of all, Heineken has to adapt to a changing shipping market, this is considered a strategic development. On the other hand, these problems boil down to operational, short-term adjustments in the production and logistic processes.

1.2. Research Problem

The long-term goal of Heineken is to be resilient to micro and macro uncertainties in the world. Currently, the operational planning process regarding outbound logistics has proven not to be robust enough. This process considers the planning of loading palletized goods into shipping containers and the physical shipment of the container. In the current state, the container loading process at the breweries is highly dependent on two physical characteristics; the first one is the capacity in the warehouse and the second is the timely availability of empty containers at the outbound container docks.

Container loading at the breweries goes according to the just-in-time (JIT) terminology. This implies proper interaction between production and logistics; once products have been produced, packed, and stacked on a pallet, they are ultimately directly loaded into the outbound container. This requires a JIT arrival of the container at the loading dock. If the container is not available, the products will be placed in a finished goods inventory warehouse. However, this warehouse has very limited storage capacity, so there might be a risk of overflowing. To enable a JIT loading process, Heineken makes use of cross-docks at the end of the production lines. Once the products have been palletized, the pallets are automatically loaded onto the cross-docks. These cross-docks have a certain capacity, therefore they can be used as temporary storage. This temporary storage is often referred to as a buffer and, provides some slack in the loading process.

These physical operations rely on the current information management systems, used for warehouse management, resource management, and loading planning. These systems communicate between different departments within the company and with third-party transportation companies outside the company boundaries. This creates an information network in which systems are interconnected. As a consequence, the current information network deals with many delays and feedback loops within departments cause for manual interventions by logistic operators. These manual interventions are a consequence of the information asymmetry which exists between the physical status and the information available in the enterprise software modules. Correcting these information asymmetries is a timely procedure and in the worst-case scenario production at the brewery is halted. Furthermore, mismatches between physical and informational flow cause inefficient product handling and delays in outstanding deliveries.

At present, there is a logistic planning tool in place whose effectiveness is dependent on the data availability of multiple systems, this data includes production schedules, inventory levels, and availability of empty shipping containers. This is a centralized system and is prone to information delays considering the stock levels in the warehouse and there is no ability to collect data regarding the stock level of empty containers; consequently, an information asymmetry is created between the centralized planning tool and the physical state of goods. Furthermore, a human operator is currently necessary to bridge the gap between the planning tool and the third-party logistic provider to consider the empty container availability and the system asymmetries.

The physical flow considered in this research is a serial supply chain where each node has a single or multiple upstream and downstream node(s). This has been visualized in Figure 1.1. Here, it can be seen that the output from the brewing process is the palletized output. These products will be directly loaded or temporarily stored before the transportation begins. Heineken is partially responsible for this process. While the transportation is mainly the responsibility of the operator of the inland container terminal, as can be seen in Figure 1.1.

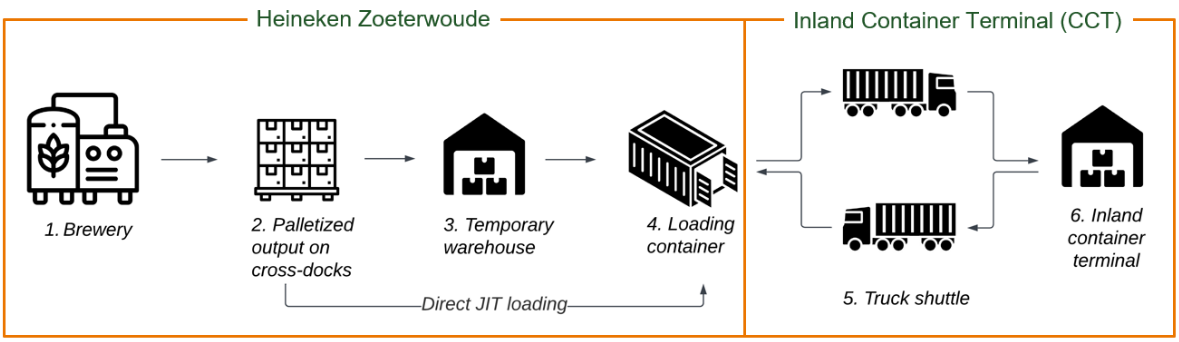


Figure 1.1: Visualization of the serial, outbound supply chain at Heineken Zoeterwoude.

1.3. Research Objective

As outlined in the research problem section (see section 1.2), the current outbound logistics planning tool suffers from several limitations that hamper its effectiveness. Notably, the tool cannot gather data on the availability of empty containers at stock on the inland container terminal (CCT), creating an information asymmetry between the planning tool and the physical status of goods. Additionally, the system relies on a single daily information update, creating another information asymmetry between the planning tool and the physical state of production lines and inventory levels in the warehouse.

The goal of this research is to increase the performance of the physical flow of goods considering the control of the outbound logistic information network at Heineken Zoeterwoude. This study aims to propose a simulation model of the current state of the planning tool, which will incorporate the existing information asymmetries. In particular, the simulation will be used to model the impact of the information asymmetry related to the availability of empty containers and the asymmetry related to the daily information update. Secondly, based on several requirements, a novel control approach will be introduced considering the outbound logistic planning. Then, the performance of the newly introduced control approach will be compared to the performance of the current state simulation model. This will be performed by introducing several key performance indicators (KPIs) to measure the performance of the planning tool. In addition to the planning horizon of 7 days currently in place at Heineken, this research also included the effects on the model's performance by considering several different planning horizons.

1.4. Research Scope

The scope of this research accounts for the planning process of the outbound goods at the Heineken brewery in Zoeterwoude. Within HNS, the brewery is the largest in produced volume. In 2022, roughly 54,000 outbound deliveries were shipped from Zoeterwoude; of which the most significant part was loaded in shipping containers and transported to the ports of Rotterdam and Antwerp. This research considers the operational planning level of the outbound logistics at the brewery. A distinction is made between container shipments and truck shipments. This research will only consider container shipments.

The physical boundaries of this research have been made visible in Figure 1.1. Here, the palletized output of the brewery is considered to be the input of the system. The departments and processes of production and logistics are considered fully decoupled in this research. That means that logistic planning cannot provide feedback on production planning and the production planning does not consider any constraints of the logistic process. Regarding the production output, it is important to differentiate between different *stock keeping units (SKUs)* in the logistic planning procedure. Every shipping container contains a single SKU and different products should therefore be recognizable in the logistic chain.

Then, the logistic planning is concerned with the timely availability of empty shipping containers, otherwise, goods are stored in the temporary warehouse. Information on the inland container terminal is necessary to monitor the amounts of available containers. While operational constraints, such as the number of available trucks for container transport are essential to plan transportation capacities. Within this research, all information systems that are currently in place to plan the outbound logistic operations will be accounted for.

1.5. Research Questions

Subsequently, after the formulation of the problem statement and the scope of the research, the main research question has been formulated:

How can the outbound logistic information network be controlled to increase the performance of the physical flow of goods and what is the impact of the information asymmetries?

In support of the main research question, several sub-questions have been formulated based on the used methodology:

1. *What are the relevant academic research components of the current logistic system?*
2. *In what ways does this thesis research contribute to the academic literature?*
3. *What is the current state of the physical flow of goods of the outbound logistic network, and what is the performance of the KPIs?*
4. *What is the current planning structure of the outbound logistics network?*
5. *What are the information asymmetries in the Current State?*
6. *What requirements should be considered regarding the supply chain model, and what modeling strategy is preferred?*
7. *How can the logistic network be modeled into an MPC framework with a single control node?*
8. *How can the general node configuration be arranged in a mathematical model using a state space representation?*
9. *What KPIs can be introduced to measure the performance of the outbound logistic network?*
10. *How can the general MPC model represent the Current and Future States?*
11. *What parameters should be chosen for the MPC simulation scenarios?*
12. *How does the Future State perform compared to the Current State when the information asymmetries of the Current State are eliminated?*

1.6. Research Design

Within this section, the research approach will be discussed, which will be used to answer all research questions. Thereafter, the research outline will be discussed.

Research Approach

The structured methodology used in this research originates from a Systems Engineering (SE) background. SE is 'concerned with the whole, the interrelationships, the synthesis, the interdisciplinarity, the emergent properties, the lifecycle, and the requirements of the system' (Ramos et al., 2010). The SIMILAR acronym can be divided into seven parts. *State the problem, Investigate alternatives, Model the system, Integrate, Launch the system, Assess performance, and Re-evaluate*. The SIMILAR approach is not linear but is designed as a sequence that is performed in a parallel and iterative manner, as can be seen in Figure 1.2. The SIMILAR methodology provides a structured approach to engineering contemporary systems. Systems that over time have gained in complexity due to increased interconnectivity. A brief description of the section with SIMILAR is provided:

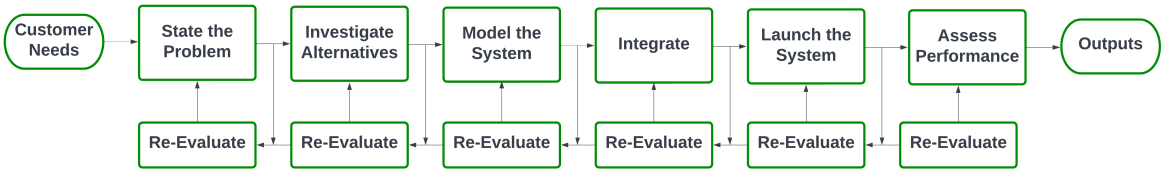


Figure 1.2: SIMILAR process model

- **State the Problem** This section will describe the problem definition considering the study's scope. Also, the main functionalities of the high-level system are provided. The stakeholders' needs are considered the main inputs to the system and will rule the project's development.

- **Investigate Alternatives** This function aims to outline alternative concepts for the current solution system to design its baseline architecture. Therefore, all system elements and characteristics are selected. Based on these evaluation criteria, an academic literature review is conducted reviewing all relevant research studies. The output of this function includes a high-level description of the system's components.

- **Model the System** Within this part, the functional decomposition of the system is provided. To generate a thorough understanding of the architecture of the connected systems, multiple visual models will be developed. These models provide an approximation of the structure and behavior of the system. Also, the current state performance of the architecture is evaluated based on predefined Key Performance Indicators (KPIs). Lastly, based on several requirements, a control model is introduced.

- **Integrate** Within the integration function, the core task is to realize the system of interest by combining the elements according to the architectural design and integration strategy.

- **Launch the System** This function is responsible for the simulation of the novel model and will ensure the complete system is working according to the requirements. Verification is an important part, which will be used to verify if the model behaves according to the mathematical design.

- **Assess Performance** Here, the system's performance will be evaluated. Also, appropriate validation is performed in this function. Lastly, this section will discuss the results and a conclusion that includes future research recommendations.

- **Re-Evaluate** This iterative step will be performed throughout the research study. Anywhere in the process, feedback will be used to revise the previously proposed systems.

Research Outline

The outline of the SIMILAR approach with the corresponding chapters and research questions has been visualized in Figure 1.3.

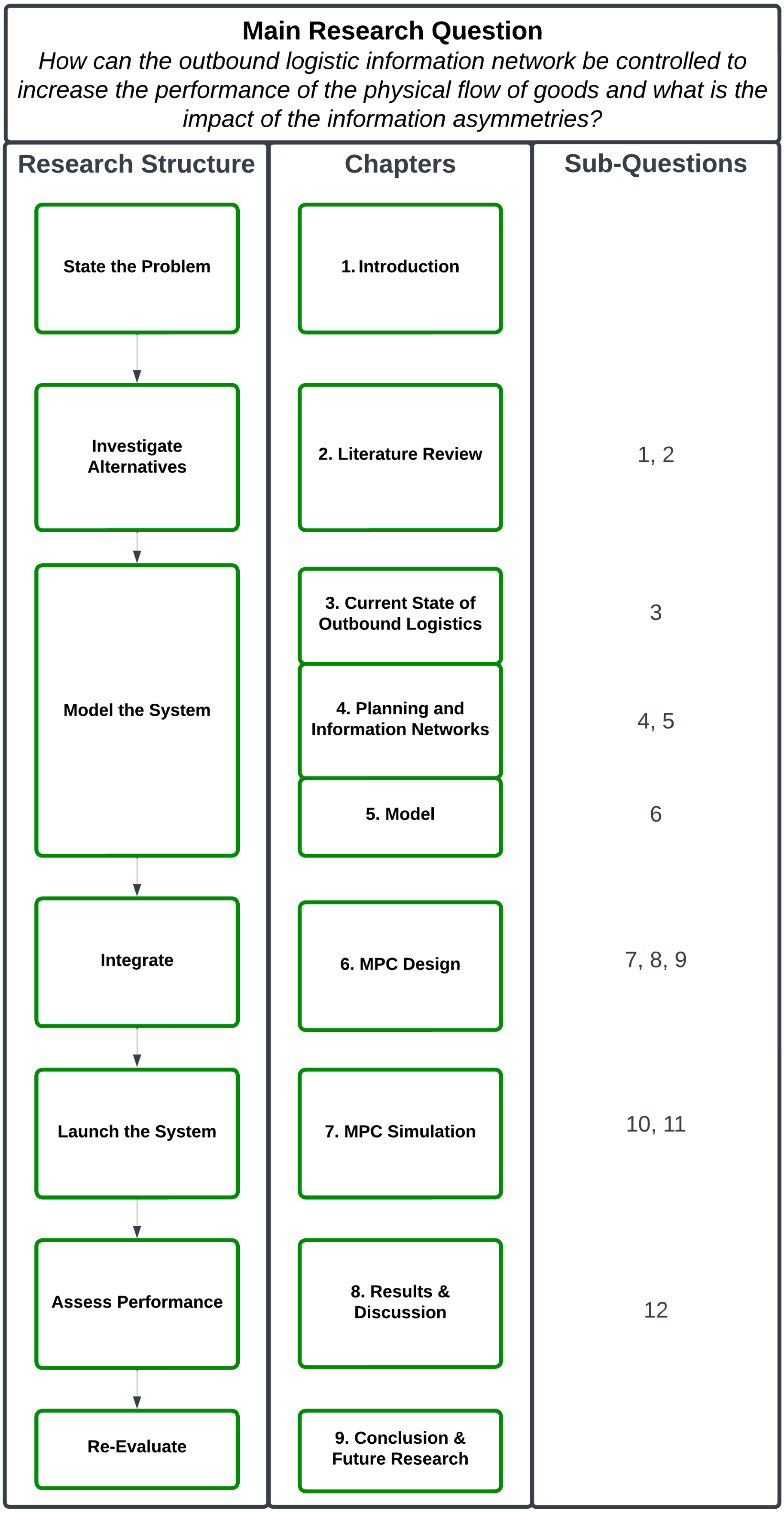


Figure 1.3: Research Outline Overview

II

Investigate Alternatives

2

Literature Review

This part of the research has been conducted to generate a better understanding of the state of knowledge on outbound supply chain logistics. In recent years, many innovative technologies have been adopted in the logistic process successfully. The main goal of this literate review is to create a thorough understanding of existing concepts in outbound logistics, information networks, and information sharing. Also, model predictive control applications in supply chains will be highlighted. Then, related literature will be analyzed and a literature matrix will be compiled based on the relevant academic research criteria. Lastly, the academic relevance of this study will be outlined. The sub-questions that will be answered in this section are formulated as follows:

1. *What are the relevant academic research components of the current logistic system?*
2. *In what ways does this thesis research contribute to the academic literature?*

2.1. Logistic Planning

The supply chain can be defined as 'a system comprising organizations, decision-makers, and technology decision policies that is responsible for transforming raw materials into finished products that are delivered to end customers (Subramanian et al., 2013). This definition describes the complete value chain, which considers all activities to bring a product to the market. Supply chain management (SCM) is a critical systematic and strategic business process within the supply chain that involves the coordination and management of all activities involved in the production and delivery of a product or service. The goal of SCM is to improve the long-term performance of the complete supply chain by balancing costs, efficiency, and responsiveness.

Logistic planning is the forward-looking planning process in production and logistics. To plan a specific logistic process, the right supply chain for the product needs to be known. Fisher (1997) describes the importance of the different types of supply chains to derive the appropriate management. Meyr and Stadtler (2005) outlined a supply chain typology, in which supply chain attributes are described. Meyr and Stadtler (2005) differentiate between functional and structural attributes. Functional attributes can be assigned to entities in the supply chain (such as each organization, member, or physical location) and consist of procurement, production, distribution, and sales type. The structural attributes describe the integration and coordination of all parties involved in the chain. An overview can be seen in Figure 2.1. The attributes will be used in chapter 3 to outline the type of supply chain this study considers.

SCM often consists of three levels of planning and decision-making. A distinction is made between strategic planning, tactical planning, and operations control (Bitran and Tirupati, 1993). These levels correspond to a long-term, mid-term, and short-term decision horizon, respectively (Fleischmann and Meyr, 2003a). Decisions on a strategic level mostly include managerial policies which are concerned with the location of a new production plant, the design of a logistic system, or the introduction of a new product. These decisions are concerned to be affecting the overall competitiveness and growth rate

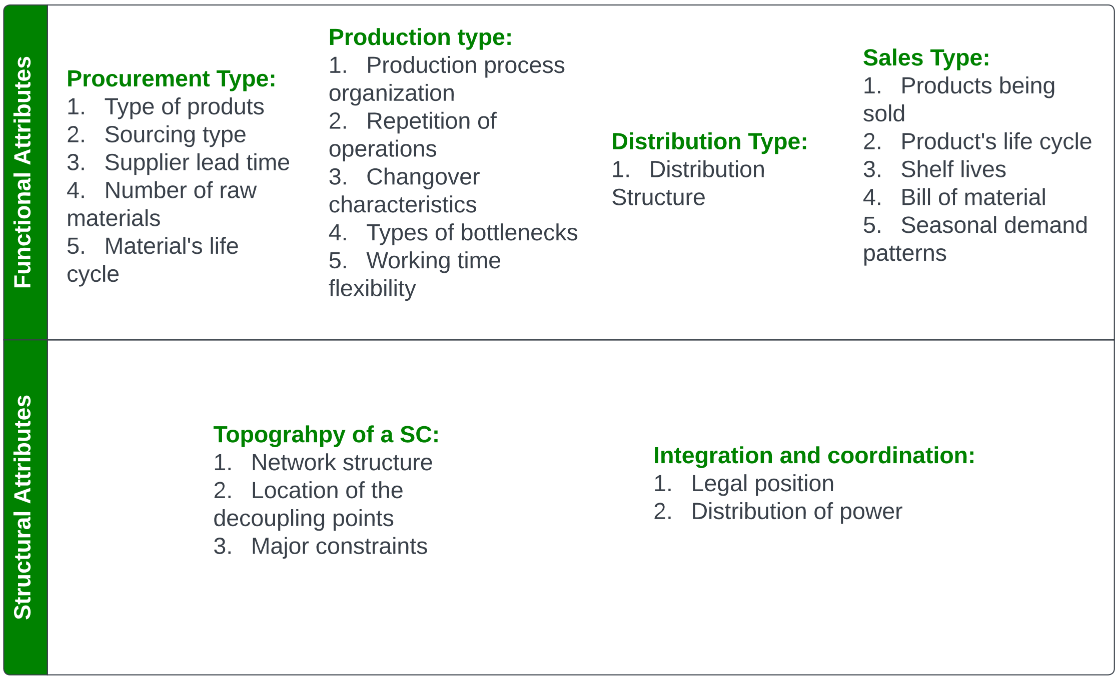


Figure 2.1: Overview of categories and attributes of SC-typology (Fleischmann and Meyr, 2003b)

of the company. Mid-term, tactical planning decisions are second-level decisions and focus on the resource utilization process (Bitran and Tirupati, 1993). These include capacity, workforce availability, and storage and distribution resources, based on demand forecasts. Lastly, the operational planning horizon involves the daily management of supply chain activities such as production scheduling, inventory management, and order fulfillment.

Integration of the different decision levels is required to model these systems due to the high level of interdependence. However, these large models have severe drawbacks because of their increased complexity. Akella et al. (1984) suggests a hierarchical approach in modeling these scheduling approaches. Hierarchical production planning consists of a sequence of models with a top-down approach. Strategic, long-term decisions are made before decisions in lower, more operational branches of the hierarchy. Strategic decisions, therefore, impose constraints on lower-level decisions. Furthermore, lower-level decisions are characterized by a shorter planning horizon. The main goal of the hierarchical approach is to control overall system capacities from a bird's eye view. Constraints of all subsystems are incorporated and based on this capacity discipline, operational congestions are prevented.

According to Fleischmann and Meyr (2003b), there are three recurring difficulties in supply chain optimization: multi-objective decision-making, combinatorial complexity, and uncertainty. Firstly, most supply chain optimization problems require the consideration of multiple objectives, which cannot be optimized simultaneously. As a result, planners must determine satisfactory levels for each objective. Secondly, due to the large number of variables involved, most problems contain a combinatorially large number of alternatives. This often requires the use of heuristics to compute near-optimal solutions instead of exact solutions. Lastly, the biggest challenge in supply chain planning is dealing with uncertainty. Fleischmann and Meyr (2003b) suggest two methods of dealing with uncertainty: incorporating a rolling planning horizon that adjusts planning based on actual developments or using a more dynamic approach that updates planning only in case of significant events.

2.1.1. Supply Chain Planning Matrix

In addition to the typology introduced in section 2.1, the supply chain planning matrix (SCP-matrix) also makes use of the chain processes *procurement, production, distribution, and sales*. These functions in combination with the planning horizons form the axes of the SCP-matrix. The length of the planning horizon decreases with each lower operational level. Hierarchical planning can be characterized in the SCP-matrix (Figure 2.2); the long-term strategic network design is decomposed into smaller planning modules.

The building blocks of the SCP matrix will be described shortly. *Strategic Network Design* includes all four supply chain processes. This long-term vision includes strategic sales planning and physical locations of plants and distribution hubs. *Demand planning* departments within supply chains are tasked with modeling long-term demand forecasts and mid-term sales planning (Meyr et al., 2015). *Demand fulfillment & available to promise* is the short-term outlook on sales. *Available To Promise* stock is the amount of product in stock that a customer party has not yet ordered. *Master planning* involves the coordination of *procurement, production and distribution* on the mid-term level. Then, *Production planning and scheduling* is mostly concerned with short-term production operations and handles day-to-day constraints such as material shortages. Based on the output of the production plant, *transport planning and distribution planning* is the next short-term module and is heavily dependent on short-term information, such as the availability of the required transportation mode. Finally, *purchasing & material requirements planning* is mostly a task of *enterprise resource planning* (ERP) software, which can handle these transactions automatically.

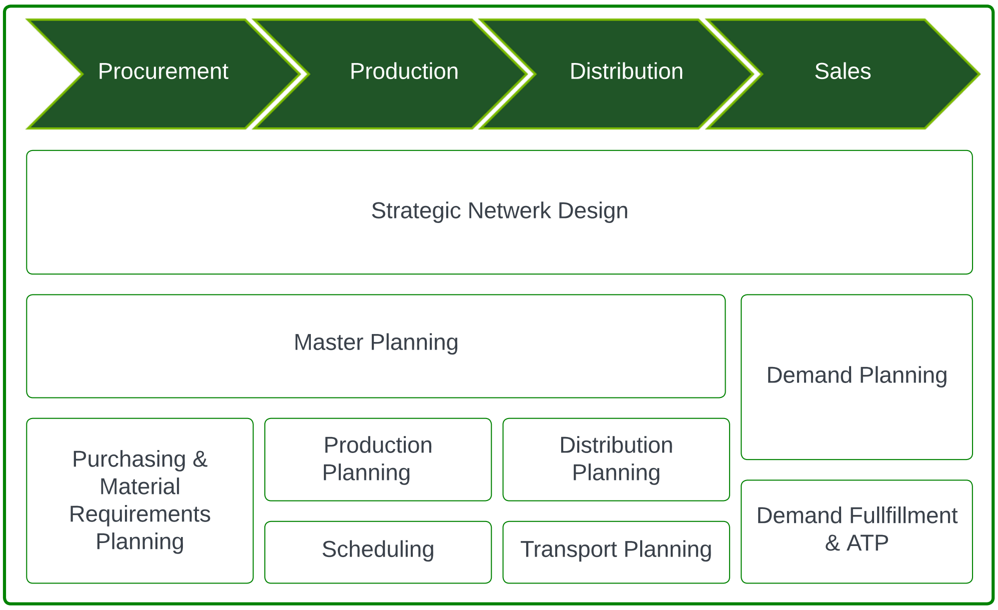


Figure 2.2: Schematic layout of SCP-Matrix Meyr et al., 2015

2.2. Supply Chain Information Networks

With the increasing complexity and volatility of supply chains, managing these networks requires the integration of information systems across organizations to support operational, tactical, and strategic planning. Supply chain integration (SCI) approaches need to be strongly supported by technological information systems (Hipólito et al., 2022). Information sharing and collaboration are essential for effective supply chain management and is a key determinant of the performance of a supply chain structure. By sharing information, organizations can coordinate activities, optimize processes, and reduce costs. Collaboration among supply chain partners can lead to better alignment of goals and objectives, improved communication, and increased trust. One of the main challenges to information sharing is the lack of trust between supply chain nodes. Trust is critical to the success of information sharing, as it allows partners to share sensitive information without fear of it being misused. According to Ghadge et al. (2012), trust is built over time through the development of personal relationships, communication, and the demonstration of competence and reliability. In addition, in a centralized supply chain, there exists a single decision maker, which has control of all information flows. In a decentralized system, there may act several stakeholders, that have conflicting objectives.

Despite the benefits of information sharing, there are still significant information gaps that exist within supply chains. These information gaps can occur at various points in the supply chain and can lead to inefficiencies and increased costs. One of the primary information gaps in supply chains is the lack of visibility. According to Lee et al. (1997), a lack of visibility can lead to increased inventory levels, longer lead times, and reduced responsiveness to customer demand. This lack of visibility can occur due to several reasons, including inadequate information systems, and poor communication. Another information gap in supply chains is the lack of information on demand patterns. A lack of information on demand patterns can lead to under or overproduction, resulting in increased costs and reduced customer satisfaction.

To close the information gaps, IT systems have been developed. *Enterprise Resource Planning* (ERP) systems focus on managing and automating a company's core business processes, such as financials, human resources, and inventory management. They provide a centralized, integrated view of a company's operations and can be used to streamline and optimize business processes. ERP systems enable organizations to automate routine tasks and improve operational level efficiency by providing real-time visibility into supply chain activities. For example, an ERP system can provide timely information about the availability of raw materials and components, which helps in scheduling production runs, managing inventory levels, and fulfilling customer orders.

Advanced planning and scheduling (APS) can be seen as an add-on for ERP systems. These systems are specifically designed for supply chain planning and optimization. They are used to plan and schedule the production, distribution, and delivery of goods and services. APS software modules cover all segments of the SCP-matrix (Figure 2.2), where each block corresponds to a separate software module. APS systems are powerful tools for supporting tactical planning by using algorithms to optimize production schedules, inventory levels, and transportation routes. APS can generate accurate demand forecasts by analyzing historical data and using predictive models to identify future demand patterns. These software modules are used in capacity planning, which involves determining the required capacity to meet future demand. Capacity planning is essential in optimizing production and distribution costs. These systems can simulate different scenarios to determine the best production and distribution plan based on different demand levels and production constraints.

2.2.1. Information Asymmetry

Information asymmetry can be described as an inefficiency in information supply, which can result in a lack of supply chain visibility. The term *information asymmetry* is often interchanged with the term *information gap*, as discussed in the previous part. Information asymmetries occur when information is not visible, mostly because a certain metric is not being measured. In addition, information asymmetry is described as a supply chain actor having more, better, or complete information on a certain metric compared to another actor (Vosooghidizaji et al., 2020). Information asymmetry can be found in supply chains where stakeholders are not willing to share information due to economic reasons. Another form of information asymmetry can be found within a certain stakeholder making use of multiple information systems. Information asymmetry can for instance occur when a single system takes more state updates into account than another system.

2.2.2. Transaction Cost Economics

Transaction cost theory can be described as being concerned with 'the optimal governance structure to minimize total cost under certain exogenous conditions regarding the nature of the transaction' (Williamson, 2008). In other words, transaction cost economics tries to minimize the cost of transactions that are prone to be influenced by uncertain events. Asset-specific investments, transaction characteristics, and uncertainty are the three key constructs identified by Williamson (1979) which influence the transaction costs of economic exchange. The first one refers to the transaction being applicable only in a specific environment, outside that scope, the transactions lose their value. The second one includes the volume and frequency of a transaction, while the third characteristic can be divided into two forms. The first form takes into account environmental uncertainty. The second form is behavioral uncertainty which occurs if the performance of a supply chain party is hard to measure after a transaction, mostly caused by information asymmetries, as has been described in subsection 2.2.1.

The definition of control in supply chains is about the coordination of the flow of goods or services to create value. Here, transaction cost theory uses control to minimize the cost of the physical flows, but also the information flows. Within a control structure, a distinction can be made between safeguarding, performance measurement, and adaptation problems. The last two will be considered in this research. Performance measurement results form behavioral uncertainty, where a supply chain node is prone to information asymmetry and therefore unable to value a certain transaction. Adaption problems, on the other hand, originate from the uncertainty created by environmental factors, such as uncertainties regarding supply and demand. For the decision-makers, it can be challenging to make decisions in these uncertain environments. In addition, Williamson (2008) points out that multiple studies concluded that uncertainty decreases with increased information sharing and transparency.

To define transaction costs, it is important to establish system boundaries and the coupling points between modules. Coupling is defined by Jeong and Phillips (2011), as the level of dependence to which one module relies on another module. From that definition, it can be assumed that there are no transactions if there is no coupling between modules. In addition, single-directional transactions are defined as one-way information flows, where the receiving module cannot provide feedback on the information flow.

2.3. Supply Chain Uncertainty

Uncertainty is defined as the difference between the amount of information required to execute a task and the available information (Peidro et al., 2009). Uncertainty is related to exception management, which can be described as stakeholders defining ways how to deal with exceptional situations occurring along the supply chain. It can be said that exceptions and uncertainty have a causal relationship. Two distinctions can be made in supply chain uncertainty. The first can be addressed as internal uncertainty, propagating from inter-functional inconsistencies. The second is external uncertainty, which is related to the supply and demand of third parties. According to Flynn et al. (2016), uncertainty can manifest itself differently, including variability, lack of information, and ambiguity.

Flexible supply chains are characterized by the ability to respond quickly to interruptions and uncertainties in supply and demand (Esmaeilikia et al., 2016). Candace et al. (2011) defined supply chain flexibility as the ability to meet particular customer needs. Recently, worldwide shipping has undergone a shipping crisis due to Covid restrictions, which has led to flexibility across significant supply chains. Fawcett et al. (1996) argue that flexibility should be included in cross-functionality along the supply chain to maximize organizational performance. Additionally, all members within the supply chain should adopt a chain perspective and react to uncertainty and a variety of customer expectations.

Esmaeilikia et al. (2016) differentiate between different levels of flexibility by using the terms *flexibility* and *robustness*. Flexibility refers to the ability to quickly adapt to more-frequent uncertainties in supply and demand. While robustness decisions affect the supply chain on a strategic level, thus decisions are made in the long term as discussed in subsection 2.1.1. Manders et al. (2016) elaborate on this by introducing flexibility dimensions on the short, mid, and long term. The relative importance of these flexibility dimensions depends on specific organizational processes.

Supply chain integration can be described as the response to uncertainty, according to Flynn et al. (2016). Supply chain integration is characterized by information flow that crosses organizational boundaries for all members of the supply chain to gain an advantage with up-to-date information. In an integrated network, the output of one entity is the input of the next. Motivation for supply chain members to share information can be low due to their interests. On the other hand, there will always be a likelihood that information sharing will benefit every member. This phenomenon is called the mixed-motive nature of supply chain relationships (Hult et al., 2010). Ultimately, properly integrated systems develop the capabilities to respond rapidly in a changing environment. Due to the large number of parameters involved when modeling integrated systems, a stochastic modeling approach is preferred.

The incorporation of information technology (IT) systems can enhance visibility, collaboration, and communication among supply chain partners, resulting in better coordination and a more responsive supply chain. IT can help reduce uncertainties by improving the accuracy of demand forecasting, reducing lead times, and improving delivery reliability. However, despite the advantages, the implementation of IT systems can also lead to information asymmetries in the supply chain. For example, the implementation of IT systems may lead to issues related to data quality, data security, and data privacy (Lee et al., 1997). Furthermore, IT systems may also lead to information overload, which can negatively affect decision-making processes (Akkermans et al., 2003). The effective management of uncertainties arising from IT implementation is therefore essential for successful supply chain management.

2.4. Just-In-Time

Just-In-Time (JIT) production is a production strategy that aims to minimize inventory and increase efficiency by producing goods only as they are needed. JIT production was first developed in Japan in the 1950s and 1960s by Taiichi Ohno, an engineer at Toyota (Ohno, 1988). In the automobile factory, just-in-time meant looking at the process in reversed order, therefore only producing a single part if it was requested further up the process. However, Lyu et al. (2020), points out that JIT production, causes suppliers to hold high inventory numbers in warehousing close to the production plant, decreasing the overall supply chain efficiency.

JIT systems, on the other hand, also have other fields of applications rather than the production industry. JIT logistics 'can be defined as the application of JIT management philosophy to four main components of logistics including (1) customer services, (2) order processing, (3) inventory management, and (4) transportation management' (Ozalp et al., 2010). Customer service is linked to the outbound logistics of a production plant and refers to the output of the systems, which creates customer loyalty and satisfaction. Order processing and inventory management are the components of inter-plant logistic systems and refer to the management of information, materials, and finished products within the production facilities. Lastly, transportation management is connected to in- and outbound logistics. Production plant logistics include raw materials, components, packaging, and finished goods transfers between suppliers, distributors, and customers. By applying JIT procedures in logistics, inventory levels are reduced and the quality and performance of outbound logistics are increased.

2.5. Control Theory

Control Theory has become an important research field in operations and supply chain management. Control has been applied in engineered systems and can be defined as the use of algorithms and feedback. Control is an information science and the first applications of CT in supply chains were single input, single output (SISO) controllers, which were used to track inventory levels (Subramanian et al., 2013). Control of supply chains was first proposed in 1961. The use of control in supply chains gained traction when information technology was implemented to predict sales, keep track of products, and Just-In-Time production (Åström and Murray, 2021). Currently, integrated logistic networks are prone to uncertainty and risks and multiple feedback cycles can be addressed. These developments have caused a transition from Industry 2.0 towards Industry 4.0. Information feedback and dynamic control by robustness and stability analysis can be incorporated with control theory (Ivanov et al., 2018). Control techniques are applicable to model the dynamic interactions in multi-player systems, therefore, they are suitable for modeling complex supply chain logistics.

2.5.1. Model Predictive Control

MPC is a control strategy that uses a mathematical model of a system to predict future behavior and optimize control decisions over a finite time horizon. It is well-suited to supply chain systems because it can integrate multiple sources of information, including demand forecasts, production schedules, and inventory levels, to make optimal decisions that balance conflicting objectives. One of the key advantages of MPC is that it can account for uncertainty in the system, such as demand variability, production disruptions, and supply chain disruptions. This is critical in supply chain systems, which are often subject to unpredictable events that can have significant impact on performance.

Pinho et al. (2015) lists several beneficial elements of using MPC to model supply chains. Firstly, MPC enables the implementation of a cost function to measure supply chain performance. Secondly, MPC can be modeled to be stable and robust, even in the presence of disturbances and stochastic demand. Thirdly, constraints in production, inventory, and dispatch capacity can be defined. Lastly, MPC algorithms can be used for the optimization of a complete supply chain operation (Hipólito et al., 2022). MPC requires less detailed knowledge of the supply chain in comparison with solutions like stochastic programming (Braun et al., 2003). In this sense, MPC can be used as a tool in supply chain management due to its ability in dealing with uncertainty, delays, and lack of information. Yet, MPC offers the same flexibility in terms of information sharing, network topology, and constraints that can be handled as traditional operation research methods. The beneficial characteristics of the use of MPC in controlling supply chains have been summarized in Table 2.1.

Key Benefits of MPC integration
1. Ability to integrate multiple sources of information
2. Ability to account for uncertainty in the system
3. Capability to handle complex supply chain systems with multiple decision levels
4. Ability to provide real-time decision support
5. Ability to handle multiple objectives simultaneously

Table 2.1: Main advantages of MPC in supply chain integration.

A schematic overview of the working principles of MPC is depicted in Figure 2.3. MPC makes use of an iterative path to find the optimal control objectives. In Figure 2.3 it can be observed that MPC uses a finite prediction horizon. Every time step within the prediction horizon the controller estimates the next state $x(k+1)$ by trying different actions $u(k)$. The action that leads to the closest state of the formulated objective will eventually be implemented. This iterative process is repeated, while the prediction horizon also shifts into a new future state. Measurement of the physical environments as used as inputs and used as a comparison to the parameters in the control model (Stuijt, 2021). MPC enables control through sensor-to-controller and controller-to-actuator connections.

Within supply chains, MPC can be implemented in a centralized and decentralized manner (Subramanian et al., 2013). In a centralized controller, there is one integrated system that needs information as input from all nodes involved in the supply chain. Whereas in a decentralized system, all nodes are responsible for their node optimization. Therefore, no integral system is needed and each node only uses the information that applies to its situation. In addition, MPC can also be used to control a part of a bigger, integrated supply chain. Decentralized MPC is mainly applicable to supply chains containing multiple companies or entities, which do not share information internally.

In addition to decentralized MPC approaches, distributed MPC is a variation of decentralized MPC, where nodes in the supply chain work together in a distributed manner to optimize the system's performance (Dunbar and Desa, 2007). In this approach, each node has its own MPC controller and makes decisions based on local objectives and information, but the controllers are designed to communicate and coordinate with each other to achieve the overall system objectives. Distributed MPC is well-suited to supply chain systems with a high degree of interdependence between nodes, where local decisions can have significant impacts on the performance of the system as a whole.

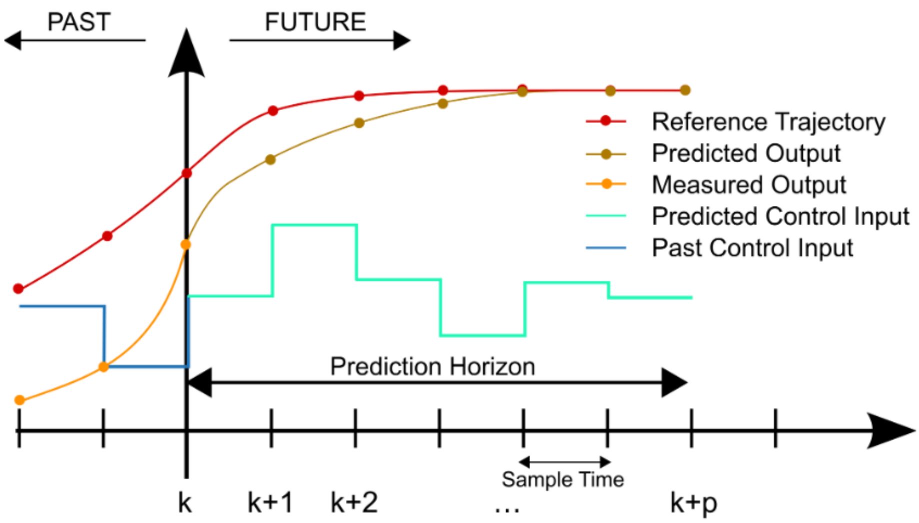


Figure 2.3: Overview of the working principles of Model Predictive Control

2.5.2. Global Control Centre

To overcome the effects of information asymmetries and physical uncertainty in the supply chain, a *Global Control Centre (GCC)* can be introduced. Dreyer et al. (2009) was the first to introduce a *Global*

Control Centre (GCC) to enable transparent information systems by an integrated and coordinated production and logistic planning control system. *GCC*s are centralized hubs that provide end-to-end visibility and control of a supply chain network. They integrate data from multiple sources to provide real-time information on the status of inventory, transportation, and production. Global control centers, also known as Control Towers, allow for greater responsiveness by mitigating information asymmetries in managing supply chains and can help to minimize the impact of disruptions and uncertainties. One of the key components of a control tower is its ability to use centralized MPC to optimize supply chain decisions. By using a mathematical model of the supply chain system, MPC can make optimal decisions that balance multiple conflicting objectives, such as cost, service level, and inventory levels (Subramanian et al., 2013).

In addition to centralized MPC, distributed MPC is another approach that has been proposed for use in control tower settings. Distributed MPC involves the use of multiple controllers that communicate with each other to optimize decisions across multiple nodes. This approach can provide greater flexibility and scalability in managing supply chains (Du et al., 2001). To allow for seamless integration of a *GCC* in an existing supply chain structure, the following requirements can be listed:

1. **Real-time Data Integration and Visibility**: A global control center must have access to real-time data from all nodes of the supply chain to make informed decisions. This requires the integration of multiple data sources, such as ERP systems, transportation management systems, and warehouse management systems.

2. **Dynamic Planning and Scheduling**: A global control center must be able to dynamically plan and schedule operations in response to changes in demand, supply, and capacity constraints. This requires the use of optimization algorithms, such as MPC, to generate optimal plans and schedules (Ivanov and Dolgui, 2021).

3. **Performance Measurement**: A global control center must be able to measure the performance of the supply chain in real-time. This requires the use of performance measurement tools, such as KPI dashboards and scorecards, to monitor key performance indicators, such as lead time and inventory levels.

The core benefit of incorporation of a *GCC* is the ability to improve decision-making from a central node. By capturing all relevant supply chain data in a central hub, bottlenecks, delays, and disruptions can be identified in real-time. Furthermore, inefficient data communication between nodes is avoided due to the central storage of data. Also, human intervention in automated control is avoided by leveraging decision-making from a central perspective.

2.6. Related Literature

This part will be used to outline the major contributions to the literature by addressing different criteria that have previously been described in this chapter. These criteria are the headings of Table 2.2. Within Table 2.2 all relevant articles are included and researched on the inclusion of the literature criteria. The relevant articles all include the use of a control model in the field of supply chain management.

Traditionally, 'supply chain management has employed heuristics or mathematical programming techniques for simplified representations of real systems, e.g., methods ignoring capacity constraints' (Li and Marlin, 2009). Hipólito et al. (2022) also addresses that typically a supply chain is modeled as a sequence of individual tasks, whereas most systems include dynamic interactions between stakeholders. To ensure effective decision-making across the supply chain, stakeholders should be able to access relevant, real-time information. Accordingly, multiple studies have emphasized the use of control theory techniques to model dynamic supply chain interactions. The main advantage of MPC is the ability to be stable and robust even if disturbances and stochastic demand are present. Ivanov et al. (2018) conducted a literature review on control theory application in supply chain management. Control theory approaches were found to be very suitable for decision management and performance achievement considering uncertainty with respect to bullwhip and ripple effects.

Hipólito et al. (2022) implemented a demand-driven model predictive control framework for a perishable goods supply chain, incorporating production, inventory, and distribution management, constrained by the due date of multiple perishable goods, while also incorporating nonperishable goods.

The overall objective was to control the flow of multiple goods in multiple scenarios. The model stores all relevant information for each product regarding the due date of the goods.

Robust MPC was employed by Li and Marlin (2009) for optimization with significant uncertainties. Li and Marlin (2009) introduced a multi-echelon supply chain problem optimization applied to an industrial supply chain. The MPC model formulated incorporated different time intervals in discrete time. For instance, the inventory level is updated every 24 hours, therefore the model incorporates an information asymmetry. The objective was set to minimize costs while also fulfilling customer demand.

Braun et al. (2003) used a two-node framework to translate information sharing in a supply chain setting into control terminology. Eventually, a six-node, three-echelon network was created for a case study on a semi-conductors supply chain. At every time iteration, the system was updated with information from each node. Therefore, the system incorporated the availability of real-time data.

In the work of Wang et al. (2007) several arguments are given to model supply chain planning with the use of control theory. The reduction of costs is addressed by the ability to implement stochastic processes. Furthermore, the model considers strategic, tactical, and operational planning. Also, 'MPC-based decision policies have the advantage that they can be tuned to provide acceptable performance in the presence of significant supply and demand variability and forecast error as well as constraints on production, inventory levels, and shipping capacity'. Wang et al. (2007) discusses the challenges of implementing MPC strategies, including the need for accurate models and real-time data, as well as the need for skilled personnel to design and maintain the control system.

Nabais et al. (2013) was the first to model the supply chain according to a flow assignment. Nabais et al. (2013) used hierarchical MPC for a multimodal supply chain for shipping containers. Hierarchical MPC was incorporated by introducing variable weights in the cost function based on the volume; the higher the volume, the higher the priority. Then, the hierarchical MPC model was compared to a centralized approach and results show that the hierarchical model performs better in terms of computation times.

In the paper presented by Perea-Lopez et al. (2003), a comparison was made between the behavior of centralized and decentralized management in supply chains. It was found that the centralized approach overall outperformed 15% the decentralized approach in terms of profit maximization. A Mixed-Integer Linear Programming (MILP) model for a multi-echelon supply chain was modeled to test the different centralized and decentralized scenarios.

Schildbach and Morari (2016) describes a scenario-based model predictive control approach to optimize the performance of a multi-echelon supply chain. The proposed method uses a scenario tree to represent the uncertainties in the supply chain and generates a set of scenarios for future demand and supply conditions. The results show that the proposed method outperforms the traditional approach in terms of profit and inventory levels. The article concludes that the scenario-based model predictive control approach can effectively handle the uncertainties in the supply chain and improve its performance.

Schwartz et al. (2006) implemented stochastic modeling while using MPC to incorporate the variation in supply in a semiconductor supply chain. The authors included a fluid representation of the three-echelon supply chain by modeling the nodes as fluid tanks.

Centralized MPC and global optimization are compared to decentralized MPC and local optimization in the research conducted by Fu et al. (2014). Both methods are compared to reduce the bullwhip effect in the proposed fictional supply chain. It was concluded that the centralized MPC approach is more effective at reducing the bullwhip effect and improving supply chain performance. However, they note that implementing a centralized MPC approach may be challenging in practice due to issues such as data privacy and coordination among different nodes in the supply chain.

Mestan et al. (2006) addresses that the success of a supply chain is dependent on its ability to integrate and coordinate the network of nodes. Therefore a mixed logic dynamical system was optimized with the use of an MPC algorithm. The considered supply chain consists of multiple products and was considered only on the operational level. A decentralized MPC model was compared to a centralized version. This study also concluded that centralized MPC performed better on average compared to the decentralized model.

Related Case-Studies at Heineken

Recently, Nanninga (2022) conducted research regarding the costs of export at Heineken, taking into account the container shortage disruption caused by the pandemic. Heineken exports products to 167 countries all over the world, in order to remain competitive, costs of shipping have to be minimized. Nanninga (2022) constructed 18 models to compare transportation costs, flexibility, and sustainability of different designs. Eventually, after a multi-criteria analysis, the best-suited model suggested raising shipping tariffs by a certain amount to strengthen Heineken's negotiation position. The study by IJfs (2015) researched the operational level of the loading process at one of the breweries. The research took into account some physical aspects of the palletized loading, such as the cross-docking systems and human-operated forklifts. Some bottlenecks were addressed that caused significant spillbacks in the system.

In addition, the work of Valk (2017) provides an extensive description of the current outbound logistic process at Heineken's brewery in Zoeterwoude. The objective of the study was to optimize the flow of export deliveries. A simulation model was created to test the efficiency increase if the flow of information of the production facility would be made available to multiple stakeholders. Pigeaud (2015) studied the complexity of outbound logistics at Heineken, taking into account strategic, tactical, and operational production planning. Complexity in this study is defined as 'the uncertainty in processes as a result of increased diversity.' The research concluded that information availability is the driving factor in complexity at Heineken. Stuijt (2021) created a digital twin using MPC for the returnable packaging logistics in Germany and the Netherlands. The centralized MPC model is used as a remote communication node which enables integrated operations. An RFID model was created to improve the information flow of the reversed logistics. Simplifications are incorporated by assuming a single-product supply chain. In the study conducted by Tuijp (2020), the design of the warehouse loading area was revised concerning safety risks. Therefore, a thorough analysis was performed of the current state of the outbound logistics at Heineken. Eventually, a new warehouse layout was proposed.

2.7. Academic Relevance

This study entails the development of a planning model utilizing Centralized Model Predictive Control (CMPC) to optimize the flow of physical goods throughout a network of nodes, utilizing a Mixed-Integer Linear Programming (MILP) approach to determine the optimal decision variables. Specifically, a Current State CMPC model was created to reflect the current outbound logistic network at Heineken Zoeterwoude, where information asymmetries are known to impact the accuracy of the logistic planning tool. The Current State model was then compared against a Future State scenario, where real-time data is utilized, thereby eliminating the aforementioned information asymmetries.

This problem is characterized by the following research criteria; the integrated supply chain consists of multiple planning levels; strategic, tactical, and operational, where only the operational level is considered. Due to the interconnectivity of the multiple network nodes, the system is prone to information asymmetries between the systems. Therefore, information flow control is required to share real-time data between network nodes and make integrated decisions. Then, within the approach of this research, the just-in-time (JIT) arrival of container trucks is necessary for the pick-up of the finished goods from the production plant since the warehousing capacity of the plant is limited.

This research contributes to the academic literature in multiple ways. Above all, this research uses Centralized Model Predictive Control to increase the performance of the physical flow of goods in the supply chain, which is prone the information asymmetries caused by information delays and information feedback loops. The current, short-term, operational planning tool is not robust and is prone to several variability uncertainties, such as the highly fluctuating production output and the uncertain arrival of empty containers.

Secondly, centralized MPC will be used to model the Current and Future states. In the Future state, the information asymmetries will be eliminated. The model will incorporate a multi-SKU (stock-keeping unit) supply chain network where each product needs to be loaded in a specific type of shipping container.

Furthermore, a Global Control Centre is modeled as a central node, able to capture each state update within the system. The system's objective is to optimize the flow of goods in the outbound network without intervention in the production plan; this includes inventory management and JIT loading of shipping containers. Then, the performance of the newly introduced control approach will be compared to the performance of the Current State simulation model. This will be performed by introducing several key performance indicators (KPIs) to measure the performance of the planning tool. These KPIs include steady-state flow and minimized accumulated node time for each product. The academic relevance of this thesis research can be summarized as follows:

Unlike the available literature on MPC models, this research incorporates an integrated, centralized MPC model that enables optimal steady-state flow through the multi-product supply chain by minimizing inventory levels and the accumulated time spent at the supply chain nodes. This includes the following topics:

1. Incorporation of centralized MPC in a network of nodes, where the current state is prone to information asymmetries.
2. Matching fluctuating, multi-SKU production outflow with specific container type in a JIT loading environment, prone to uncertainty.
3. Two scenario analysis; the Current State with the current information asymmetries will be compared to a state where real-time data is used by an autonomous decision maker, the Global Control Centre, which is assumed to have complete visibility.
4. Multiple KPIs of supply chain nodes will be evaluated simultaneously while using company data to assess the feasibility of the model.

Table 2.2: Characteristics of related literature

Articles	Info Asymmetry	Planning Level[a]	Uncertainty	Just-In-Time[b]	Objective	Control Method [c]
Braun et al. (2003)	✗	T, O	✓	✗	profit maximization	DMPC
Fu et al. (2014)	✗	O	✓	✗	cost minimization	CMPC, DMPC
Hipólito et al. (2022)	✗	O	✗	✓	flow optimization	CMPC
Li and Marlin (2009)	✓	O	✓	✗	cost minimization	CMPC
Perea-Lopez et al. (2003)	✗	O, T	✓	✓	profit maximization	CMPC, DMPC
Mestan et al. (2006)	✗	O	✓	✗	cost minimization	CMPC, DMPC
Nabais et al. (2013)	✓	O, S	✗	✗	wait time minimization	CMPC, HMPC
Schildbach and Morari (2016)	✗	T, O	✓	✓	cost minimization	SBMPC
Schwartz et al. (2006)	✗	O	✓	✗	stock minimization	CMPC
Wang et al. (2007)	✗	O, T, S	✓	✗	stock minimization	CMPC
This Study	✓	O	✓	✓	flow optimization	CMPC

[a] Operational level: S Strategic, T Tactical, O Operational
[b] Just-In-Time Transportation
[c] Control Method: **C**entralized, **D**ecentralized, **H**ierarichacal and **S**cenario-**B**ased Model Predictive Control (**MPC**)

III

Model the System

3

Current State of Outbound Logistics

This part of the research will be dedicated to outlining the current state of the outbound supply chain at Heineken Zoeterwoude (HZW). Therefore, the current structure of the logistic network will be outlined, and later on, the physical performance of the different parts will be assessed based on key performance indicators that are currently in place at Heineken. The sub-question that will be answered is formulated as follows:

1. *What is the current state of the physical flow of goods of the outbound logistic network, and what is the performance of the KPIs?*

3.1. Company Background

In 1873, Heineken started off as a single-product brewery near the city center of Amsterdam. Within the next 150 years, through company growth and company acquirement, Heineken would become the world's second-largest producer of beers by volume. After first acquiring Amstel in 1968, Heineken's portfolio has grown to over 300 brands across more than 190 countries. In 2021, Heineken produced an accumulated volume of 231.2 mhl (millions of hectolitres). Heineken Netherlands Supply (HNS), is the Dutch producing operating company of Heineken. HNS consists of three breweries:

- **Zouterwoude:** This brewery is named 'The Flexible Global Brewery' the largest of the three and mainly used to produce high volumes of beer.
- **Den Bosch:** This brewery is the second largest and produces more than 40 sorts of beer.
- **Wijlre:** This brewery is the smallest one and produces mainly Brand beer.

In all three breweries products are produced for the domestic and export markets. Overall, roughly 70 percent of the produced volume is exported and the breweries are able to produce around 1,500 different types of Stock Keeping Units (SKUs) (Stuijt, 2021).

Within HNS, the Department of Customer Service and Logistics (CS&L) is responsible for regulating all outbound logistics and customer demands. Different departments exist for the domestic and export markets. Customer Service Export (CSE), a subsidiary of CS&L regulates all orders that are bounded for export. This includes the process from scheduling the loading of products at the production facility, until the delivery of the goods to a customer.

Heineken Zoeterwoude

The framework proposed in this research will be implemented and validated at the Heineken brewery in Zoeterwoude, which is the largest brewery in Europe with approximately 18 mhl produced every year. The Heineken Brewery in Zoeterwoude opened its door in 1975. The brewery was designed for large bulk production mainly for domestic and American markets. Nowadays, the packaging and loading processes at the brewery have gained complexity. This complexity increase can be partially explained by the increased number of produced SKUs, as has been researched by Pigeaud (2015). Also, HZW is currently being used as the global brewing plant, therefore products from HZW are exported to more than 160 countries worldwide. The combination of SKUs, export variety, and macro-events, such as the worldwide container shortage has resulted in a complex outbound logistics process, that is currently being managed by operators and a variety of supporting information technology infrastructures.

3.2. Terminology

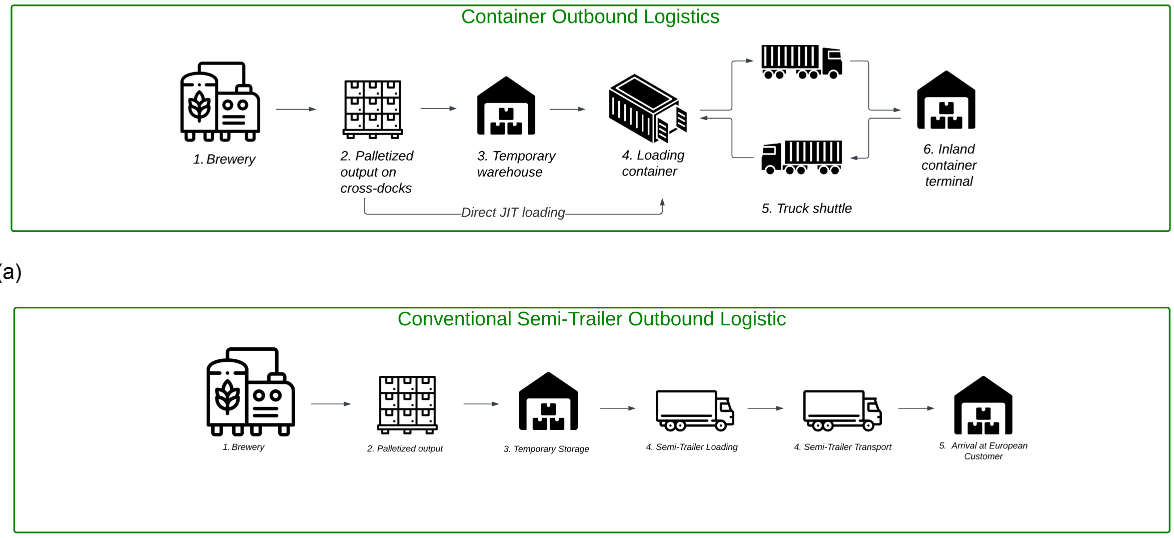
In this section, terminology related to outbound logistics will be introduced. This will ensure consistency throughout this research and confusion regarding any terminology will be avoided. This presented list will indicate several terms used in this research that will not be evidently clear from previous text, graphs, or flowcharts.

- **Stock Keeping Unit (SKU)** An SKU refers to a product type with distinct packaging and labeling. Each SKU carries a unique recognition number. A single type of beer being produced at the brewery can therefore carry multiple SKUs. After this beer has been labeled and packed, only one single SKU is identified with these products.
- **Order** An order can be placed by a customer and consist of one or multiple SKUs and quantities that they want to receive in a moment in time. Some constraints are in place when ordering at Heineken, for instance, a minimum order quantity (MOQ). The order also carries the final destination and other related shipping information.
- **Shipment** An order will in time be linked to a production process in the brewery and is then called a Shipment. A Shipment consists of one or multiple SKUs. The minimum quantity of a shipment is a full container or truckload.
- **Delivery** For all container loads, a shipment with the sea carrier has to be reserved. Therefore, if a single shipment consists of multiple container loads, multiple deliveries will be created for maritime transport. A single delivery corresponds to a single shipping container. So, one shipment can contain multiple deliveries.
- **Operating Company (OpCo)** An Operating Company is a Heineken entity based in a foreign country and is responsible for the market in that country or region. Some OpCos operate their own breweries. Within this research, however, all considered OpCo do not have their own brewery and are depending on the delivery of beer produced by HZW.

3.3. Outbound Logistics Network

In Figure 3.1, a schematical overview of the physical outbound logistics at Heineken has been visualized. The supply chain of the outbound logistics can be structured as a serial supply chain, where each node has one or multiple upstream and downstream actor(s). This part will give a very comprehensive outline of the outbound logistics of finished goods at HZW. A distinction is made between *Container Outbound Logistics* (Figure 3.1a) and *Conventional Semi-Trailer Outbound Logistics* (Figure 3.1b). In Figure 3.1a, the logistic network regarding container deliveries can be observed. Following the brewing production process (1), the items are packaged and loaded onto pallets, marking the final production stage at Heineken Zoetewoude. The finished palletized products will move on to the cross-docking lanes (2), which serve as buffer conveyors with limited storage capacity. Then, the pallets are directly loaded in an empty shipping container (4) or temporarily stored at the warehouse (3). The arrival of empty containers is the responsibility of CCT, the operating company of the inland container terminal (6). CCT's duty is to operate the truck shuttle (5) between the brewery and the inland terminal. CCT provides the brewery with empty containers as they are needed (Just-In-Time) while also transporting the full container back to the inland container terminal. At every moment, multiple trucks are used for the shuttle between the brewery and the inland container terminal. On average, a round trip takes an hour.

The outbound logistic network depicted in Figure 3.1b is applicable to truck shipments, which will be transported by semi-trailers and not in shipping containers. Most of the end destinations of these shipments are within the European mainland. After the brewing process, the palletized output is stored



(a)

(b)

Figure 3.1: (a) Outbound logistic network for shipping containers, (b) Outbound logistic network for conventional truck loads.

in the finished goods warehouse (3), visible in Figure 3.1b. Then, a semi-trailer of a third-party logistic service provider will pick up the goods at the production plant (4). After the pallets have been loaded, the semi-trailer will deliver the goods directly to the end customer (5).

This study will focus on container deliveries, which form the most significant part of the export deliveries at Heineken Zoeterwoude. Therefore, the container deliveries are considered to have the most impact on the current logistic system at Heineken.

3.3.1. Production

This part will briefly describe the physical production procedure at HZW, with a focus on the final stages of production, where products are packed and ready to be loaded. An understanding of the production procedure is required for a complete understanding of the outbound logistic network. It is important to note that the production process takes place in batches. Each batch produces a single SKU, including beer type, packaging material, and labeling. Such a batch is made based on customer orders. At HZW, multiple SKUs can be produced simultaneously on different production lines. Some lines can only produce bottle SKUs, while others can only produce cans or draught kegs.

A distinction can be made between *make-to-oder* (MTO) and *replenishment* orders. The former is based on specific order requirements from a single customer, and the latter is based on the stock levels of Heineken OpCo's. If these levels are below a certain benchmark, HZW will automatically create an order to replenish the specific operating company. This will ensure a sufficient stock level in the warehouses of the OpCo. A third production type is the Make-To-Stock principle, which is only used for the domestic market. This means that HZW is responsible for maintaining a sufficient stock level for the domestic market at the brewery warehouse. This concept is chosen to ensure product availability for the Dutch customers of HNS, thereby maintaining the required service level. It must be noted that this research only considers the export market, which uses a separate warehouse at the brewery.

A certain batch is not linked to outbound deliveries during the packaging and labeling process. This linkage process will take place during the loading planning. Deliveries are matched to production batches based on the required delivery date of a single delivery, which consists of a single shipping container load. The output of the production process is a palletized SKU that will flow onto the cross-docking lanes, described in subsection 3.3.2. Over 2022, the weekly average production levels are visible in Figure 3.2. These weekly numbers represent the palletized output of the production plant for a specific week bounded for export. The average weekly production accounts for $20,778$ pallets, with a weekly standard deviation of $3,203$ pallets, which is equal to $15,4\%$ (Table 3.1 and Figure 3.3). Based on 22 pallets per container on average, during an average week, more than 944 containers are being loaded. In 2022, $1,0808,466$ pallets were produced for export markets only. Due to different SKUs being produced simultaneously and over time, the weekly production output fluctuates heavily over a years period. In total, 277 SKUs were produced in 2022 at the brewery in Zoeterwoude. Furthermore, seasonality causes higher demand during specific periods of the year.

Production in pallets (2022)	
Total Produced	1 080 466
Weekly Mean	20 778
Weekly Standard Deviation	15,4%

Table 3.1: Weakly production deviation at Heineken Zoeterwoude in 2022.

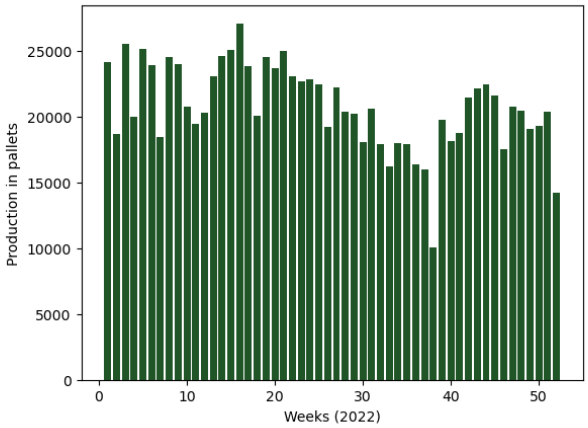


Figure 3.2: Weekly palletized production output.

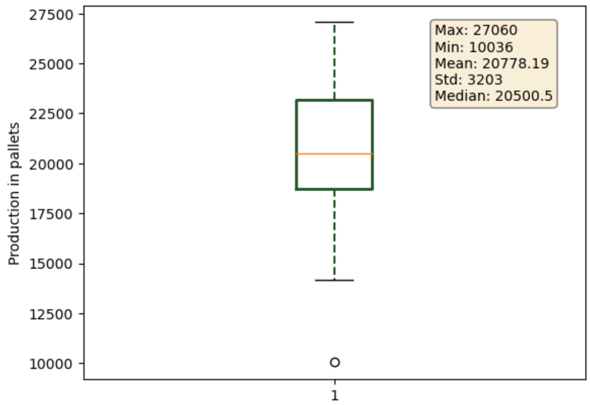


Figure 3.3: Boxplot displaying deviation in weekly output.

3.3.2. Just-In-Time Pick Up & Cross-Docks

As has been briefly described, a distinction is made between the deliveries being loaded into containers or conventional semi-trailers (see Figure 3.1). The containers are all bounded for export through a deep-sea port. At the same time, conventional semi-trailer deliveries are driven to their destination on the European mainland. These processes are visible in Figure 3.1a and Figure 3.1b. Over 2022, a total number of over *53,000* deliveries were completed. Over *47,000* of those deliveries were loaded in containers, and slightly over *6,000* semi-trucks were loaded. A total overview is visible in Figure 3.5. Here, *40DR, 40NW, 40HC, 40HR, and 40RF* all refer to different types of 40-foot containers. *45PW and 20DR* refer to a 45-foot and 20-foot container, respectively. Lastly, *9900, 99TB, and 99GP* are all conventional truck deliveries. It must be noted that in Figure 3.5, only export deliveries are accounted for.

HZW makes use of cross-docks to improve the outbound logistic process. Cross-docks were originally designed for direct trans-shipments of goods from in- to outbound transportation, therefore the need for warehousing was omitted. Cross docking enables more flexibility and lower labor costs. At HZW, cross-docks connect the end of the packaging line with the outbound container and truck docks. In Figure 3.7, the end of the production lines, where the products are being palletized is denoted in blue. The red areas in Figure 3.7 are the cross-docks that connect the palletizers with the loading docks, visible in green. A photograph of the cross-docks and warehouse is presented in Figure 3.4, where the cross-docks are visible on the left side. The right side of the photograph depicts the warehouse. At HZW, there are 24 loading docks available for export. The movement of products from the end of the cross-docks to the loading docks is performed by human-operated forklift trucks. Next to the cross-docks, denoted in yellow, are the pallet places of the warehouse (see subsection 3.3.4).

With the use of cross-docks, also called buffer conveyors, the need for a relatively large finished inventory warehouse steeply declines due to the dynamic storage capacities of the cross-docks. Moreover, these conveyors are mainly used to ease the loading process of shipping containers by enabling just-in-time logistics at the brewery's output. Conventional trucks are mainly loaded through the warehousing system, which will be discussed in subsection 3.3.4. At HZW, 13 conveyors are installed, all

Cross-Docks	
Number of cross-docks	13
Capacity per cross-dock	40 pallets

Table 3.2: Cross-dock characteristics at Heineken Zoeterwoude.

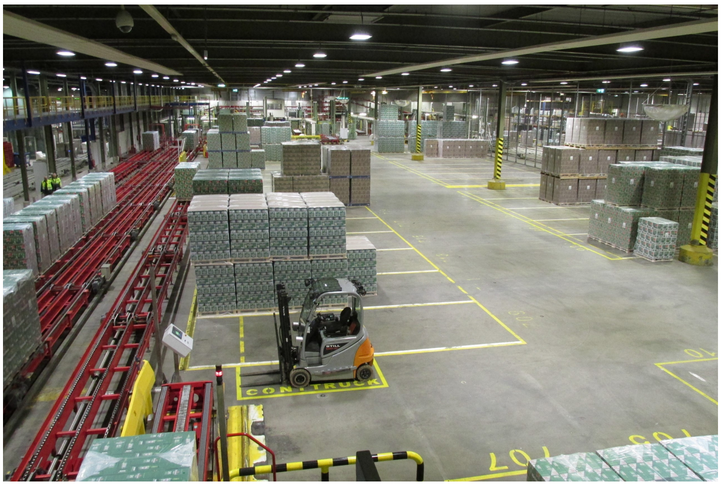


Figure 3.4: On the left, the cross-dock lanes are visible in red.

capable of holding up to 40 pallets. The limited storage time at the cross-docks gives the outbound transportation some slack to arrive at the loading bay and load the containers.

Just-in-time (JIT) logistics is a production strategy that aims to minimize inventory and increase efficiency by producing goods only as needed. It was first developed in Japan in the 1950s and 1960s by Taiichi Ohno, an engineer at Toyota (Ohno and Bodek, 2019). Just-in-time pick-up refers to the process in which outbound transportation arrives timely to directly load and pick up finished goods from the production lines. At HZW, the JIT pick-up system was directly implemented with cross-docking installation. In conventional production plants, finished goods are stored in an inventory warehouse, waiting to be transported to the next node in the supply chain. However, this approach causes many more individual pallet movements, which is a timely and labor-intensive procedure.

3.3.3. Inland Container Terminal

To apply the JIT terminology and ensure a smooth loading process at HZW, the arrival of empty containers at the loading docks must be precisely planned. Manufacturers and suppliers must be connected to an information network for a JIT system to be efficient. According to Kaneko and Nojiri (2008), JIT requires long-term business relationships for all parties involved. Based on the structure, JIT systems can benefit suppliers and manufacturers, primarily if strict criteria exist.

Within the production chain at HZW, Heineken holds a business relationship with Combined Cargo Terminals (CCT). CCT is a provider of inland terminal services and operates an inland container terminal, Alpherium, located in Alphen-aan-den-Rijn. Heineken shares electronic data on production and loading with CCT; more regarding this topic can be found in chapter 4. CCT uses this data to carefully plan the pick up of goods from the production plant with containers. Therefore, CCT arranges truck rides from Alpherium to HZW to load finished goods in the required shipping containers. Afterward, CCT is responsible for delivering the shipping container to the corresponding deep-sea terminal. Therefore, CCT transports the container firstly by truck to Alpherium. CCT ensures enough trucks to transport the containers from the brewery to the inland container terminal. Based on production data over 2022, CCT arranges the shipments of roughly 950 containers every week. Historical data pointed out that, on average, a round trip takes an hour. The logistic process from HZW to the deep-sea port is known as pre-carriage.

Each delivery at Heineken requires a specific container type, depending on the container carrier and port of destination. Based on these deliveries, CCT is responsible for supplying the production plant at HZW on time with the required container. At the inland container terminal, more than *200,000*

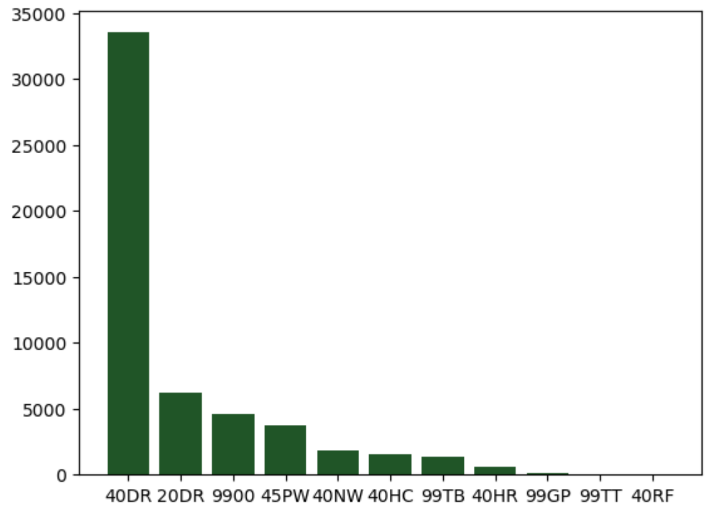


Figure 3.5: Overview of export deliveries in 2022, categorized by means of transportation.

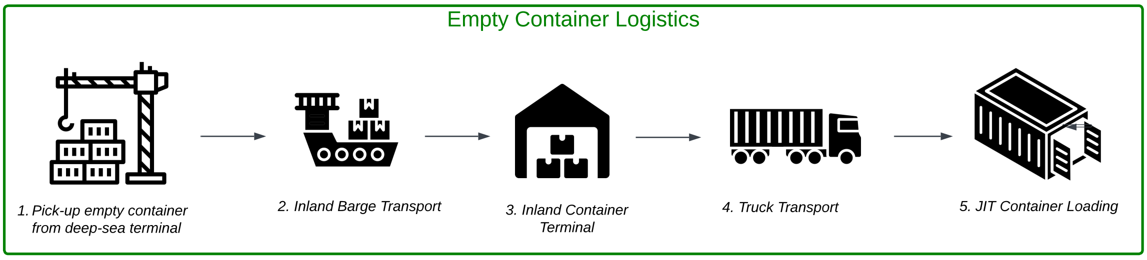


Figure 3.6: Schematic overview of empty container logistics

TEU (twenty-foot equivalent units) are being transshipped yearly. With a storage capacity of more than *4,000* TEU, the inland terminal is an important node in the JIT system operation at HZW.

Reverse Logistics CCT

Additionally, CCT is responsible for collecting empty containers at the deep-sea port for the loading process at HZW, as has been visualized in Figure 3.6. Depending on the production plan and the associated deliveries and shipments, CCT has to pick up empty containers in the deep-sea terminals (1). At these terminals, large amounts of empty containers are being held and are available to be loaded by customers of the deep-sea shipping carriers. CCT will load empty containers onto a barge and ship them to the inland container terminal (3). From there, the containers will be transported to the brewery according to the JIT terminology; only the containers directly being loaded will be transported to the brewery.

CCT carries the responsibility to have the required containers available on time. The storage capacity at CCT causes some redundancy in the system; CCT will always make sure to have to most common containers in stock. On that account, the loading planning gains some flexibility. However, during high season, the output of the production plant increases, and the redundancy created at the inland terminal might not be sufficient.

3.3.4. Warehousing

The integrated cooperation between Heineken and CCT, as described in subsection 3.3.3, is wholly focused on container shipments. Therefore, CCT is not responsible for the transportation of products in semi-trailers. As seen in Figure 3.5, around *6,000* semi-trailers were loaded at HZW in 2022. The supply chain of semi-trailers deviates from the network integration with CCT. Truck deliveries do not work in a JIT system due to significant deviations in the planning of road trucking. Therefore, palletized products for semi-trailer transportation are always temporarily stored in the warehouse. When a semi-trailer arrives, the products will be moved into the trailer. As a consequence, semi-trailer deliveries have a significant impact on warehouse levels. The warehouse area at Heineken Zoeterwoude is denoted by the yellow areas in Figure 3.7.

In addition, the warehousing capacity is around *20,000* pallets, where most of the inventory is reserved for domestic products. Around *3,500* pallets are available for export storage. Besides the storage needed for semi-trailer deliveries, storage must be available for container deliveries in the case of any supply chain obstruction. For instance, CCT might not be unable to deliver the required container on time, whereby the pallets will be moved to the warehouse.

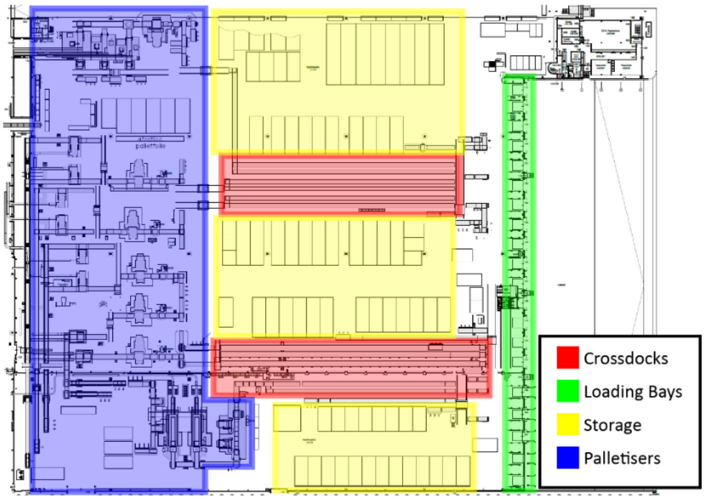


Figure 3.7: Map of the loading area at HZW, retrieved from Valk (2017).

3.4. Key Performance Indicators

This section presents an outline of the outbound logistic Key Performance Indicators. In the current state, several KPIs are being measured and will be briefly described in this section. These KPIs are interwoven and affect each other; this will be elaborated on in chapter 4.

1. **JIT Loaded Deliveries** This KPI represents the outbound container deliveries that are directly loaded in a JIT framework and of which the pallets are thus not being stored at the finished goods warehouse at HZW. This is the preferred procedure; a higher percentage represents better performance. This KPI is complex and incorporates multiple processes at once. To load the deliveries in a JIT manner, multiple branches of the outbound logistics have to cooperate. In this way, this KPI combines the performance of multiple subsystems, which are solely hard to quantify. These subsystems include the performance of the production lines and the on-time arrival of empty shipping containers. Therefore this KPI is considered the leading performance indicator of the finished good loading process.

2. **Warehouse Occupation** Following the first KPI, the preferred procedure is to directly load the palletized products into the required shipping container when rolling off the production lines. In the case of intermediate warehouse storage, more pallet movements are necessary, and more extended storage causes increased costs. High warehouse levels are often the result of production peaks or misalignment in the planning between Heineken and CCT.

3. **Empty Container Arrival** In addition to the first KPI, which depicts the percentage of directly loaded deliveries. This KPI indicates the performance of the arrival of containers at the brewery. As outlined in subsection 3.3.3, CCT is responsible for the timely arrival of empty containers from the inland container terminal to the brewery. CCT measures the performance of measuring the difference between the requested containers by Heineken and the actual empty containers delivered by CCT.

3.5. Current State Performance Analysis

Here, the current state performance analysis is performed based on the KPIs introduced in section 3.4. This analysis focuses on the physical flow of goods regarding the outbound logistics at HZW. This analysis is performed to quantify the current performance of outbound logistics. Therefore, historical data has been used in the analysis. The first performance indicator presented in section 3.4 will be reviewed. Data over the full year 2022 is used to include seasonal demand fluctuations. To quantify the percentage of JIT-loaded deliveries, all export deliveries are considered.

As mentioned in subsection 3.3.2, over 2022, more than *53 000* export deliveries were loaded in Zoeterwoude. Within the sake of the first KPI, only the container export deliveries are considered here since semi-trailers are never loaded directly from the cross-docks. Within the container deliveries, a distinction is made between *Cross-Docked, Warehouse, Shortages and Mix Containers*, see Table 3.3. *Warehouse* deliveries are stored in the warehouse before being loaded into containers. Due to the required container's unavailability, products are temporarily stored in the warehouse. *Shortages* are deliveries loaded with a production shortage. Due to several reasons, containers are loaded with a shortage, but mainly because the production amounts were insufficient to fulfill all deliveries with enough products. Lastly, *Mix Containers* are deliveries with more than one SKU. Consequently, these deliveries cannot be JIT loaded because the productions of the different SKUs are not likely to run simultaneously. Therefore, these products are temporarily stored in the warehouse.

Total Deliveries Loaded (2022)		**53 903**	**100%**
Container Deliveries	Cross-Dock	43 163	80%
	Warehouse	3 347	6.2%
	Shortages	914	1.7%
	Mix Containers	409	0.7%
Semi-Trailer Deliveries		6 070	11.4%

Table 3.3: Loaded Deliveries at Zoeterwoude in 2022.

Moreover, this research solely concerns deliveries being loaded into shipping containers. Therefore the performance of the container deliveries have been tabulated separately in Table 3.4. It can be seen that overall, more than 90% of the container deliveries are loaded via the cross-docking lanes. Combining the number of the warehouse and mix containers in Table 3.4, almost 8% of the pallets are temporarily being stored in the warehouse.

Container deliveries Loaded (2022)	**47 533**	**100%**
Cross-Dock	43 163	90.2%
Warehouse	3 347	7.0%
Shortages	914	1.9%
Mix Containers	409	0.9%

Table 3.4: Container Deliveries at Zoeterwoude in 2022.

In addition to the yearly numbers presented in Table 3.4, the monthly performance of the JIT loading process is presented in Table 3.5. These monthly numbers account for the performance of the container loading, and the monthly percentages represent the successful JIT loading of a delivery. As can be seen, the maximal month-to-month deviation of the percentage is 4%. This deviation is not considered significant, but with the limited warehouse capacity, minor deviations might lead to major obstructions in absolute terms.

Besides the performance of the JIT loading, an analysis has been conducted on the performance of the arrival of empty containers by CCT from the inland container terminal to the brewery in Zoeterwoude. Based on the loading schedule, CCT will provide the empty container in a JIT manner to the brewery. CCT is also the party that operates the trucks for the container shuttle. Furthermore, they are in charge to arrange enough trucks to shuttle all containers requested by Heineken.

This data is closely related to the JIT loading performance measured by Heineken (Table 3.5) since JIT loading can only be performed with the timely arrival of the required empty container in close coordination with the production process. The CCT data over 2022 was only available for week 17 till week 52. The weekly mean over this period was 89%, with a weekly standard deviation of 4.8% (Table 3.6). A

Performance JIT Container Loading (2022)	
January	92%
February	91%
March	92%
April	93%
May	93%
June	94%
July	94%
August	90%
September	91%
October	90%
November	90%
December	92%

Table 3.5: Outbound Logistic Performance over the year 2022.

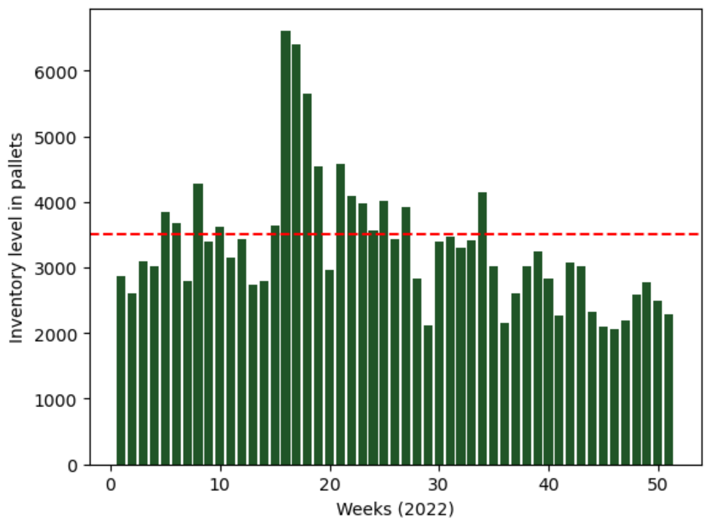


Figure 3.8: Weekly Inventory Occupation over 2022

high standard deviation would suggest a lot of volatility the in the weekly container arrival performance, which would be a sign of high uncertainty regarding the container's arrival. With a standard deviation of 4.8%, it is observed that the relative deviation is low, however, the absolute deviation is considered to be significant.

Performance CCT JIT Container Arrival (2022)	
Performance (Weekly Mean)	89%
Weekly Standard Deviation	4.8%

Table 3.6: Performance CCT container arrival week 17 until week 52 (2022).

Lastly, the performance of the loading process has been analyzed based on the occupation level of the export warehouse. The occupation level of the warehouse is available on a daily average. For this analysis, the weekly mean of the daily volume was taken, which has been made visible in Figure 3.8. In Figure 3.8, the red dotted line represents the preferred maximum occupation of the warehouse (3 500 pallets). The physical limits of the export warehouse are roughly 4 000 pallets; depending on the palletized products, some SKUs cannot be stacked on top of each other, thus occupying more space. Close to the export warehouse in Zoeterwoude, the domestic warehouse is located. If levels in Figure 3.8 exceed the red dotted line, they are most likely stored in the domestic warehouse, which is unfavorable.

Furthermore, for the occupation levels, the mean and standard deviation have been calculated (Ta-

Warehouse Occupation in Percentage (2022)	
Performance (Weekly Mean)	95%
Weekly Standard Deviation	28%

Table 3.7: Weekly Warehouse Performance (2022).

ble 3.7) based on the preferred warehousing level of 3 500 pallets; the weekly average occupation level is 95%; however, with a standard deviation of 28%, the weekly average levels fluctuate significantly—especially weeks 16, 17, and 18 display high occupation with levels exceeding 6000 pallets.

3.6. Conclusion

This chapter has outlined the current physical export flow at the brewery in Zoeterwoude. A distinction was made between container and truck deliveries, while this research mainly focuses on container deliveries. Pallets are ideologically directly loaded from the cross-docks into a shipping container. Therefore, the shipping container must arrive on time at the brewery, which is the responsibility of CCT. Due to production fluctuations and the unavailability of empty containers, pallets might be temporarily stored in the warehouse. This procedure is not preferred due to the limited capacity in the warehouse and the extra pallet handling involved. Ultimately, if the capacity in the warehouse is reached, production could be halted, which is an expensive procedure.

Based on a weekly analysis of 2022, it can be concluded that the palletized production output fluctuates weekly. The standard deviation of $15,4\%$ is considered to be high. This stochastic production output causes uncertainty in the logistic system. Over 2022, almost 8% of the pallets are temporarily stored in the warehouse, while over 90% are being cross-docked and loaded into a shipping container according to the JIT procedure. Based on data from CCT, it was found that 89% of the required shipping containers arrived on time at the brewery. The difference in the cross-dock performance and the performance of on-time container arrival can be explained by considering the cross-docking lanes. Due to their buffer capacity, pallets can still be cross-docked if containers are unavailable on time. However, the storage capacity of the cross-docks is limited. As a consequence, pallets still flow into the warehouse. Due to the fluctuating production output and the uncertainty in container availability, the warehouse inventory levels deviate heavily every week. The deviation of the production output and the key performance indicators has been displayed in Table 3.8.

Although, the performance of the cross-docking and JIT arrival are 90% and 89%, respectively. The absolute number of pallets that do not follow the desired path is considered high and therefore causes a lot of strain on the outbound logistic network. Furthermore, the deviations in Table 3.8 show that the performances of the considered parts of the logistic chain fluctuate on a weekly level.

Outbound Logistic Deviations (2022)	
Palletized Production Output (weekly)	15,4%
JIT Container Loading (monthly)	4.0%
CCT Container Arrival (weekly)	4.8%
Warehouse Occupation (weekly)	28.0%

Table 3.8: Deviation in percentage based on key performance indicators.

4

Planning and Information Networks

In chapter 3, it was concluded that the current performance of the outbound logistics fluctuates a lot on a weekly level due to the stochasticity created by the production output. As a result, the absolute number of pallets not following the desired path of directly being cross-docked was considered to be high. Consequently, this chapter will examine the current logistic planning structure at Heineken Zoeterwoude. Logistics planning is very much related to information technology, as planning is done based on the available information in the different information technology systems. This chapter outlines the planning and information sharing regarding the outbound logistic planning at the Heineken production plant. Therefore, the system has to be analyzed from a bird-eye perspective, and the information flows need to be outlined. The first part will be used to describe the planning horizons based on the supply chain planning matrix. Then, a swim lane diagram visualizes the interconnectivity of the physical flow of goods and the information network. The structure of the centralized planning tool will be outlined and the information asymmetries present in the system will be quantified. The following sub-questions will be answered in this chapter:

1. *What is the current planning structure of the outbound logistics network?*
2. *What are the information asymmetries in the current state?*

4.1. Planning Horizons

In section 2.1, the supply chain network was briefly described based on the typology introduced by Meyr and Stadtler (2005). This chapter will discuss all of the functional and structural attributes. This part will define the planning structure based on a hierarchical structure adapted from the SCP matrix in Figure 2.2. As seen in Figure 2.1 and Figure 2.2, the functional attributes are the core building blocks of the SCP matrix. Consequently, the SCP-matrix structure will be used to discuss the functional attributes, after that, the structural attributes will be described separately.

The SCP matrix combines the chain processes *procurement, production, distribution* and, *sales* while simultaneously accounting for the different time planning horizons, *strategic, tactical* and *operational* planning. The modules that build up the SCP matrix are horizontally and vertically interconnected by information flows. Moreover, the higher planning module constrains the lower modules. In most use cases, the SCP matrix is implemented with a rolling planning horizon. Especially in a system prone to uncertainty, rolling horizons are common (Meyr and Stadtler, 2005). Rolling horizons can be described as an implementation of plan-control-revision. For instance, a planning horizon of a year is taken (see Figure 4.1) and divided into monthly periods. Initially, planning is done for the total horizon, e.g., a year. The frozen period, the month of January in this case, is put into practice. Subsequently, at the start of the second period, a new plan is implemented for the next year, hereby considering new developments and forecasts.

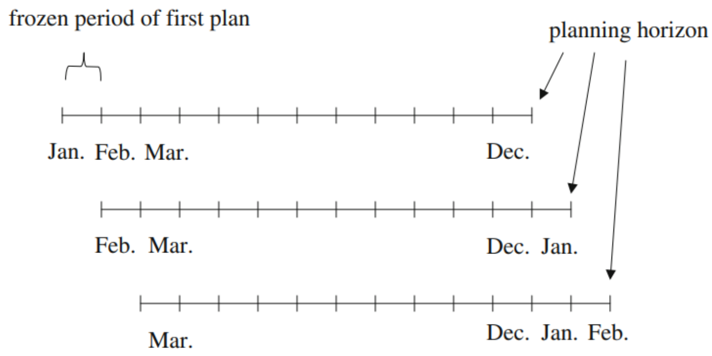


Figure 4.1: Planning horizon visualization, retrieved from Meyr and Stadtler (2005).

4.2. Supply Chain Planning Matrix

This section will review the current planning operations and horizons within the production and outbound processes at Heineken Zoeterwoude. Eventually, the goal is to construct the supply chain planning matrix and analyze the operational levels and planning horizons within Heineken. Also, the functional and structural attributes applicable to HZW will be outlined, especially the parts of the SCP matrix most relevant to this specific research. HZW covers all three hierarchical planning levels; furthermore, HZW is part of the global Heineken brand and, therefore, also prone to decisions being made outside the company scope. Heineken, as a global brand, sets out strategic targets with a horizon for more than five years. This, for instance, includes decisions to start serving a new geographical market. This research, however, focuses on the long-, mid-, and short-term planning at the brewery in Zoeterwoude.

Firstly, the long-term planning will be revised and correspond to the matrix's upper box, as seen in Figure 4.2. Long-term planning involves all four functional attributes. At HZW, the long-term planning horizon consists of 78 weeks. This decision-making level consists of decisions taking into account new product launches and modifications to the existing brewing plants regarding capacity. The horizon of 78 weeks also consists of a demand forecast received from customers, which is the basis of supply chain planning. The forecast contains the number of products per SKU for each customer. Based on this forecast, it is checked if the production plants can, for instance, coop with seasonal demand peak. The long-term planning considers a rolling planning horizon, every month a new long-term forecast is generated for the next 78 weeks. Downstream of the long-term planning, the mid-term tactical planning is observed in Figure 4.2. This planning level also consists of a rolling horizon which is updated every week. The tactical planning makes use of a 13-week forecast, in which capacity constraints regarding suppliers and specific product types will be revised. Mostly statistical models are used to estimate the demand per customer. In Figure 4.2 the demand under the attribute sales covers the mid-term aggregate and short-term detailed basis.

At Heineken, the operational planning referred to as short-term in Figure 4.2 is known as the 'drum-beat' process. The upstream levels of strategic and tactical planning are solely based on demand forecasts on future customer orders. The drumbeat has real customer orders as input and consists of an operational chain of planning activities. These orders consist of MTO and replenishment orders, as has been briefly described in chapter 3. The drumbeat chain takes 5 weeks from start to end. After orders have been received from international customers, a production plan will be made in the second week, the production will eventually start in the fourth week. During the second and third week, all suppliers are updated with detailed information about the expected production cycle. This is done after suppliers have been updated on the tactical level with the production forecast. Based on this forecast, suppliers can plan 13 weeks ahead. Eventually, during the drumbeat process on an operational level, the suppliers will be informed of the difference between the actual and forecasted demand. Within the short-term planning, orders with container carriers will be created and third-party logistic companies are informed about the expected outflow. After production has taken place in the fourth week, shipments of products will take place from week 5 onwards. This total process is repeated every week (rolling horizon) and is therefore called the 'drumbeat'.

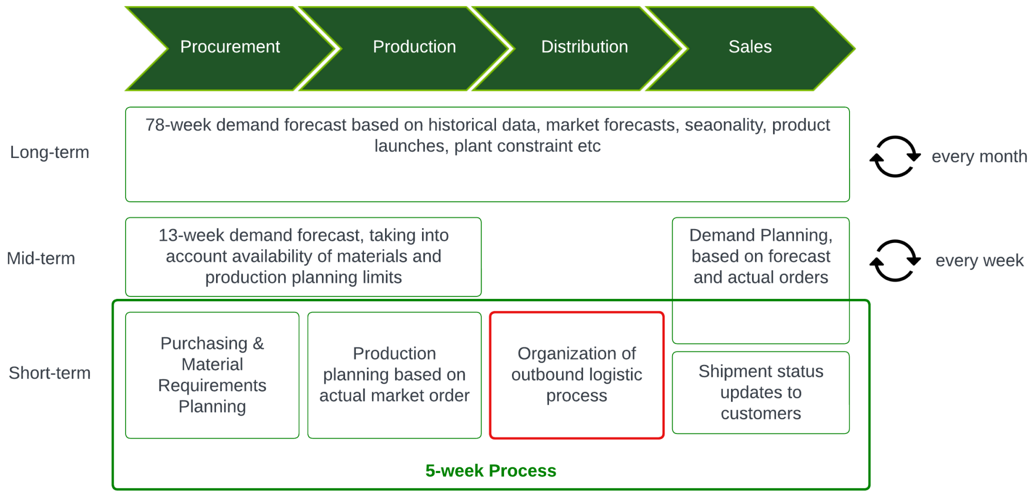


Figure 4.2: SCP matrix applied to Heineken Zoeterwoude, based on Meyr and Stadtler (2005).

4.2.1. Planning Scope

It is noteworthy to address that the outbound logistic process is only considered in the short-term planning horizon, as has been made visible in Figure 4.2. Other factors, such as procurement and production are already considered in long-term planning horizons. The planning regarding the outbound logistic has only an operational level since planning only starts when customer orders have been created, at the beginning of the drumbeat process. Strategic and tactical planning horizons are based on forecasts and therefore outbound logistics are not taken into account within these rolling horizon plannings. The loading planning is made by using the planned packaging time of a single SKU. Based on this hourly packaging planning, logistics planning is made considering the deliveries per SKU.

Not considering the effects of tactical planning on the logistics process results in unexpected events in the loading process. According to Pigeaud (2015), to incorporate the logistic process in the tactical planning horizon, measurements on the logistic process should be incorporated to create logistic demand forecast based on the currently in-place production forecast. The parameters that have been addressed by Pigeaud (2015) include the amount of palletized items being directly loaded by means of cross-docking, loading type per SKU, and average warehouse storage time per SKU. By incorporating these parameters, the strain on the warehousing and cross-docking systems can be forecasted. However, the forecasting does not include the matching of the required empty container with the output from the production, and therefore the complexity of the outbound logistics is only partially considered by Pigeaud (2015). Furthermore, providing forecasts for systems under uncertainty is extremely complicated, for that reason, this research will not take logistic forecasting into account.

During the short-term drumbeat process, described in section 4.2, the customer orders are considered as the system input. Based on these orders, batch sizes per SKU are calculated and the products will be produced in batches. These batch productions have been planned on the mid-term level, but the exact amounts are thus based on specific customer orders in the short term. During this batch production, the decoupling between orders and production takes place. The orders are still visible in the ERP systems, together with the *Loading Due Date (LDD)*, which is the ultimate delivery date of the order in the deep-sea terminal. However, the orders are not directly coupled to a production batch. Therefore, the production is based on customer demand but does not account for individual orders.

The process of 'recoupling' is considered the first step in the loading planning process. In *Production Scheduling (PS)*, which is a software tool used by Heineken, the coupling between production batches and deliveries (which follows from the customer orders) is performed. Here, the loading process uses information flow from the production module, but there is no feedback from the loading module to the production module. Before this step, the deliveries are created based on the orders, which means transportation has been booked by a container carrier. This coupling is done based on the output of the production line and the characteristics of the delivery. For instance, a delivery with an earlier LDD, will be loaded before a delivery with the same SKU with a later LDD. Because this decoupling exists in the process, the outbound logistics will be planned only on the operational level. Following the aforementioned reasoning, this research will only consider the loading on the operational level.

4.3. Information Networks and Asymmetries

This part will provide a comprehensive description of the information networks between the physical flow of goods and information management systems. Firstly, a Swim Lane diagram will be created presenting a simplified information network based on the physical flow of outbound logistics. Afterward, specific parts of the information network will be addressed in more detail to address the information asymmetry caused by information delays and feedback loops.

4.3.1. Swim Lane Diagram

A *Swim Lane Diagram* is a cross-functional chart and differs from a conventional flow chart by the addition of so-called *swim lanes* in which activities of one entity are bundled. The connections between the swim lanes are used to address cooperation or information sharing between IT systems involved in the process. By visualizing flows in a swim lane diagram, responsibilities per system are made visible. It becomes evident which systems share information. Conventional swim lane diagrams are built up in chronological order and display different parties involved. This swim lane, however, is slightly adjusted to visualize the information network in place for the JIT outbound logistics. This swim lane diagram is constructed based on the physical flow of goods, which can be observed in the bottom swim lane in Figure 4.3. The scope of the swim lane diagram is similar to the scope discussed in subsection 4.2.1, where the input of the system is marked as the output of the production plant, which consists of palletized goods for a range of SKUs. All information systems that are used for the planning of the logistic flow take up a swim lane in the diagram. Also, a swim lane is reserved for the information system regarding the barge operator CCT, which is responsible for the JIT availability of empty containers at the loading docks of the brewery. All swim lanes contain multiple modules which indicate a process step in the information flow. All swimlanes have been briefly described:

- **Pluto Database** Pluto is a database used by HZW. In this centralized database, information regarding the production process is stored and updated. The departments responsible for the tactical and operational planning of production cycles will update the database. Other departments are then able to query this data.

- **SAP** SAP is the enterprise resource planning (ERP) system that is used within HZW. SAP provides supply chain software that is used to streamline production, warehouse management, and outbound shipment planning. Customer orders will be entered in SAP. Based on the requirements, deliveries will be made and shipments will be arranged with the required container carrier. Planned production per SKU will also be visible. However, as discussed in subsection 4.2.1, the production in this stage is decoupled from the deliveries. SAP is currently bounded by processes within Heineken solely. Data flowing from Heineken to third parties, such as CCT, is extracted from SAP and manually transferred.

- **WMS** The warehouse management system (WMS) is the software used to control the state of the finished goods warehouse at the production plant in Zoeterwoude. Information that is available in WMS is the type and amount of products that are stored, which also includes the timestamp of goods entering the warehouse. Also, data on the exact positions within the warehouse is available.

- **PS** Production Scheduling (PS) is another software package that operates in close cooperation between physical production and JIT loading. PS is used to match deliveries with the associated production process in the brewery. This matching is crucial to minimize inventory by loading in a JIT manner as much as possible. PS is updated daily at 6 AM by querying information from SAP and central data from the Pluto database. Due to the single daily update, the data in PS is relatively static and can not be considered real-time data.

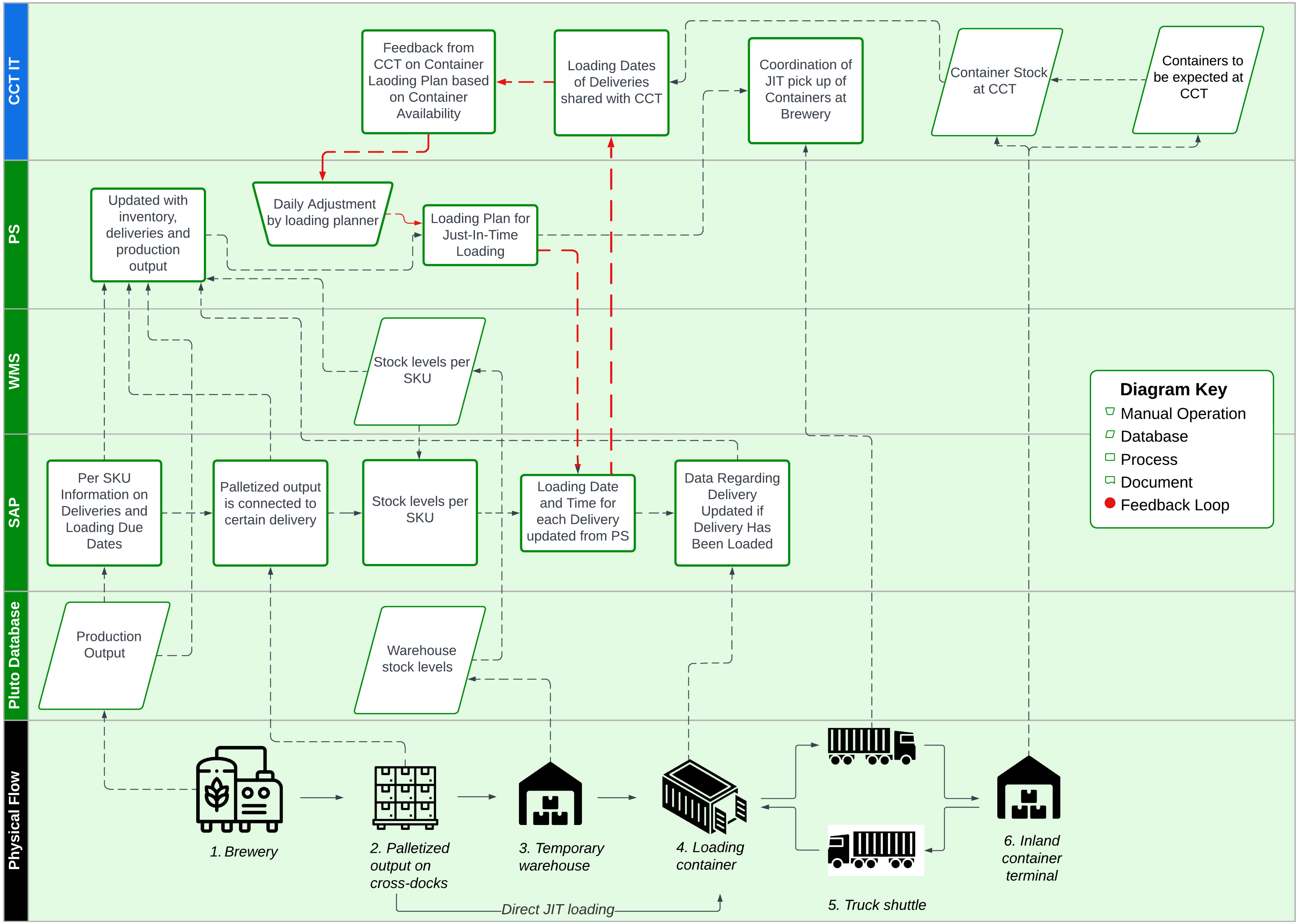


Figure 4.3: Simplified Information Flow in Swim Lane Diagram

- **CCT IT** The output data from PS is pushed to SAP and from there a document is pushed to CCT. CCT is responsible to provide the required containers in time at the production plant based on the production schedule. When they receive data from Heineken, they will provide feedback on the feasibility of the current logistic plan. Important information made available by CCT is their empty container stock and the flow of empty container that is expected to arrive at the inland container terminal.

Centralized Loading Planning

The swim lane diagram, visible in Figure 4.3, contains all information systems used to coordinate the outbound logistics in a simplified form. The most significant parts in Figure 4.3 will be briefly described. Information flows in Figure 4.3 are denoted by dotted line arrows. While the physical flow is bounded by the palletized output of the production plant and the inland container terminal on the other hand. *SAP* is considered the backbone of the information system as this ERP system considers the complete process flow. Within *SAP* the production process is planned but also shipments with carriers are visible within *SAP*. Furthermore, *SAP* can log changes to the system, therefore it is always possible to review what changes have been made to a certain process. On the other side, the decoupling between production batches and customer orders has yet not been solved by SAP.

The daily loading planning process is terminated in *PS* by the collection of the production plan from the *Pluto Database* and the deliveries available in *SAP*, this system state update is performed daily to account for changes in production or deliveries in the prior 24 hours. *PS* has a rolling planning horizon of 14 days and every weekday a loading plan is created in *PS* for the upcoming 14 days, based on updated information every 24 hours. As can be seen in Figure 4.3, *SAP* is updated simultaneously with the movement of the physical goods. *Ps* will be used by a loading planner to perform the process of matching the batch production to deliveries. The output of this process will be communicated via a manual data transfer with the operators at the inland container terminal (CCT). CCT will then provide feedback on the loading plan based on their data on container availability. The container stock levels at CCT are currently not available to Heineken, and therefore an information feedback loop is created. This feedback loop is visible in Figure 4.3 by the red dotted lines.

As has been denoted, *PS* forms the centralized backbone of the outbound operational planning. *PS* is responsible for the matching of the production plant output with the required shipping container, based on the delivery coupling to the palletized plant output. Therefore, Figure 4.4 depicts a visual representation of the required modules in the swim lane diagram of Figure 4.3. Here, *PS* is visualized as a central node that is dependent on the input data of 3 modules; production data, delivery data, and inventory data. This planning is centralized due to the centralized collection of data, based on which the loading plan will be created.

This data query by *PS* takes place every 24 hours, as a consequence, there is no real-time data available to *PS*. This time delay between *PS* and the 3 modules is denoted as the first information Asymmetry. Secondly, due to the unavailability of the container stock data to Heineken, CCT has to provide feedback on the daily loading plan created by Heineken, as can be seen in Figure 4.4. As a consequence, a Heineken operator has to adjust the loading plan in hindsight based on insights from CCT, creating a lot of rework. This feedback loop, including the 24-hour delay of the daily update from Heineken to CCT, is denoted as the second information asymmetry. Both the asymmetries are denoted in red in Figure 4.4.

> The planning tool *PS* receives daily updates of the four modules. Therefore, if the produced pallet flow is considered to be uniform, the average information asymmetry which is created is 12 hours and the feedback loop between CCT and Heineken, including the time delay, results in an average container availability of 89%, which can be seen in Table 3.6. The feedback loop will be elaborated on in subsection 4.3.2.

4.3.2. UML Sequence Diagram

In addition to the diagrams in Figure 4.3 and Figure 4.4, this section will provide a *UML Sequence Diagram*. The sequence diagram will be able to display an approximation of the time delay caused by the feedback loop between *PS* and *CCT IT*. The uncertainty of the timely arrival of empty containers at the brewery is a direct result of the feedback loop that will be analyzed in the sequence diagram.

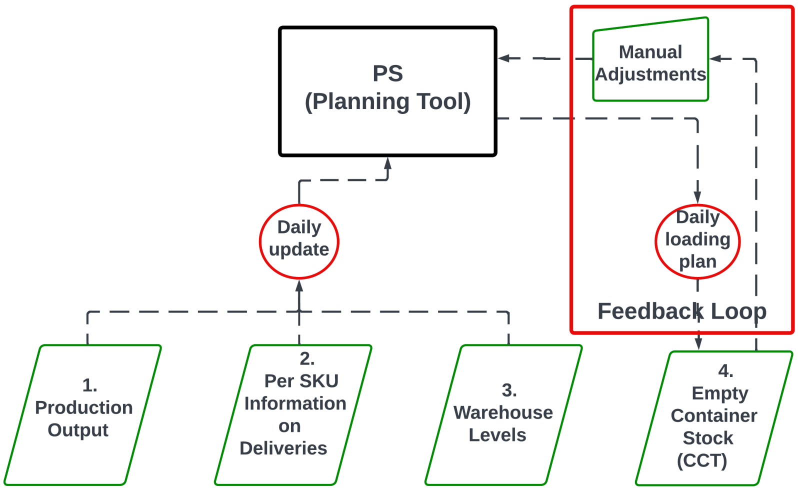


Figure 4.4: Visualisation of created information asymmetries based on time delays and a feedback loop

Unified Modeling Language (UML) is a visual modeling language that is used to represent software systems. It is a standardized notation that provides a way for developers and stakeholders to communicate and understand the design and behavior of a system. A UML sequence diagram is a type of UML diagram that shows the interactions between objects in a software system over time. It is used to model the dynamic behavior of a system and can be used to visualize how objects interact with each other to perform a particular task.

In a UML sequence diagram, objects are represented as rectangles, and their interactions are represented as arrows. The arrows show the order in which messages are sent between objects, and they can include information such as the name of the message, and the information passed. UML sequence diagrams are commonly used in systems engineering to model the behavior of complex systems, such as software applications or industrial control systems. They can help developers and stakeholders understand the flow of control and data through a system, identify potential issues or bottlenecks, and refine the design of the system to improve its performance and reliability.

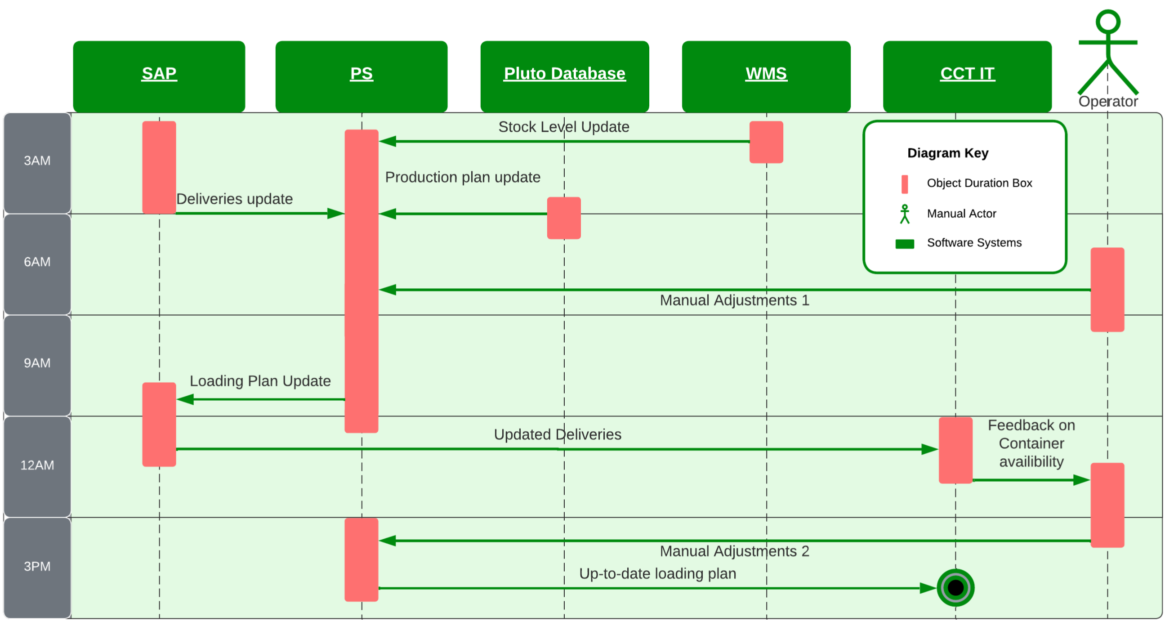


Figure 4.5: UML Sequence Diagram of simplified daily loading planning operation

Figure 4.5 depicts the sequence diagram of the outbound logistic information network. The length of the red rectangles indicates the duration of the object's involvement in a particular interaction. The main objective for displaying the information network in a sequence diagram is to visualize the duration of the daily loading planning cycle. Every day, with the associated time estimates, this sequence is followed to communicate between the different systems and actors to make a loading plan. Due to the time it takes for an operator to review the process and manually adjust to uncertainties in the system. The sequence starts with a daily update to *PS* from *SAP*, *WMS*, and the *Pluto Database* at $6AM$. After $6AM$, the loading plan operator has to perform several checks and adjust the plan if necessary. Depending on the duration of these operations, the adjusted loading plan is sent to the CCT operator through *SAP*. A manual operation is necessary to transfer data outside the company boundaries. Then, the CCT operator will provide manual feedback on the plan, which is again processed by the loading plan operator. Due to the number of interactions, especially human interactions, the process of creating a loading plan for the outbound logistics, is a timely procedure. Important to note is that CCT has no access to any of the information systems in place at Heineken. CCT is solely updated with data extracted from one of the information systems. Again, two main contributions to an overall information asymmetry between *PS* and the physical state can be identified; time delays due to only daily system updates and manual operations and feedback loops created by the unavailability of data regarding the container availability. As can be concluded from Figure 4.5, the daily routine of creating a loading plan starts at $6AM$ and, depending on the circumstances, ends between $1PM$ and $5PM$.

4.4. Current State Performance Analysis

Information Asymmetries

In Figure 4.5, the operational delay caused by the system interactions can be observed. As earlier denoted, these asymmetries are the root cause of inefficient procedures due to a lack of data visibility. This will eventually lead to an increased workload for the operators at HZW. Furthermore, manual labor is necessary to handle the logistic uncertainty due to the operational planning horizon at HZW for outbound logistics. In section 4.3, a swim lane diagram was first used to address the key features and information flows related to the physical logistic operation. Based on this diagram, a sequence diagram was created to display the estimated time delays associated with the different process steps in the outbound logistic planning. As a result of these time delays, asymmetries between different IT systems arise and cause several related operational issues. The most common information asymmetries have been identified:

1. Information delay between *PS* and other information systems (see Figure 4.4) has been identified to cause information asymmetries between the systems. *PS* only queries data daily at $6AM$. This query includes all data related to customer orders, inventory, and production outputs. Asymmetry between *PS* and the physical state starts arising when the physical state changes before the daily query. As a result, *PS* cannot match deliveries with updated stock levels, while data in *SAP* is updated in real-time with the physical state change. The severeness of the asymmetry increases over time as the likelihood of a data update in *SAP* increases with time. This process has been visualized in Figure 4.6. Here, at $6AM$, a system update takes place; however, after a state update over time, *PS* will not be able to measure this state change. This applies to all data shared from *SAP* to *PS* and includes inventory and production levels data. Currently, information asymmetry can take up to 24 hours, where the average is assumed to be 12 hours (based on uniform production output over time). Note that the process depicted in Figure 4.6 is also applicable to the data from *WMS* and the *pluto database.*

2. Due to the unavailability of empty container stock data from CCT to Heineken, an information asymmetry is created. Currently, a loading plan is made in *PS* without the data of CCT, then the feedback on the loading plan is requested from CCT. Consequently, this feedback must be processed manually by a Heineken operator. This procedure causes uncertainty about the timely arrival of empty containers at the brewery. A more robust and less labor-intensive solution would be to use the container availability at CCT directly as an input to the information network. Moreover, as depicted in Figure 4.5, the daily operation of creating a loading plan takes up several hours, and therefore the data used is already outdated. Historical data shows that the container availability asymmetry causes a container availability of 89%.

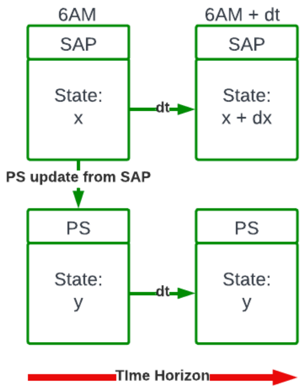


Figure 4.6: Information system asymmetry between SAP and PS

Transaction Costs

The transaction costs of the information network can be measured by means of the complexity of the information network. The current *Swim Lane Diagram* (Figure 4.3) of the outbound logistic network consists of 34 information flows. Where each system communicates with multiple other systems. According to Jeong and Phillips (2011), a modular design aims to reduce interactions across multiple components in the system, ultimately reducing the number of components. For the *Swim Lane Diagram*, several components of the IT systems are essential to the outbound logistic process. These components, listed in Table 4.1, provide the essential information for outbound logistic planning. Modules in Figure 4.3 that have not been listed in Table 4.1 have been identified as dispensable and contribute to the current system's complexity.

Essential Modules	
Production Output	Pluto Database
Delivery Information	SAP ERP
Stock Levels	WMS
Container Availability	CCT IT

Table 4.1: Essential Information Network Modules

Human Interventions

Due to the lack of visibility created by several information asymmetries, operators must intervene and manually adjust the lagging system. Regarding the loading process, there are mainly two issues arising regarding the data discrepancies in the Production Scheduling software. The first one arises due to information in PS lagging, which creates a fictional shortage. Consequently, PS will raise a shortage message as a result of which the container cannot be loaded. The second arises when PS plans a container to be loaded with products from the warehouse. This is often impossible because of production and products being in quality control. By taking the number of container loading interventions as a percentage of the total number, the performance of the current information network can be quantified. The lower the number of manual interventions, the better the information flows have been aligned. Figure 4.7 displays the measured interventions of a loading operator monthly over 2022.

Secondly, the feedback loop (Figure 4.4) regarding the container availability at the inland container terminal causes interventions of the loading planner daily. It has been identified that a loading planner has to make adjustments to the planning daily. Even if there are no adjustments to be made, the loading planner has to review the planning based on the container availability, which causes a lot of rework. In the most extreme case, the production process has to be halted last minute due to the unavailability of empty containers at the inland container terminal.

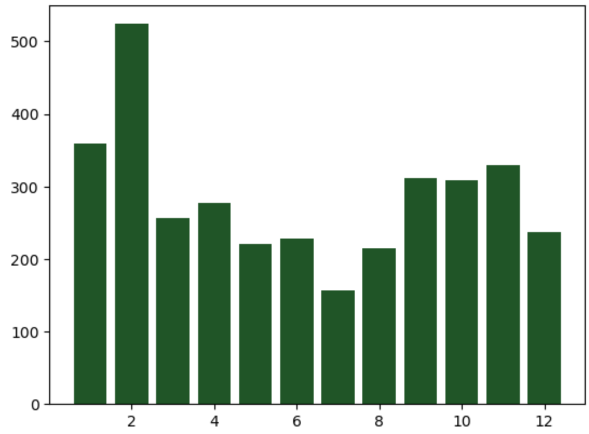


Figure 4.7: Manual interventions in the PS loading process grouped per month over 2022.

4.5. Conclusion

This chapter describes the current state of the planning and information networks in place at Heineken Zoeterwoude. This chapter aimed to analyze the current planning levels in place at Heineken regarding outbound logistics. Secondly, the aim was to identify and quantify the information asymmetries influencing the current planning system.

First, it can be concluded that in the present system, outbound logistics are only planned from an operational perspective. No long-term planning or forecasting takes place to estimate the impact of the supply chain on the outbound logistics. In the present system, outbound logistics is planned with a horizon of two weeks, where the rolling horizon is set to a week. Every week, data regarding production and deliveries are updated. Furthermore, the production plant is decoupled from the logistic planning. Consequently, the production planning does not consider the impact of the production output on the logistic network, which was denoted as an uncertain input in chapter 3.

In addition, the information network has been analyzed within this chapter. The Swim Lane Diagram in Figure 4.3 shows the integrated network of information systems needed for operational logistic planning. On a daily routine, a loading plan is created in *PS* with a horizon of two weeks. Currently, *PS* depends on the data input regarding production, delivery, and warehouse levels. Then, a loading planning is created and communicated with the third-party logistic provider. This plan is updated every 24 hours and this update is shared daily with the third-party logistic provider. This timely procedure of creating a loading plan has been displayed in the UML sequence diagram (Figure 4.5).

Information Asymmetry	**Effect (average)**
Production Output	12 hour delay
Delivery Information	12 hour delay
Stock Levels WMS	12 hour delay
Container Availability	89% timely arrival

Table 4.2: Current State Information Asymmetries

It could be concluded that in the as-is state, on the one hand, a time delay is created by only updating *PS* with state updates regarding production, deliveries, and warehouse inventory. In the worst case, this delay is 24 hours and 12 hours on average, considering a uniform production output. On the other hand, data regarding the empty container availability at CCT is not considered while creating the loading plan in *PS*, which creates uncertainty in the system. Currently, a loading plan is shared with CCT, and they will provide feedback on the feasibility of the loading plan. Consequently, it has been analyzed in chapter 3 only 89% of the requested empty containers by Heineken arrived on time. The information asymmetries affecting the loading planning have been displayed in Table 4.2.

5
Model

In chapter 3, the current state of the physical flows of the logistic chain has been analyzed. While chapter 4 was used to outline the information flows and technology currently in place at Heineken Zoeterwoude. This chapter will bridge the gap between the key features of the existing academic literature, which has been reviewed in chapter 2 and the current state analysis in chapter 3 and chapter 4. In the current state performance analyses, it could be concluded that the information technology network is not performing according to the company's needs and causes several information asymmetries in the logistic planning. In the academic literature, control theory has been researched extensively, especially in the field of Model Predictive Control. According to the literature, MPC is a very suitable construct for controlling supply chains prone to uncertainty. MPC enables robust control since it can integrate multiple sources of information, including demand forecasts, production schedules, and inventory levels, to make optimal decisions that balance conflicting objectives. Within the SIMILAR approach in Systems Engineering, the *Model the System* describes the system. This includes the functional decomposition of the system and the development of models. This chapter will focus on the model which can be used to simultaneously simulate the Current State with information asymmetries and the Future State without information asymmetries. This will be guided by several requirements listed within this chapter.

1. *What requirements should be considered regarding the supply chain model, and what modeling strategy is preferred?*

5.1. Approach

Within this research, the goal is to increase the performance of the physical flow of goods considering the control of the outbound logistic information network. In chapter 3, it was concluded that the palletized production output fluctuates heavily considering the weekly average (15,4%), this stochasticity causes variation on the impact of the production on the logistic network. This could be seen in the fluctuating warehouse levels. Moreover, in chapter 4, the information asymmetries regarding the logistic planning were analyzed. The outbound logistic network needs to be modeled to study the effect of these information asymmetries. Furthermore, the performance of the Current State, prone to information asymmetries, must be compared to the performance of the Future State. Assumptions must be made to model a Future State in which the model is not exposed to the current information asymmetries. Due to these assumptions, the Future State model is not compared to the performance of the real-world logistic network but to a similar model in which the information asymmetries are modeled. Again, the information asymmetries observed in chapter 4 are listed in Table 5.1.

Information Asymmetry	Effect (average)
Production Output	12 hour delay
Delivery Information	12 hour delay
Stock Levels WMS	12 hour delay
Container Availability	89% timely arrival

Table 5.1: Current state information asymmetries

5.2. Model Requirements (Current & Future State)

To model a Future State and compare this state to the Current State, Future State requirements have to be determined. Several requirements can be listed which apply to the Current State and Future State model. After that, specific requirements for the Current and Future State models will be listed. These requirements are essential in selecting the appropriate Future and Current State modeling strategy. Also, these requirements will be used to construct the model design.

General Requirements

For the models to be representative of the logistic network in place at Heineken Zoeterwoude, the models should be high-fidelity, which means that they are modeled in such a way that they represent the real-world scenario as closely as possible. Considering the high fidelity, the following requirements need to be considered:

1. **Stochasicity** The model should handle stochastic input such as production variability and the uncertainty in the JIT arrival of empty containers at the brewery.

2. **Differentiate between SKUs** The model should be able to differentiate between different SKUs. The information per SKU is necessary to create a container loading plan, where a specific SKU must be loaded in a specific container. Also, data regarding the number of products of each SKU should be known.

3. **System Characteristics** To model the loading process at the brewery in Zoeterwoude, the real-life system characteristics should be known. These include the characteristics of the production output and the number of SKUs being produced. Moreover, system constraints should be known such as the maximal amount of trucks available, capacity limits of the cross-docks, capacity limits of the warehouse, and the number of containers that can be loaded simultaneously at the brewery. Also, constraints regarding the capacity of pallet movements per time unit should be known.

4. **Real-World Data** For the model to represent the logistic network at Heineken, the model should be used with real-world data. This data includes information regarding the palletized output per SKU at the brewery. Also, information on deliveries regarding the number of pallets per container and container type should be known and accounted for in the model.

5. **Centralized** In chapter 4, it was concluded that the current state planning tool operates in a centralized way; *PS* collects data daily and creates a logistic loading plan considering the input data of multiple modules. To research the effects of information asymmetries, the Future model should be comparable to the Current State, which is centralized.

Current State Requirements

1. **Information Delay** The current state model requires a time delay between the centralized planning module and the physical state of goods. In accordance with the real-world state, this information delay is, on average, 12 hours.

2. **Feedback Loop** The current state model must also consider the effects on the logistic network caused by the information feedback loop between Heineken and CCT. It was concluded that this feedback loop causes uncertainty in the timely availability of empty containers from CCT at the brewery in Zoeterwoude. Historical data analysis found out the performance over 2022 was on average 89%.

Future State Requirements

1. **Real-Time (Third-Party) Data** In the novel approach, it is required that state updates of physical are real-time available to the involved information systems. When a product or batch of products moves from one node to another, a state change occurs to both nodes; one node receives goods from the other node. This also includes information on the container availability at third parties to create a loading schedule based on this availability. As denoted in chapter 4, the current planning tool is prone to two information asymmetries. Access to real-time data will be required to overcome these asymmetries. Real-time data on the warehouse's physical state is required to consider the products in the warehouse when creating a loading plan at the brewery. Moreover, the planning tool is currently dependent on the feedback of the third-party logistic provider. In the novel approach, this data should be available real-time to the centralized planning tool.

Criteria

Several criteria should be considered in the design of the simulation model. These design criteria will be used to evaluate the Current and Future State in the simulation.

1. **Movement of palletized goods** For Heineken, it is important that the produced goods spend a limited amount of time at the brewery to avoid physical obstruction. Therefore, it is necessary to move pallets as fast as possible to the inland container terminal. Cross-docks are used to load pallets directly into containers. The availability of the required container is an important metric.
2. **Output deviation** In chapter 3, it was analyzed that the production output at the brewery fluctuates heavily $(15,4\%)$. Therefore, creating an accurate plan regarding the need for empty containers, warehouse inventory levels, and the required number of trucks to shuttle the containers to the inland container terminal is a complex task. The aim is to reduce the variation in the number of trucks and containers required daily, despite the fluctuating production input, to make the logistic network more steady-state. To enable this, the warehouse has to be available to store goods during peak production outputs.
3. **Warehouse Levels** By considering the optimal flow of palletized goods of the supply chain, the warehouse levels are likely to stay low. However, during extreme conditions, the warehouse can overflow (the preferred level is 3500 pallets). Therefore, besides the first criteria, it is still necessary to consider the inventory levels of the warehouse separately by monitoring average and peak inventory levels.

5.3. Centralized MPC in Supply Chains

Based on the requirements defined in the previous section and the studied literature in chapter 2, Centralized Model Predictive Control is found to be a suitable modeling technique to represent the Current State model, as well as the Future State model of the logistic planning tool at Heineken. The current centralized planning tool collects data from multiple sources, and based on certain requirements and constraints, a plan for loading containers is created. Similarly, CMPC can simulate the current system interaction by the ability to model the Current State information asymmetries; this will be elaborated on in chapter 6. Also, MPC is a control strategy that uses a predictive system model to optimize control actions over a finite time horizon while also considering constraints and objectives, therefore considering the system characteristics of the logistic network present at Heineken.

Furthermore, MPC has proven to be a suitable modeling technique to support decision-making in supply chains due to its control-oriented approach, adaptability, and predictive capabilities. MPC is particularly suited to handle the complexities of supply chain systems by modeling and optimizing the entire system's behavior rather than focusing on individual components in isolation. The predictive capabilities of MPC stem from the use of a model of the supply chain, which takes into account historical data and current states. This allows supply chain managers to make better decisions about allocating resources and planning for the future. The core characteristics of MPC in the supply chain have been enumerated:

1. **Adaptability** Model Predictive Control can adapt to changing model disturbances over the prediction horizon. Within this research, those disturbances are the fluctuating palletized production output and the uncertainty in container availability.

2. **Predictability** MPC can handle multiple constraints (capacity, flow) simultaneously over the length of the prediction horizon while optimizing the flow in the logistic network based on the objective function.

3. **Complete Network** With an MPC algorithm, the complete logistic network can be represented in the model. Consequently, the model can consider all network characteristics in the global optimization problem.

Because of these characteristics, MPC is a suitable strategy as a decision-support tool in the outbound logistic planning at Heineken; multiple information systems must be combined to get the required data at a central hub. Secondly, MPC can account for all physical constraints of the network and match the current system's rolling horizon by integrating data from the third-party logistic provider. Lastly, by modeling a required objective function, the MPC model can optimize the movements of goods according to the KPIs in place at Heineken. Then, a centralized MPC is preferred for the Future State model over a decentralized structure for several reasons;

1. Centralized MPC can optimize the entire system, leading to improved performance compared to decentralized MPC, which can only optimize local subsystems. This is especially true for systems with strong interdependencies between subsystems.

2. Reduced communication requirements: Centralized MPC can reduce the communication required between nodes, as a central controller makes the optimization decisions. This can help reduce communication delays and increase the system's speed.

3. Better handling of constraints: Centralized MPC can more effectively handle constraints that affect multiple subsystems. By considering the entire system, the controller can find solutions that satisfy all constraints, whereas decentralized MPC may struggle.

4. Easier implementation and maintenance: Centralized MPC can be easier to implement and maintain than decentralized MPC, as it requires fewer controllers and communication links. This can reduce the complexity and cost of the system.

5. Better robustness: Centralized MPC can be more robust to disturbances and uncertainties, as the controller can take a global view of the system and adjust the control strategy accordingly. Decentralized MPC may be more vulnerable to disturbances and uncertainties, as each local controller only has a limited view of the system.

6. All required data sources are available at the company level. Decentralized control is often used in structures where supply chain nodes do not want to share data.

5.4. Control Centre

In addition to the centralized layout of the control architecture, this section will outline the control structure of the proposed model. As denoted by the academic literature, the operation of a global supply chain has very challenging characteristics and, therefore, needs information processing, coordination, and decision control. Dreyer et al. (2009) was the first to introduce a *Control Centre* to enable transparent information systems by an integrated and coordinated production and logistic planning control system. Due to just-in-time deliveries, increased product availability, and an interwoven network, Heineken faces a complex network prone to increased complexity. 'Inefficient information and communication processes combined with historical and static information often causes limited performance knowledge and reduces the ability to control the network activities' (Dreyer et al., 2009).

This model assumes that there is only a single control agent, which aligns with the current planning structure, where *PS* can be seen as the single control agent. In such a single-agent control, the agent has access to all sensors and actuators in the supply chain (the operator of *PS* is in the current system, the one which has control over the different actuators). From the single point of control of the Control Centre, all movements in the supply chain will be planned and controlled. According to Dreyer et al. (2009), a Control Centre can establish coordinated and integrated operations control in supply networks and enable efficient management of material flows and capacities in these networks.

The Control Centre acts as an integration node that accumulates information on the states of all underlying nodes in the supply network. The Control Centre will use *Model Predictive Control* to operationally manage flows between nodes based on production, inventory level, and, ultimately, customer demand. While the output of the production plant acts as a disturbance to the system. In addition, a Control Centre will make globalized decisions while considering all operational constraints of the single nodes. The main advantage of a globalized decision node is that local optimization decisions are avoided, and all local decisions are made while considering their effects on the complete scope and goal of the Control Centre. Also, the globalized decisions will be based on an objective function optimized by the Control Centre. Due to the single point of control, the decision structure becomes hierarchical, and therefore, the decision node needs access to information flow from all network nodes.

To implement a Control Centre in an existing supply chain, the decision node has to cooperate closely with some of the current ICT systems. Hence, the characteristics of these ICT systems need to be taken into consideration. Human operators and IT systems are currently used to optimize local systems in the complete network, as depicted in Figure 4.4. In Figure 4.4, the *PS* is displayed as a central node, which is prone to information asymmetries due to time delays and feedback loops. This Current State will be modelled using centralized MPC while accounting for the addressed information asymmetries.

Then, the Future State introduces a similar central node, but the information asymmetries will be avoided by introducing real-time data between the information systems and the central node (as outlined in the requirements). Also, the feedback loop is avoided by using the data regarding container availability as input data to the central controller. Furthermore, only the essential modules of each IT system (displayed in Table 5.2) are incorporated into the architecture, in accordance with the information transaction cost, only necessary information flows are used. This modular design allows for a network with minimized interactions, ultimately leading to minimized complexity.

This novel architecture is visible in Figure 5.1. Here, the Control Centre receives data from all four essential modules. Within this future state architecture, it can be seen that the Control Centre makes use of real-time data. It can be seen that these modules cannot share information, and all information is guided toward the Control Centre. Additionally, the module containing the production output data is incapable of receiving feedback from the Control Centre, as this data is seen as a system input and can therefore not be changed. In Figure 5.1, the dotted lines represent the information flow, while the arrows represent the material flow through the chain.

Essential Modules	
1. Production Output	Pluto Database
2. Delivery Information	SAP ERP
3. Stock Levels	WMS
4. Container Availability	CCT IT

Table 5.2: Essential Information Network Modules, as in item 4.4.

In the proposed real-time control architecture in Figure 5.1, all modules are incorporated to establish coordinated and integrated operations control of the outbound logistic planning by the Control Centre. The Control Centre coordinates the material flow through the supply chain by considering operational constraints on all nodes and material flows incorporated. To do this, information from the IT systems in place at Heineken is crucial; however, only specific data of these IT systems are required to control the overall outbound logistic network. For instance, the WMS system collects data on the warehouse's in and outflow of products. It also tracks information regarding the exact position of goods in the warehouse. For the operational control of the logistic network, not all data of the WMS system is required; only stock levels and capacity constraints are important. Nonetheless, the WMS system has to streamline local operations, which are part of the outbound logistic network but does not propose any strain on the control of the complete network. In addition, the SAP ERP system is the information backbone regarding customer orders, which are eventually shipped to the final destination. This system carries an extensive amount of information, while only a limited part is necessary for the control network of the outbound logistics.

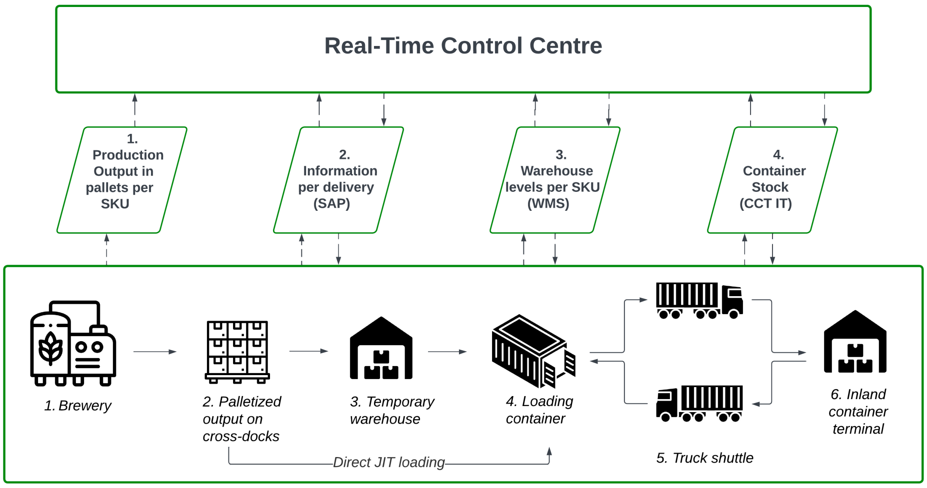


Figure 5.1: Architecture with essential modules and the Global Control Centre

5.5. Conclusion

Within this chapter, the modeling method for the Current State and Future State of the outbound logistic network has been outlined. By modeling the layout of the logistic network at Heineken, several assumptions and simplifications have to be made. As a result, to simulate the effects of real-time data compared to the current information asymmetries, both the Current and Future States need to be modeled. Multiple requirements and criteria of these models were determined, and centralized MPC was found to be a suitable technique for modeling the Current and Future State. In chapter 2, it was highlighted that MPC is a useful technique for modeling supply chains due to its control-oriented approach, adaptability, and predictive capabilities.

This chapter pointed out that CMPC is an appropriate modeling technique for the Current State of the planning tool at Heineken due to the centralized layout of *PS* and the ability to simulate the information asymmetries. It was concluded that CMPC is also fit for the Future State model because the information flows are within company boundaries. And by comparing a CMPC current state model with a CMPC Future State model, the effects of the information asymmetries become evident. Lastly, a single agent Control Centre was introduced as an autonomous, central decision-maker.

IV

Integrate

6 General CMPC Design

This chapter aims to provide a detailed mathematical account of the centralized *Model Predictive Control* structure for the outbound supply chain at Heineken, considering the Current State and Future State model and requirements as denoted in chapter 5. The sub-questions that will be answered in this part are constructed as follows:

1. *How can the logistic network be modeled into an MPC framework with a single control node?*
2. *How can the general node configuration be arranged in a mathematical model using a state space representation?*
3. *What KPIs can be introduced to measure the performance of the outbound logistic network?*

To answer these sub-questions, based on the Control Centre architecture proposed in chapter 5, an MPC control model will be created within this part. Hence, the current state analysis conducted in chapter 3 regarding the physical flow of goods and the analysis in chapter 4 considering the information network, will be used to create a general mathematical model with the same characteristics as the real-world scenario at Heineken. Thereafter, a distinction is made between the Current State and the Future State model, and the KPIs to measure the performance of the model will be introduced. This chapter refers to the *integration* function within the SIMILAR approach in systems engineering. Within the *integration* function, the core task is to realize the system of interest by combining the elements according to the architectural design and integration strategy.

6.1. Control Model

The approach proposed in this research to model the network architecture in combination with the *Control Centre* consists of a *Centralized Model Predictive Control* framework. MPC will perform network management on the outbound logistic network by controlling the flow between the network nodes while considering the optimal flow time of each SKU and, the infrastructural limitations. Consequently, building on the work of Hipólito et al. (2017) and Hipólito et al. (2022), whose research incorporated the expiration date of perishable goods in the supply chain, this research will incorporate the accumulated time per SKU spent in the network of nodes, which will be used to measure the performance of the network. Control-based techniques are suitable for modeling dynamic systems in an interconnected supply chain. MPC uses current and historical system measurements to predict the behavior at future time instances.

6.1.1. Preliminary Flow Model

Similarly to the research by Nabais et al. (2013), the outbound logistic process at Heineken can be categorized as a flow assignment problem. This means that the control model ensures the flow of goods is performed while accounting for the infrastructural constraints and product specifications. The

Control Centre is in this paper responsible for the flow assignment and is therefore the decision node in the modeled system. This model is not constructed based on customer demand, but the first exogenous system inputs are the brewery plant's production outputs in Zoeterwoude. Whereafter, a flow assignment based on the objective function will pull the physical goods to the required storage facility.

From a modeling perspective, a supply chain can be seen as a sequence of events, where products can be stored or transported through the network. The events are modeled as nodes and arcs in the network. A distinction will be made between handling nodes and ordinary nodes. Where center nodes can perform the function of a storage facility, the handling nodes can be used to model delays in the system, required to incorporate the transportation time between nodes. Multiple nodes can be modeled in a sequence to display the length of the delay in the transportation flow. The nodes are connected by arcs, which represent the transportation movements between the nodes. These arcs are constrained by the capacity of each arc, which is directly related to the real-world transportation capacities between the nodes. Each timestamp can model the flow assignment, which forms the core of the model by looking at the previous state and the current in and outflow of that node. This can mathematically be expressed as in Equation 6.1.

$$I_i(k) = I_{i-1}(k-1) + I_i(k-1) - \sum_{j \in Dn(i)} S_{ij}(k) + \sum_{j \in Up(i)} S_{ji}(k) \tag{6.1}$$

In which $I_i(k-1)$ is the inventory level at node i at discrete time $k-1$, $I_{i-1}(k-1)$ is the state of the handling node I_{i-1} at $k-1$ (see the right image in Figure 6.1), $Dn(i)$ is defined at the set of downstream nodes to which the node supplies material, while $Up(i)$ is the set of nodes from which the node receives the material. Lastly, S_{ij} is the amount of material that flows from node i to node j. Equation 6.1 can visually be presented (Figure 6.1) by a central node (left) or central node, including a handling node (right) that receives and sends goods directed to and from different up- and downstream nodes. .

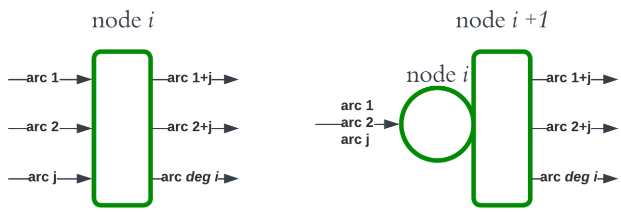


Figure 6.1: Central node (left) and central node with handling node (right)

In chapter 5, the *Control Centre* was introduced as an integrated supply chain decision maker based on several requirements. In Figure 6.2, the general supply chain network based on the flow model and the integration of the *Control Centre* has been made visible. Here, the circular nodes represent handling nodes used to model time delays. While the rectangular nodes can hold inventory and are modeled as storage locations based on the simulation constraints. In Figure 6.2, the orange arrows depict the optimal path through the network of nodes. The first arrow depicts the fastest pallet flow, and the second arrow the fastest container flow. The flow is considered sub-optimal if goods do not follow this path in the minimum amount of time.

6.1.2. Model Environment

This section will provide the mathematical model which will be needed to construct an MPC algorithm, that includes all specific design requirements considered within this case study. In addition, the model node configuration presented in Figure 6.2 will be represented by a mathematical format using indices, sets, parameters, and decision variables. Later on, the node equation and the system constraints will be presented.

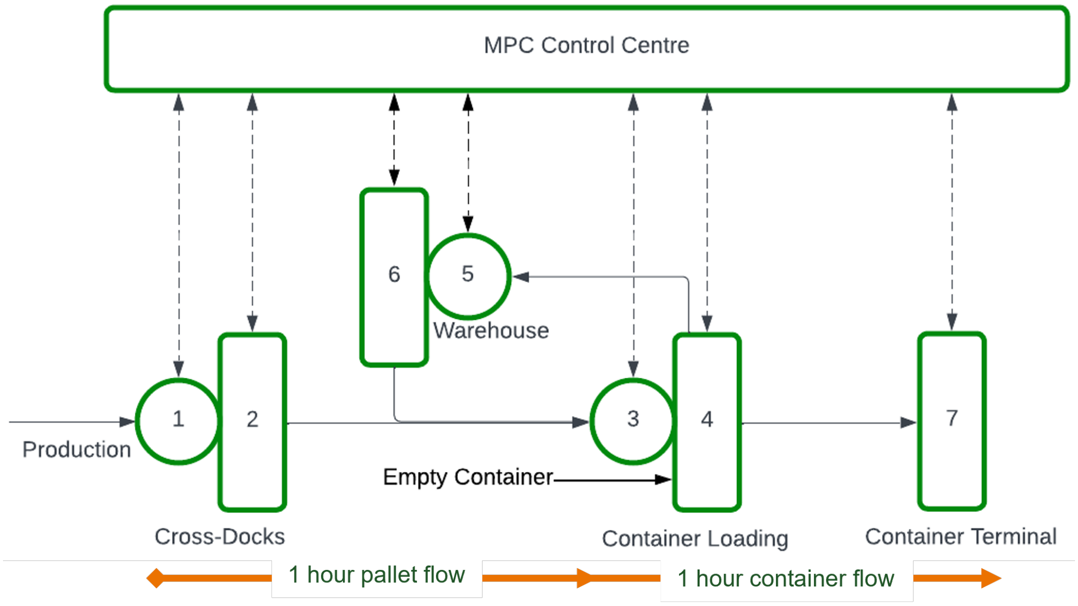


Figure 6.2: Node Network Configuration

Indices	
k	*index of discrete time instant*
j	*index of single product type (SKU)*
i	*index of supply chain node*
i'	*index of node upstream to node i*
i''	*index of node downstream to node i*
n	*index of number of trucks*

Sets	
X	*Network of supply chain nodes*
U	*Set of flows for palletized goods*
P	*Set of SKUs*

Variables	
x_{ij}	*Stock level of SKU j at node i*
$u_{i'ij}$	*Palletized flow of SKU j from node i' to node i*
l_j	*Binary Container flow of SKU j for each truck n*

Parameters	
p_j	*Palletized Production output per SKU j*
c	*Binary value for container availability*
x_{max}	*Storage capacity for each SKU j at node i*
u_{max}	*Palletized flow capacity for each SKU j from node i to node i''*
X_{max}	*Total storage capacity at node i*
z_j	*Number of pallets of SKU j per container*
N_p	*Prediction Horizon of MPC model*

6.1.3. Dynamic State Space Representation

Based on the mathematical model, a state space representation is created. In this state space representation the *states, actions, measurements* and, *disturbances* in the MPC model will become evident. Firstly, the supply chain model's dynamic equation in discrete time can be formulated according to the flow formulation in Equation 6.1. The general dynamic node equation, applicable to each SKU j for each node k is written as:

$$\begin{aligned} x_{ij}(k+1) = x_{ij}(k) + \sum_{j\in P} p_j(k) + \sum_{i'\in X} u_{i'ij}(k) - \sum_{i''\in X} u_{ii''j}(k) \\ + \sum_{i'\in X} c(k) * z_j(k) * l_j(k) - \sum_{i''\in X} c(k) * z_j(k) * l_j(k) \\ \forall i \in X, j \in P \end{aligned} \tag{6.2}$$

Subjected to the following non-negative constraints:

$$x_{ij} \geq 0 \quad \forall i \in X, j \in P \tag{6.3}$$

$$u_{i'ij} \geq 0 \quad \forall i \in X, j \in P \tag{6.4}$$

And subjected to the following container flow constraint:

$$\sum_{j\in P} l_j(k) \leq 1 \tag{6.5}$$

Equation 6.2 differentiates between different SKUs by creating a vector of every node with the length of the total SKUs in the production data. This is necessary to enable the loading of palletized goods in the required container. Moreover, the model makes a distinction between pallet and container flow; the number of pallets per container differentiates per SKU, in this way different container types are considered based on historical data provided by Heineken.

In Equation 6.5, the number of SKUs per container flow is limited to one. So, it is considered that every container can only hold a single product type. Lastly, the capacity constraints for the flows and nodes are presented in Equation 6.6, Equation 6.7, and Equation 6.8. Where, Equation 6.6 denotes the total capacity constraint for each node *i* for all products j, whereas Equation 6.7 is concerned with the capacity limits of each node i for each SKU j. Equation 6.8 represents the flow constraint of each SKU j from node i' to node i.

$$\sum_{j\in P} x_{ij}(k) \leq X_{max} \quad \forall i \in X \tag{6.6}$$

$$x_{ij}(k) \leq x_{max} \quad \forall i \in X, j \in P \tag{6.7}$$

$$u_{i'ij}(j) \leq u_{max} \quad \forall i \in X, j \in P \tag{6.8}$$

The general node equation presented in Equation 6.2 can be presented in a matrix representation where the characteristics per node will be set according to the design in Figure 6.2:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}_u\mathbf{u}(k) + \mathbf{B}_l\mathbf{l}(k) + \mathbf{B}_p\mathbf{p}(k) \tag{6.9}$$

$$\mathbf{y}(k+1) = \mathbf{x}(k+1) \tag{6.10}$$

The output, $\mathbf{y}(k+1)$ of the model is equal to the state, $\mathbf{x}(k+1)$ of the system; therefore the supply chain is fully observable. $\mathbf{x}(k+1)$ is determined by considering the current state $\mathbf{x}(k)$, the actions $\mathbf{u}(k)$ & $\mathbf{l}(k)$ and, the production output $\mathbf{p}(k)$ is modeled as a disturbance to the system.

In Equation 6.9, $\mathbf{A}$ is the state matrix for each node, while $\mathbf{B}_u$ represents the pallet flow characteristics. $\mathbf{B}_l$ represents the container flow property of each node. Lastly, $\mathbf{B}_p$ holds the production input details for each node. The following matrices were constructed to the specific node layout of the considered supply chain:

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{6.11}$$

$$\mathbf{B}_u = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \\ 0 & 0 & 0 \end{bmatrix} \tag{6.12}$$

$$\mathbf{B}_l = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ -1 & -1 & -1 & \dots & -1 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix} \tag{6.13}$$

$$\mathbf{B}_p = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{6.14}$$

6.2. Performance Indicators

In chapter 3, several KPIs that are currently being measured were highlighted and analyzed with data over 2022. Building on these existing KPIs, this section will introduce several KPIs to measure the performance of the simulation models considered in this research. Considering the criteria presented in chapter 5, four key performance indicators will be introduced.

Accumulated Node Time

The first criterion stated that the palletized output of the production plant should be moved to the inland terminal in a minimum amount of time, to discharge the logistic network at Heineken and to avoid warehouse obstruction. Obstructions could eventually lead to the shutdown of the production plant which is a costly procedure. Ultimately, all container deliveries are being cross-docked and directly loaded into the required empty container. Therefore, this KPI is introduced to measure the accumulated time SKUs spend in the network of nodes, longer than the optimal path. The optimal path is depicted in Figure 6.2, where the optimal path takes one hour for the pallet flow and one hour for the container flow (see orange arrows). If goods are stored in the warehouse or goods spend more time on a node, the optimal path is not followed, and the goods consequently spend more time in the node network.

Due to information asymmetries, or plant constraints, goods will spend more time in the network of nodes. For instance in the warehouse, when no container is available for cross-docking. If this is the case, the integral over all SKUs will be taken. The performance of the network can be measured by considering the integral over the duration of the simulation. This has been mathematically described in Equation 6.15.

$$\tau = \sum_{j \in P} p_j(k) - \sum_{j \in P} x_{ij}(k + len) \qquad \forall k \in N_p \tag{6.15}$$

τ, which represents the *Accumulated Node Time* for each iteration k, is equal to zero if the products entering the network from the production lines follow the optimal path to the inland container terminal. If products spend more time in the supply chain, the equation becomes larger than zero. The goal is to minimize this accumulated sum over time. len denotes the number of handling nodes that are part of the optimal path before products reach node x_{ij}. When products take the preferred route through the supply chain, they are required to spend one time instant k at a particular handling node. As a result, products are required to spend a minimum of two iterations in the network.

By monitoring the performance of this single KPI, multiple KPIs as discussed in chapter 3 and chapter 4 are accounted for simultaneously. This KPI will perform poorly if products are stored in the warehouse and if empty containers are not available. Furthermore, the transaction costs and information lead times are low when the indicator performs well. Lastly, the objective of the optimization algorithm will ensure that goods will move to the inland container terminal in the most efficient way. This can be seen as a pulling effect from the inland container terminal, as a result, the *Accumulated Node Time* is minimized. The working principles of the KPI have been verified in subsection 7.3.3.

Truck Shuttle Deviation

As has been denoted in the second criteria listed in chapter 5, the production output fluctuates heavily on a weekly level. This KPI will be able to measure the deviation in transportation that is needed based on the fluctuating production output. If the transportation deviation is considered high, it is hard to plan and predict future needs in terms of containers and trucks. If this deviation is low over time, the number of trucks and containers required per hour will be more steady state.

This deviation will be measured by monitoring the output of the container flow decision variable l_j. Within the simulation, this decision variable has a certain length which denotes the maximum number of trucks per iteration. Based on this capacity constraint, the decision variable chooses the most optimal number of trucks per iteration. The variance formula is depicted in Equation 6.16.

$$\sigma = \sqrt{\frac{\sum_{k \in N_p} (l_j - \mu)^2}{N_p}} \tag{6.16}$$

Where σ is the standard deviation and μ denotes the average number of trucks needed for container transportation for each iteration k the prediction horizon N_p.

Warehouse Inventory Levels

Besides ensuring the *Accumulated Node Time* for all nodes within the Heineken logistic network is minimized, it is regarded as of great importance to consider the warehouse levels separately. The average warehouse level can be measured over the prediction horizon N_p by the equation presented in Equation 6.17.

$$\nu = \frac{\sum_{k \in N_p} \sum_{j \in P} (x_{5j}(k) + x_{6j}(k))}{N_p} \tag{6.17}$$

Where, ν represents the average inventory level at node x_{5j} and x_{6j} for all SKUs j over the complete prediction horizon N_p. Besides the average level, the peak inventory level (ρ) of the simulation run will also be measured. This formula is presented in Equation 6.18.

$$\rho = \max_{k \in N_p} (x_{5j}(k) + x_{6j}(k)) \tag{6.18}$$

6.3. Design Assumptions

The aim of the MPC design is to represent the outbound network at the Heineken brewery as close to reality. However, some assumptions have been made, this section will list the assumptions that can have an effect on the result of the MPC simulation.

1. **Pallet Flow** Due to the iterative way in which an MPC model operates, the production data, which functions as input data, is cut into hourly parts. As a result, the output of production lines can take up any positive real number. While in reality, the output is an integer number of pallets. However, for container loading, it is required in the model to load an integer multiple of pallets. So, the output still contains an integer number of pallets.

2. **Container Availability** In the real-world scenario, it is required that products are loaded in the required shipping container, this includes container type (20ft, 40ft, etc.) and carrier. In this model, different types of containers per carrier are not considered. Instead, based on historical data, the probability that a certain container will be available is modeled. This historical performance is visible in Table 3.5.

3. **Container Loading** Based on the container type, SKU, and customer order, the number of pallets per container can differ. In this research, with the use of historical data over 2022, the most common number of pallets per container per SKU was determined. This dataset contains $53,000$ container deliveries. This data will be used in the model to constrain the number of pallets per container per SKU. This is a simplification of reality since the actual number can be different for each delivery.

4. **Handling Nodes** Considering the handling nodes in the current flow layout in Figure 6.2, the handling nodes are in place to model a time delay needed to handle the palletized goods. At the brewery warehouse, the pallets are moved with a forklift from the cross-docks into a container or into the warehouse. These movements take up time. Therefore the handling nodes are introduced to constrain pallets from flowing through multiple nodes in a single iteration. Due to the time instant used in the simulation in this research, the handling nodes have a duration of an hour.

5. **Effects of Semi Truck Deliveries** In the real world, a distinction is made between pallets being loaded into a container and into a semi-trailer. This research only considers container loading. Therefore the impact of the loading of the semi-trailers is neglected in this research.

V

Launch the System

7

MPC Simulation

In chapter 6, the design of the general centralized MPC model and the key performance indicators were presented. The mathematical model will be used in this chapter to describe the scenarios that will be used to simulate the Current and Future State of the outbound logistic network at Heineken Zoeterwoude and the parameters used to run the simulations. The following sub-questions will be answered within this chapter:

1. *How can the general MPC model represent the Current and Future States?*
2. *What parameters should be chosen for the MPC simulation scenarios?*

Simulating the Current State and the Future State is necessary to obtain results and to understand the possible benefits of the Future State where the information asymmetries are eliminated. Firstly, the simulation parameters are presented. Then, the simulation objective is presented, which aligns with the KPIs presented in chapter 6. Then, model verification takes place by considering several feasibility and sensitivity checks. Finally, the simulations of the Current and Future State are presented. This chapter represents the *Launch the System* part of the SIMILAR approach.

7.1. Simulation Parameters

This section will describe the parameters set for the simulation runs to compare the Current State with the Future State. The dynamic mathematical model presented in chapter 6 has been implemented in Python with the use of the Gurobi solver. All simulation runs were performed on a laptop with 16GB onboard memory, a 3.10GHz quad-core Intel Core i7 processor, and Gurobi Optimizer version 10.0.1.

In chapter 2, it has been briefly described that MPC models consist of optimization cycles with a predetermined prediction horizon. Every time step within the prediction horizon, the controller estimates the next state by trying different actions. The action leading to the formulated objective's closest state will eventually be implemented. Therefore, it is necessary to carefully determine the prediction horizon and the associated discrete time step k, considering the increasing computational burden with smaller time steps and larger prediction horizons.

Moreover, the system dynamics should be considered. The discrete time step must align with the changing dynamics of the supply chain. Hence, the dynamics of the production output and the truck shuttle between the brewery and the inland terminal are considered. The production at the brewery takes place in batches for each SKU; they have a continuous start and end time. Over 2022, the average batch production time was roughly $12 hours$. The shuttle between CCT and Brewery took on average, roughly an hour. Therefore, a discrete time step of $1 hour$ has been chosen to incorporate the system's dynamics. Then, the operational logistic planning level is based on the production plan, which is planned with a rolling horizon over a week for the upcoming week. Consequently, the parameters presented in Table 7.1 have been set for the simulation runs.

Simulation Parameters	
Prediction Horizon (N_p)	1 week
Discrete-time instant (k)	1 hour

Table 7.1: Simulation Parameters

In addition to the rolling horizon of a single week, several experiments will be conducted with varying prediction horizons. These experiments will be performed to research the effects on the model's performance with different planning horizons.

7.1.1. Simulation Data

The Current State and Future State simulation will be performed using the production output data of the Heineken brewing plant in Zoeterwoude. Production output data has been taken over 2022, where only data points regarding the container shipments were selected. Over the year 2022, 277 different SKUs were produced in Zoeterwoude. This production process takes place in batches. Therefore, this batch data has been preprocessed to represent the number of pallets produced per time instant k for each SKU j.

The batch process is continuous and with a continuous start and end time. In this model, it will be assumed that the start and end date coincide with the time instant k. Every production batch produces a single SKU and the number of pallets produced per production batch deviates. For the simulation runs, two datasets will be used, each representing the palletized production output per SKU over a complete week. The first week contains 21440 pallets over 63 unique SKUs and represents an average production week, as has been analyzed in chapter 3. Then, the second dataset represents a week with peak production output; a total number of 24075 pallets are produced with 64 different SKUs (see Table 7.2).

Production Data	
Average Production Week	
Number of Pallets	21 220
Number of SKUs (j)	63
Estimated containers required	964
Peak Production Week	
Number of Pallets	24 075
Number of SKUs (j)	64
Estimated containers required	1 094

Table 7.2: Production data for all simulations with a prediction horizon of 7 days.

Then, the initial conditions $x_{initial}$ (number of pallets per SKU stored at each node) are computed similarly for each simulation run and depend on the dataset used. The initial conditions are based on the first hour of the production output of the brewery. This output is multiplied by three and assumed to be present on each node. In this way, the nodes are not empty at the initialization of the simulation.

Lastly, based on all container deliveries in 2022, the most common number of pallets per container for each SKU was determined. This is based on the assumption that an SKU is always loaded in a specific container type. It was concluded that mainly 22 pallets were loaded per container, corresponding to a 40 ft container. This is also in line with the analysis in chapter 3, where it could be seen that most deliveries are loaded into a 40 ft container. The graph representing the number of pallets per container per SKU is depicted in Appendix B. Based on an average production week in which 21220 are produced, daily 137 empty containers are required to load all pallets. During a peak production week, even 156 containers are needed every day.

Varying Prediction Horizon

Multiple datasets will be used to model the simulations to measure the model's performance with varying prediction horizons. These datasets cover production data for 3,5 and 14 days prediction horizon, as depicted in Table 7.3. These datasets are comparable to a *peak production week* regarding average pallet output.

Production Data used for Varying Prediction Horizons	
Production Data 3,5 Days	
Number of Pallets	12 037
Number of SKUs (j)	41
Estimated containers required	547
Production Data 14 Days	
Number of Pallets	48 088
Number of SKUs (j)	108
Estimated containers required	2 186

Table 7.3: Production data for simulations with 3,5 and 14 days.

7.2. Simulation Objective

In line with the introduced *Accumulated Node Time* KPI, the objective is to optimize the flow for each SKU through the network of nodes, as displayed in Figure 6.2. The *Control Centre* will be implemented as a central computer that will run the Mixed-Integer Linear Programming (MILP) optimization problem; therefore, a linear objective function is introduced that will be minimized to simulate the required behavior in which the accumulated time per SKU spent in the supply chain is minimized. The objective implemented in the MPC model, and applicable to both the Current and Future State scenario, can mathematically be represented in the following way:

$$J = min \sum_{i \in X} \sum_{j \in P} x_{ij}(k) * Q \quad \forall k \in N_p \tag{7.1}$$

In Equation 7.1, the number of pallets of each SKU j stored at each node i is minimized based on the associated weights **Q** for each *i* in the network of nodes. To align the mathematical expression in Equation 7.1 with the introduced KPIs, the nodes modeled as the warehouse nodes carry the highest weight in **Q**. Therefore, within the system boundaries, the flow assignment will avoid storage in the warehouse, and the inland container terminal node will have a pulling effect on the products. Therefore the accumulated time spent in the network of nodes is minimized. The associated weights are presented in Table 7.4.

Node i	**Weights Q**
1	10
2	10
3	10
4	10
5	100
6	100
7	1

Table 7.4: Objective weight **Q** for each node

Due to the lowest objective weight at node 7, the optimal solution will be found if as many products are moved to node 7.

7.3. Current State and Future State

Based on the general MPC model provided in chapter 6, this section will provide the layout of the Current State with information asymmetries which will be introduced as the *Asymmetric Control Center* (Figure 7.1). At the same time, the Future State with real-time data will be introduced as *Real-Time Control Centre* (Figure 7.2).

7.3.1. Asymmetric Control Centre Model

The current state planning tool has been described in chapter 3, where the information asymmetries were visualized in Figure 4.4. In the current state MPC model, these information asymmetries, consisting of time delays and feedback loops, will be modeled. In Figure 4.4, it could be seen that due to the daily update, the planning tool is not in line with the *SAP*, *WMS*, and the *Pluto* database. In this simulation, the production output, including data regarding the deliveries, is used as input data. Therefore, the time delay will only be modeled between *WMS* and the planning tool. The warehouse time delay will be 12 hours considering a uniform production output.

The feedback loop between CCT and Heineken will be modeled by varying the shipping container availability. In the current state, Heineken is not taking the input from the container availability into account while planning the outbound logistics. Therefore, planning is based on the assumption that a certain container is available. However, this is not always the case. This behavior will be modeled using a probability distribution to represent the timely container arrival. This distribution will have a certain probability that an empty container is available to model the uncertainty in the asymmetric model. The probability will align with the *current state analysis* and set to 89%.

In Figure 7.1, the schematic node representation of the *Asymmetric Control Centre Model* can be observed. Here, the information asymmetries are displayed in red. On the one hand, the delay between the control center and the physical state of the warehouse. On the other hand, the uncertainty of container availability. The information asymmetries are modeled using the quantification performed in chapter 4. Due to the warehouse asymmetry, the state space of the asymmetric model differs from the previously introduced model. The mathematical state-space representation of the asymmetric model can be found in Appendix B. Also, the capacity constraints can be found in Appendix B.

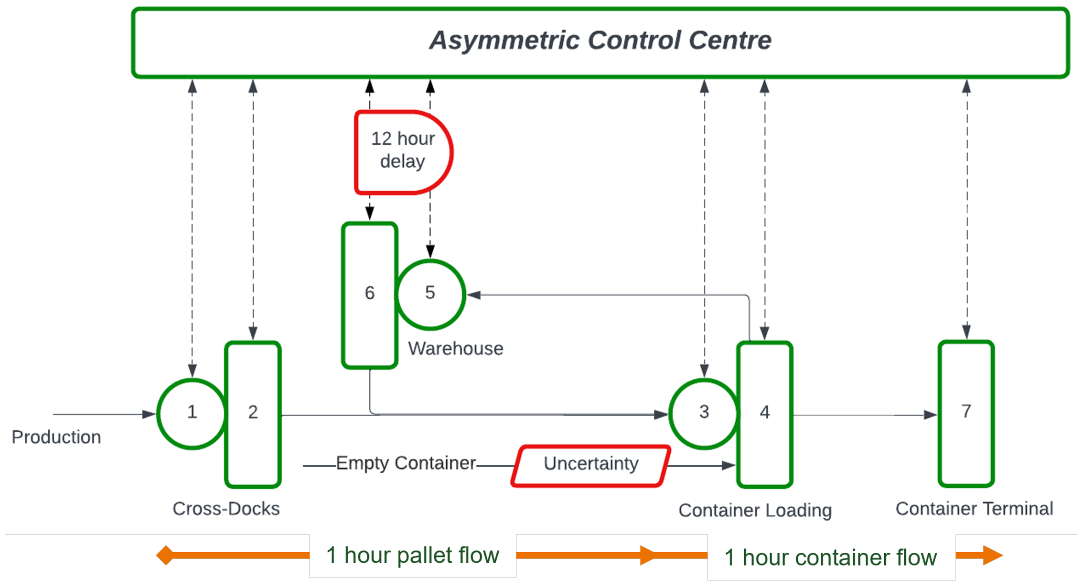


Figure 7.1: Node Network Configuration of asymmetric model

7.3.2. Real-Time Control Centre Model

Figure 7.2 represents the symmetric, real-time model without information asymmetries. The mathematical state-state representation is similar to the general model introduced in chapter 6. The capacity constraints used in the simulation runs are visible in Appendix B.

7.3.3. Verification

Building a mathematical model involves translating a real-world problem into a set of equations that can be solved using computer algorithms. Therefore, verifying that the model is implemented correctly before using it for any analysis is essential. Within this chapter, a feasibility check and a sensitivity analysis will be performed to ensure that the model has a feasible solution and that the results are reliable. The verification simulations are performed using two-day production data with a discrete-

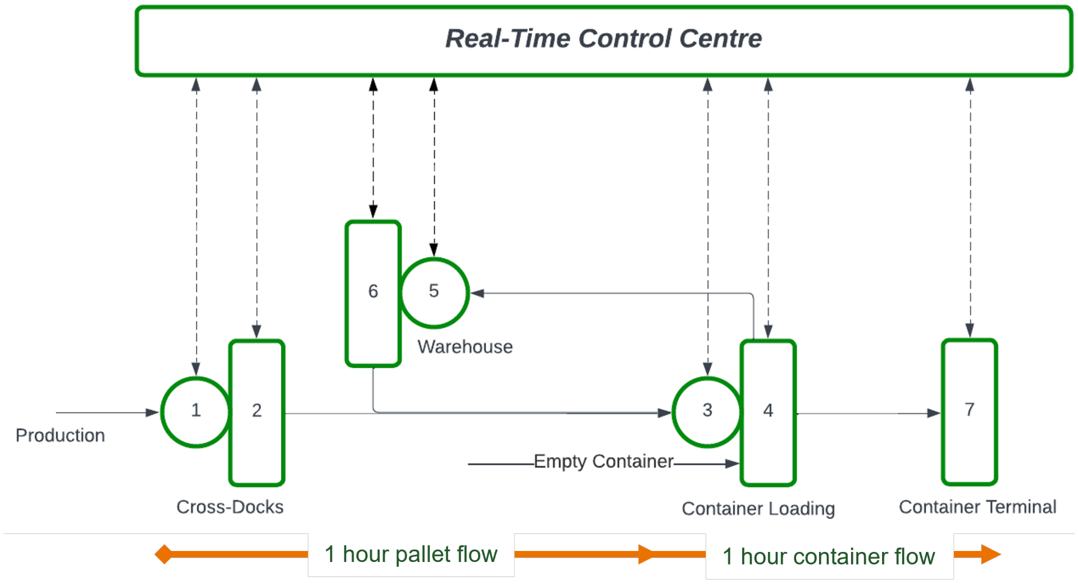


Figure 7.2: Node Network Configuration of symmetric model

time instant of an hour (see Table 7.5). This short prediction horizon is chosen due to computational efficiency reasons. Furthermore, the general model introduced in chapter 6 will be used for verification. And the model is simultaneously validated against the real-world system by implementing Heineken's production output.

Verification Parameters	
Prediction Horizon (N_p)	2 days
Discrete-time instant (k)	1 hour
Number of unique SKUs (j)	26
Total pallets produced	6 188

Table 7.5: Verification Parameters

The initial conditions at the nodes ($x_{initial}$) are set for the complete verification process. At $k = 0$, the first production output p_j is added to the first five nodes.

Flow Feasibility

Firstly, the feasibility of the intended flow model is verified. The model presented in Figure 6.2 consists of storage and handling nodes. Due to the characteristics of these nodes, goods are not necessarily stored at each storage node. However, goods must spend at least 1 iteration at the handling nodes. The orange arrows depict this in Figure 6.2 and align with the *Accumulated Node Time* KPI. The model was reviewed at the individual SKU level to verify these characteristics.

Time instant k	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6	Node 7
26	0	0	0	0	0	0	0
27	46.06	0	0	0	0	0	0
28	46.06	0	46.06	0	0	0	0
29	46.06	0	46.06	2.06	0	0	44
30	46.06	0	46.06	19.94	6.19	0	66
31	46.06	46.06	6.19	0	0	0	132
32	46.06	0	92.13	0	6.19	0	132

Table 7.6: Node States for specific SKU.

In Table 7.6, a snippet of the simulation has been displayed. In Table 7.6, the states of all seven nodes per iteration k are displayed. It can be observed that at discrete time instant 27, the first pallets enter $node1$. In the next iteration, these pallets have been moved to $node3$, which is a handling node, without being stored at $node2$. The same reasoning applies to $node5$ and $node6$. Consequently, these pallets follow the optimal path and require two discrete time steps to move from $node1$ to node 7. Also, it can be seen that only an integer number of pallets moves to node 7. This movement represents the container flow constrained to only integer pallet numbers.

Constraint Feasibility

The constraint feasibility test will verify that the constraints behave as intended. Table 7.7 shows constraints that have been used in the verification simulation, where x_{max} and u_{max} are constraints for each node and flow per SKU and X_{max} denotes the capacity of each node accumulated over all SKUs.

Constraint Values	
x_{max}	[200, 200, 400, 400, 400, 5 000, 10 000]
u_{max}	[200, 400, 400]
X_{max}	[600, 600, 600, 600, 20 000, 30 000, 50 000]

Table 7.7: Maximum values for all flows, nodes, and SKUs per node.

On a single SKU level, the SKU with the highest production input over the simulation horizon has been taken. Over two days, a total number of 734 pallets were produced. In Figure 7.3, it is observed that the nodes do not surpass the levels of x_{max} and the pallets per SKU stay within the bound of u_{max} (see Figure 7.4). Furthermore, in Figure 7.5 it can be observed that the storage of the combined SKUs does not surpass the level of X_{max}.

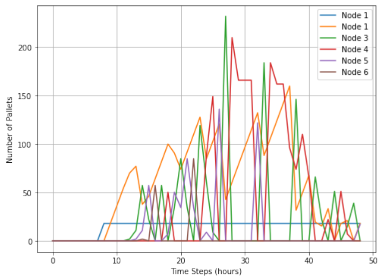


Figure 7.3: Node constraints for single SKU.

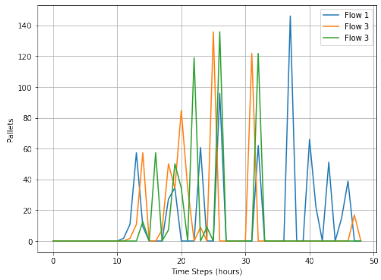


Figure 7.4: Flow constraints for single SKU.

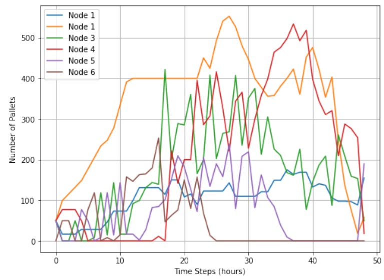


Figure 7.5: Node constraints all SKUs in production.

Container Loading Feasibility

Here, the feasibility of the container loading will be verified. In chapter 6, the mathematical representation of the loading process has been presented. The size of the decision variable l_j, and consequently the size of the state matrix B_l, determines the maximum number of trucks available every instant in the simulation. However, deciding whether a truck is needed is up to the decision variable. The maximum number of trucks per iteration is set to 10 for this verification. Also, one truck carries a single container type. Depending on the SKU, the number of pallets per container is set (z_j).

The constraint presented in Equation 6.5 ensures the number of SKUs per container is equal to one, and c provides the probability distribution of the availability of a single container. Therefore, it is possible to have plenty of trucks available, but there might not always be a container available. For this verification simulation, the container probability distribution is set to 100%. Figure 7.6 displays the number of trucks needed according to the decision variable l_j for all SKUs. It can be concluded that over the prediction horizon, no more than ten trucks were used simultaneously. Therefore, it is verified that the truck ride is bounded by the length of the binary decision variable l_j. Moreover, in Figure 7.6, it can be seen that not all ten trucks are utilized over the complete prediction horizon. When the number of trucks is set to 5 per iteration, it can be seen that they are all being utilized in Figure 7.7, and therefore the *Accumulated node time* KPI also performs worse due to the limited amount of trucks.

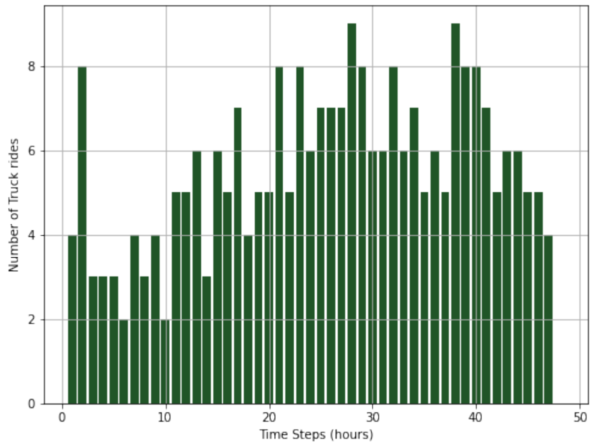


Figure 7.6: 10 Trucks Available

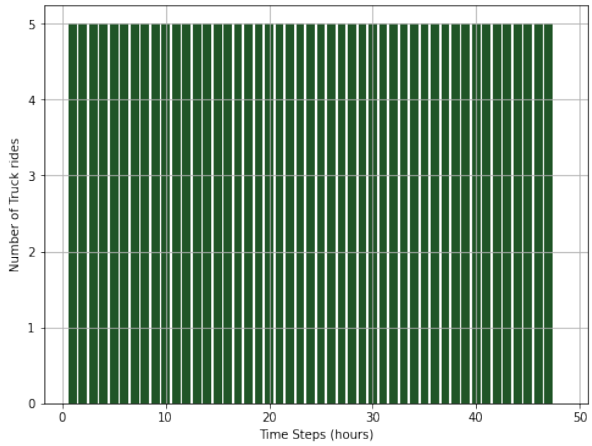


Figure 7.7: 5 Trucks available

Objective Sensitivity

The sensitivity analysis of the objective function can be performed by adjusting the weights of the vector **Q**. The weights **Q**, as provided in Table 7.4, are chosen such that storage in the warehouse is costly and storage at the inland terminal is cheap, creating the desired pull effect through the network of nodes. In this analysis, the weights of the warehouse nodes are lowered such that storage in the warehouse is as beneficial as at the inland terminal. The new weights are provided in Table 7.8, where the standard high warehouse objectives will be compared to the low stand objectives. It is expected that goods will be stored in the warehouse until the constraints are met, so products will not be triggered to flow to the inland container terminal.

Node i	1	2	3	4	5	6	7
High Warehouse Objective	10	10	10	10	100	100	1
Low Warehouse Objective	10	10	10	10	1	1	1

Table 7.8: Objective weight **Q** for sensitivity analysis.

In Figure 7.8, it is evident that with the objective weights of the low warehouse objective in Table 7.8, the warehouse levels are, on average higher over the complete horizon in comparison to the objective weights of Table 7.4. Overall, it is concluded that the original objective weights cause the desired pulling behavior toward the inland container terminal.

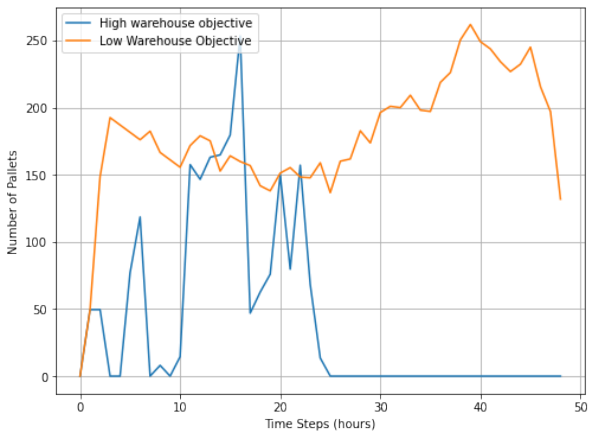


Figure 7.8: Warehouse Objective Weights Comparison.

Accumulated Node Time KPI Sensitivity

In accordance with the *Accumulated Node Time* KPI as introduced in chapter 6, this part will evaluate the functioning of the *Accumulated Node Time* under altered capacity constraints (x_{max}, u_{max} and X_{max}) and different container availability. Softening the constraints is expected to lead to increased flow possibility; therefore, the KPI will perform better. Firstly, the capacity constraints are simultaneously eased by 50%. Secondly, the container availability is increased from 90% to 100 % per iteration. The results of the simulations are visible in Table 7.9. The number of trucks available per iteration in these verification simulations is set to 5.

Simulation	**Capacity Constraints**	**Container Availability**	**KPI**
Run 1	100%	90%	3 618
Run 2	150%	90%	3 094
Run 3	100%	100%	2 804

Table 7.9: Performance Indicator simulations under softened capacity constraints.

It is concluded that softening the capacity constraints by 50% provides better KPI performance. However, only an increase in performance of 15% was measured. Therefore, it can be concluded that capacity constraints do not solely bound the system. Raising the container availability from 90% to 100% in run 3 provided a better performance of nearly 24% compared to the first run. It can be concluded that the *Accumulated node time* KPI behaves in line with the expectations when constraints are softened.

7.3.4. Simulation Scenarios

Simulation scenarios are a crucial tool for validating and improving the performance of the two different CMPC models. The model's ability to adapt to changing circumstances and optimize performance is tested by subjecting it to scenarios that reflect real-world conditions. This section will describe the different simulation scenarios that will be used to evaluate and validate the MPC models. The simulation runs will be performed using complete production data from the production plant of Heineken in Zoeterwoude to ensure that the dynamics of the existing system are accurately reflected. The main objective of the simulation runs is to measure the performance of the introduced KPIs under changing parameters and data inputs. Simulation runs will be conducted for each scenario. The simulation runs will be performed for two production datasets: the first containing average production output data and the second consisting of a week with exceptionally high production output in 2022. Then, the two datasets will be used to compare the performance of the *Asymmetric Control Centre* in accordance with the *Real-Time Control Centre* where a distinction is made between an average production week and peak production week. Also, each run will be performed thrice, where 5, 7, and 9 trucks are considered the maximum available number. Lastly, after running all simulations with a prediction horizon of seven days, the most significant runs will be performed with varying prediction horizons in line with the data presented in Table 7.3.

Scenario 1: Warehouse Information Asymmetry

Firstly, the effects of the time delay at the warehouse in the *Asymmetric Control Centre* will be compared to the *Real-Time Control Centre*. In the asymmetric model, the daily update of the warehouse state is modeled by a time delay of 12 hours. The state-space representation of this model can be found in Appendix B. The *Real-Time Control Centre* assumes all states are directly available, so there will be no time delay at the warehouse. The performance indicator is expected to perform better in the *Real-Time Control Centre* model. The details of the simulation are visible in Table 7.10.

Scenario 2: Container Availability Asymmetry

Secondly, the effects of container availability will be modeled in this scenario (see Table 7.10). Due to the feedback loop present in the current state between Heineken and the third-party logistic provider, an information asymmetry is created. This asymmetry can be modeled as uncertainty in the *Asymmetric Control Centre*. This will then be compared to the real-time simulation, where the container availability is known due to the availability of real-time data. Moreover, the number of trucks available will be altered in this simulation to find the optimal number of trucks with the average and peak datasets.

Scenario 3: Combination Scenario 1 & 2
After the simulation runs of the first scenarios have been performed, they will be combined in this last set of simulation runs. In this scenario analysis, the current state at Heineken, with the information delays and feedback loops, is compared to the novel approach in which the global control center is assumed to have real-time access to all state changes in the physical system. In Table 7.10, it can be observed that scenario 3 is a combination of scenarios 1 and 2.

Scenario 4: Real-Time Control
The simulations performed within this scenario represent the Future State model. In this model, all data is assumed to be real-time available to the *Control Centre*. Therefore the information asymmetries are eliminated. It is expected that this simulation runs outperform the one in the previous scenarios.

Simulation		**Data**	**Max Nr of Trucks Available**	**Warehouse Asymmetry**	**Container Asymmetry**
Scenario 1					
	Run 1.1	Average	5	✓	✗
	Run 1.2	Average	7	✓	✗
	Run 1.3	Average	9	✓	✗
	Run 2.1	Peak	5	✓	✗
	Run 2.2	Peak	7	✓	✗
	Run 2.3	Peak	9	✓	✗
Scenario 2					
	Run 3.1	Average	5	✗	✓
	Run 3.2	Average	7	✗	✓
	Run 3.3	Average	9	✗	✓
	Run 4.1	Peak	5	✗	✓
	Run 4.2	Peak	7	✗	✓
	Run 4.3	Peak	9	✗	✓
Scenario 3					
	Run 5.1	Average	5	✓	✓
	Run 5.2	Average	7	✓	✓
	Run 5.3	Average	9	✓	✓
	Run 6.1	Peak	5	✓	✓
	Run 6.2	Peak	7	✓	✓
	Run 6.3	Peak	9	✓	✓
Scenario 4					
	Run 7.1	Average	5	✗	✗
	Run 7.2	Average	7	✗	✗
	Run 7.3	Average	9	✗	✗
	Run 8.1	Peak	5	✗	✗
	Run 8.2	Peak	7	✗	✗
	Run 8.3	Peak	9	✗	✗

Table 7.10: Simulation scenarios

7.4. Pseudo-Code

This section will outline the working principles of the MILP algorithm that was originally written in Python using the Gurobi solver. Pseudo-code is a general way of displaying code without specific programming language definitions.

Algorithm 1 General CMPC MILP Algorithm

Insert ProductionData = PD
Input Q, $x_{initial}[p]$, x_{max}, X_{max}, u_{max}, $c[k]$, $z[p]$

$num_{products}$ = number of SKUs in Production Data
N_p = Prediction Horizon
k = Discrete time instant (1 hour)

Initialize Gurobi Solver ('MPC')

Initialize empty variable arrays x, u, l
Initialize empty state space arrays A, B_u, B_l, B_p

for $p \leftarrow 0$ to $num_product s$ **do**
    Define state space arrays A, B_u, B_l, B_p
    for $k \leftarrow 0$ to N **do**
        Create variables x, u, l
    end for
end for

$objective = 0$
for $p \leftarrow 0$ to $num_{products}$ **do**
    for $k \leftarrow 0$ to N **do**

        $objective \leftarrow objective + x[p][k] \cdot Q$

        $Constraint(x[p][k+1] = A[p] \cdot x[p][k] + B_u[p] \cdot u[p][k] + B_p[p] \cdot PD[p][k] + B_l[p] \cdot l[p][k] \cdot c[k] \cdot z[p])$

        $Constraint(u[p][k+1] \leq u_{max})$

        $Constraint(\sum_{p=0}^{num_product s} x[p][k+1] \leq X_{max})$

        $Constraint(x[p][k+1] \leq x_{max})$

        $Constraint(x[p][0] = x_{initial}[p])$

        $Constraint(\sum_{p=0}^{num_product s-1} l[p][k] = 1)$

    end for
end for

Return $GurobiMinimize(\sum_{p=0}^{num_{products}} \sum_{k=0}^{N} objective)$

VI

Asses Performance

8
Results & Discussion

In chapter 3, the physical state of the outbound logistic was analyzed, while in chapter 4, the information network and planning levels were addressed. After it was concluded that the Current State planning tool is prone to information asymmetries, a novel approach method of controlling the outbound logistic container loading process was introduced in chapter 5. Then, chapter 6 outlined the design and mathematical formulation of the MPC model. Lastly, chapter 7 differentiated between the *Asymmetric Control Centre* and the *Real-Time Control Centre*, and the different simulation scenarios were presented after the MPC model's feasibility and sensitivity were verified. This chapter will present the results of the simulation runs as have been presented in chapter 7. This chapter marks the final step of the SIMILAR approach, in which the goal is to assess the model's performance. This will be done by measuring the introduced key performance indicators. Also, within this chapter, the model validation will be performed. The validation will evaluate if the CMPC model is suitable to present the supply chain at Heineken. The following sub-question will be answered in this part:

1. *How does the Future State perform compared to the Current State when the information asymmetries of the Current State are eliminated?*

Within this chapter, the different simulation results will be presented. The structure will align with the Simulation Scenarios description in chapter 7, tabulated in Table 7.10.

Each run depicted in Table 7.10 has been performed three times where the maximum number of available shuttle trucks will be 5, 7, and 9, respectively. This way, the *Truck Shuttle Deviation* KPI can be measured. As a result, it can be concluded what parameters cause the minimal deviation in the outbound logistic network, which is prone to a fluctuating production input.

8.1. Scenario 1: Warehouse Asymmetry

The simulations in this section will represent the Current State model, which is solely prone to information delay regarding the inventory levels in the warehouse. The performance of the different runs considering the KPIs has been listed in Table 8.1, where the first run is performed using data from an average production week, and the second run with peak production data. It is observed that the *Accumulated Node Time* decreases, with increasing available trucks for the shuttle between the production plant and the inland container terminal.

Simulation		**Max Trucks Available**	**Data**	**Accumulated Node Time (hours)**	**Truck Shuttle Deviation**	**Average Warehouse Level (pallets)**	**Peak Warehouse Level (pallets)**
Scenario 1							
	Run 1.1	5	Average	10 291	0.38	1 055	2 374
	Run 1.2	7	Average	6 271	1.72	2	322
	Run 1.3	9	Average	5 744	2.03	2	277
	Run 2.1	5	Peak	14 041	0.38	4 548	5 830
	Run 2.2	7	Peak	10 493	0.89	1 330	2 479
	Run 2.3	9	Peak	8 080	2.45	134	943

Table 8.1: Scenario 1 Performance

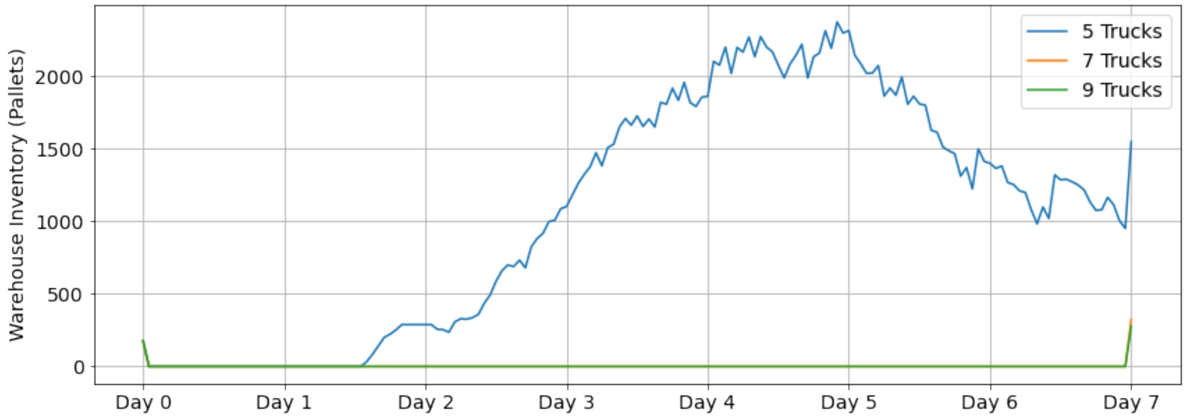


Figure 8.1: Run 1: warehouse levels

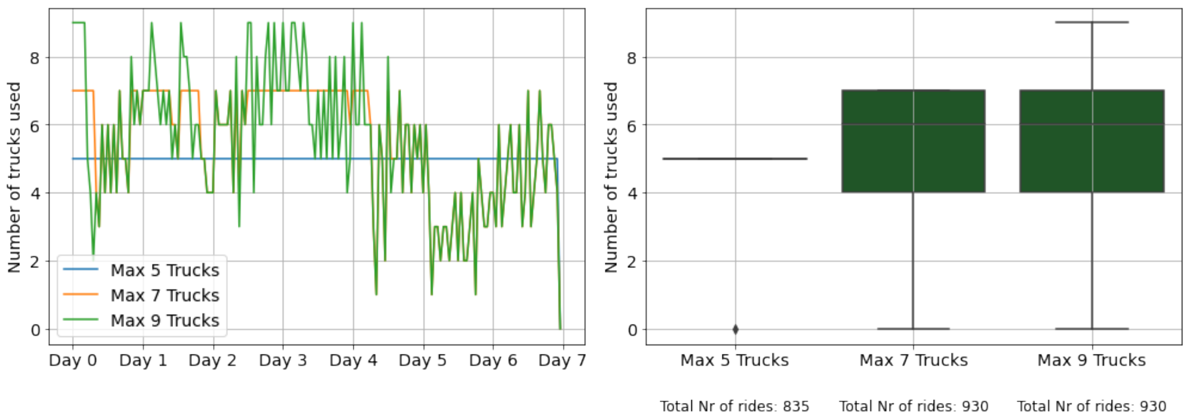


Figure 8.2: Run 1: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

Furthermore, for Run 1.1, the *Truck Shuttle Deviation* is low compared to the runs with 7 and 9 trucks available per iteration. This can be observed in Figure 8.2. If a maximum of five trucks is available, the decision variable l_j will assign five trucks for each iteration. Therefore, the *Truck Shuttle Deviation* is low and the warehouse levels increase (Figure 8.1). If the number of trucks available rises, the variation will rise since not all trucks are required every iteration to move the pallets from the production plant to the inland container terminal. This can be seen in Figure 8.2 when the maximum number of trucks is set to 9. The left-hand side plot in Figure 8.2 shows larger peaks in trucks required when the maximum number of trucks increases. Also, if only five trucks are available, a total of 835 containers is moved to the inland terminal. Considering 7 and 9 trucks are available, this number rises to 930 (see Figure 8.2).

This differs from simulation Run 2, where the peak production input is used. In Figure 8.3, the warehouse levels for 7 and 9 trucks have risen compared to Run 1. Due to the higher production output in this simulation, it can be observed in Figure 8.4 that for the first three days, the maximum number of trucks are being utilized. This can be explained by the high production output in the first part of the simulation, which has been visualized in Figure B.4.

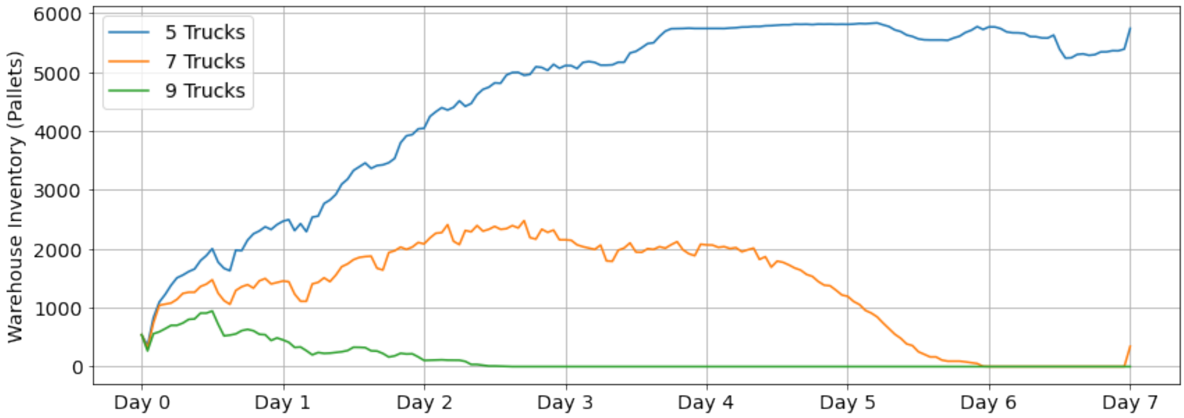


Figure 8.3: Run 2: warehouse levels

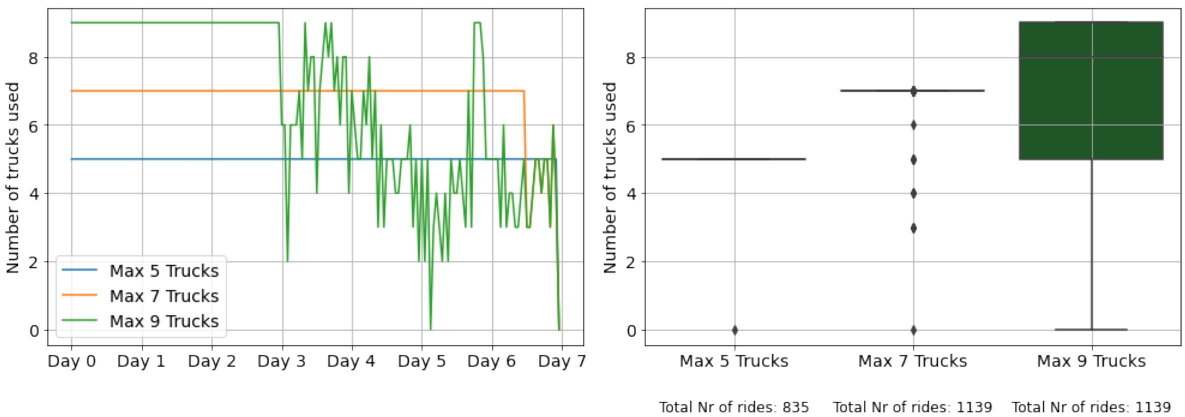


Figure 8.4: Run 2: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

8.2. Scenario 2: Container Availability Asymmetry

In Scenario 2, the information asymmetry is simulated by setting the probability distribution regarding the container availability (c) to 89%. Consequently, only 89% of the required containers will be randomly available, in addition to the restricted number of trucks available for each simulation run. As a result, no trucks will be needed for the shuttle ride if containers are unavailable. Furthermore, the warehouse asymmetry is not considered in this simulation run.

Based on the numbers in Figure 8.6, it is concluded that 7 trucks are sufficient to move all containers to the inland terminal. Also, the warehouse levels stay close to zero throughout the simulation (Figure 8.3). Furthermore, increasing the number of trucks to 9 yields no better performance; this causes the *Truck Shuttle Deviation* to increase. Due to the unavailability of containers, it can be seen in Figure 8.6 that for some iteration no truck rides take place.

Simulation		Max Trucks Available	Data	Accumulated Node Time (hours)	Truck Shuttle Deviation	Average Warehouse Level (pallets)	Peak Warehouse Level (pallets)
Scenario 2							
	Run 3.1	5	Average	12 579	1.55	1 828	3 520
	Run 3.2	7	Average	8 332	2.34	1	177
	Run 3.3	9	Average	7 594	2.91	1	177
	Run 4.1	5	Peak	15 169	1.43	5 250	7 260
	Run 4.2	7	Peak	12 861	2.17	2 363	3 540
	Run 4.3	9	Peak	9 514	2.88	215	799

Table 8.2: Scenario 2 Performance

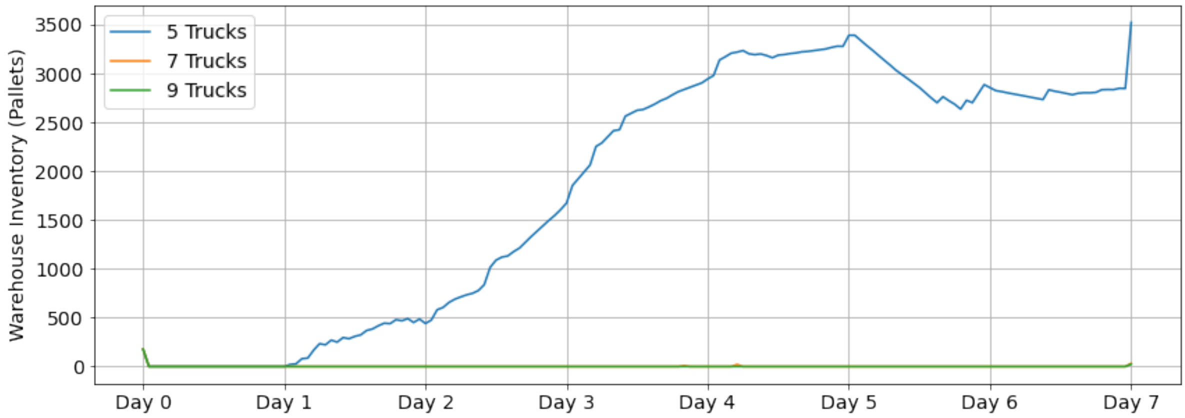


Figure 8.5: Run 3: warehouse levels

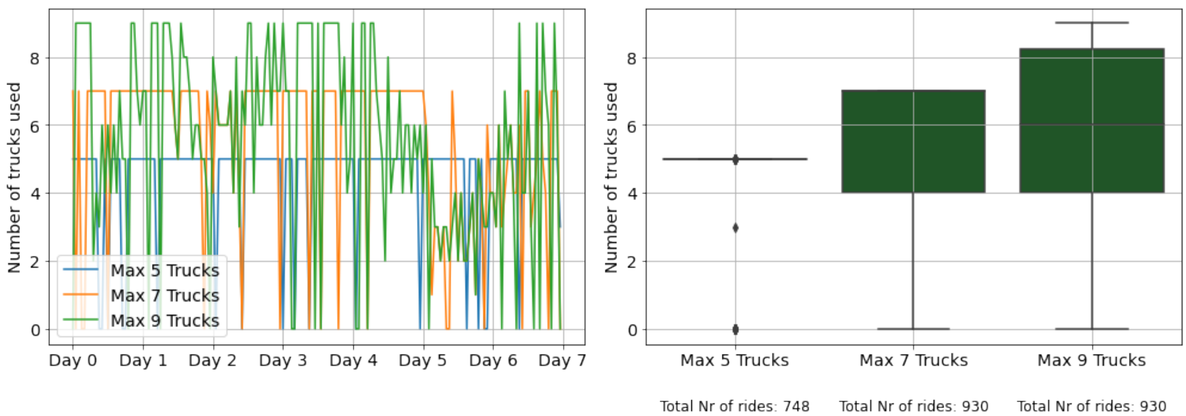


Figure 8.6: Run 3: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

Then, while using peak production data for Run 4, it can be seen that even with 9 trucks, an increase in inventory levels is observed compared to Run 3. Due to the higher production output, 7 trucks are not sufficient and only 1050 containers are transported, while with 9 trucks a total of 1139 containers are transported to the inland terminal. Again, having 9 trucks available, an increase in *Truck Shuttle Deviation* is observed.

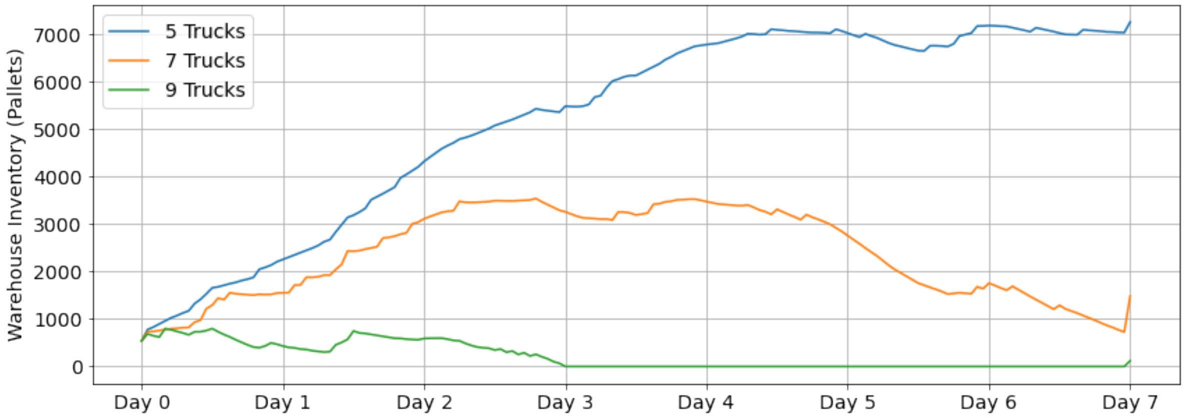


Figure 8.7: Run 4: warehouse levels

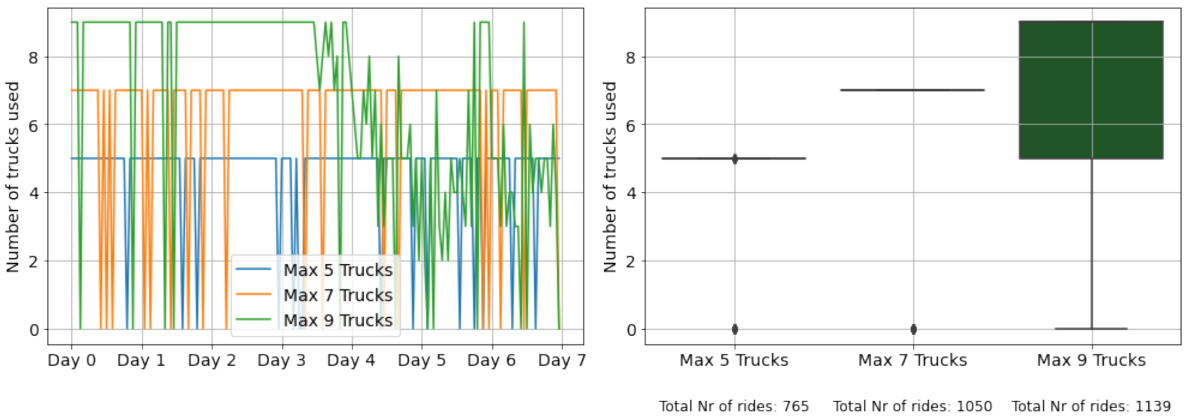


Figure 8.8: Run 4: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

8.3. Scenario 3: Combination Scenario 1 & 2

This scenario combines the previous two scenarios and shows the results if both information asymmetries are present in the system. Table 8.3 presents the performance of the introduced KPIs. Regarding the *Truck Shuttle Deviation*, it can be seen that *Scenario 3* has high values compared to *Scenario 1* and *Scenario 2*, which indicates that there is a fluctuating demand for trucks over the length of the prediction horizon. This fluctuating pattern is visible over the complete prediction horizon on the left-hand side of Figure 8.10 and Figure 8.12.

Again, it is observed in Figure 8.9 that the inventory levels for Run 5.2 and 5.3 stay close to zero due to the high amount of available trucks (similar to the runs with average production amount in scenarios 1 and 2). While the warehouse inventory levels do see an increase in the simulation runs with peak production data visible in Figure 8.11. Run 6.2 and Run 6.3 even exceed the maximum warehouse level of 3500 pallets and thus causing an infeasible solution.

Simulation		Max Trucks Available	Data	Accumulated Node Time (hours)	Truck Shuttle Deviation	Average Warehouse Level (pallets)	Peak Warehouse Level (pallets)
Scenario 3							
	Run 5.1	5	Average	12 942	1.65	2 005	3 642
	Run 5.2	7	Average	8 232	2.35	17	322
	Run 5.3	9	Average	7 779	3.05	2	322
	Run 6.1	5	Peak	14 834	1.45	4 825	6 198
	Run 6.2	7	Peak	13 556	2.42	3 179	4 687
	Run 6.3	9	Peak	10 128	3.35	496	1 243

Table 8.3: Scenario 3 Performance

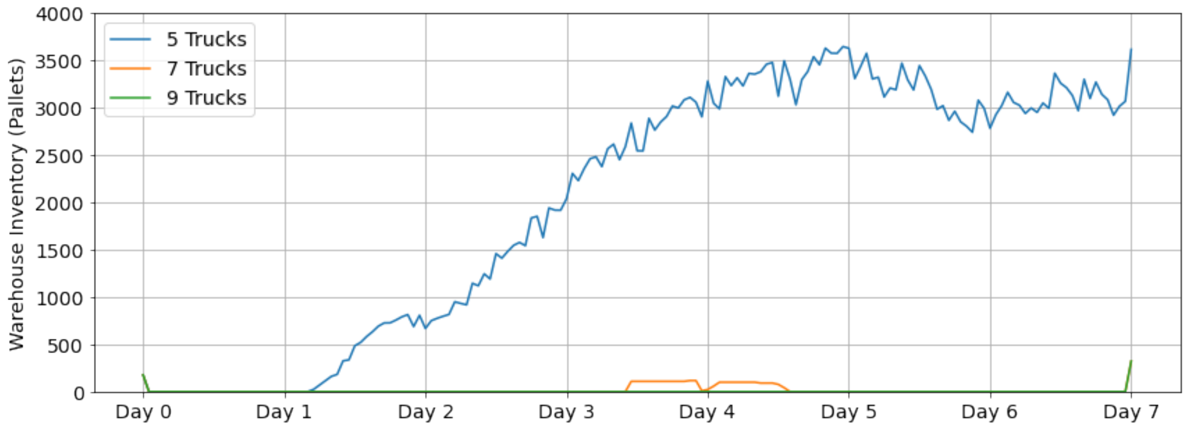


Figure 8.9: Run 5: warehouse levels

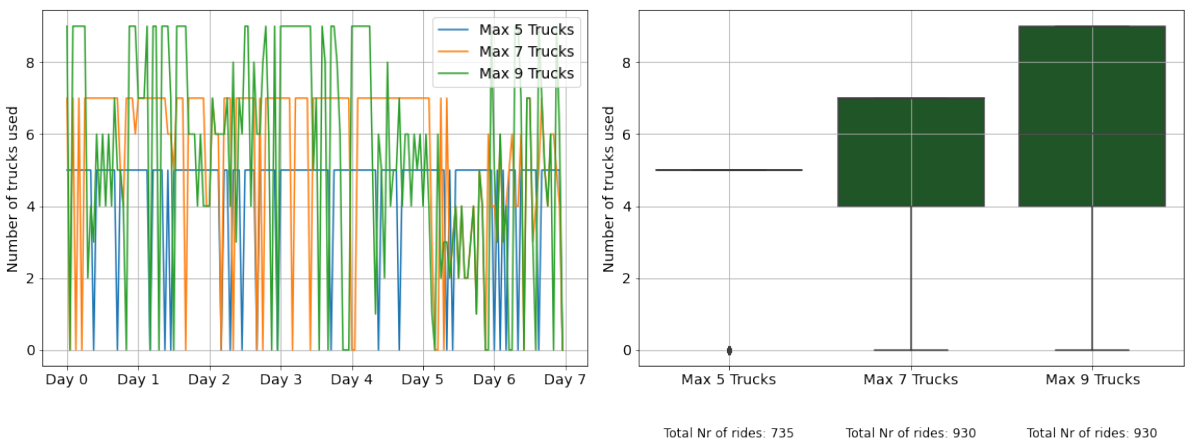


Figure 8.10: Run 5: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

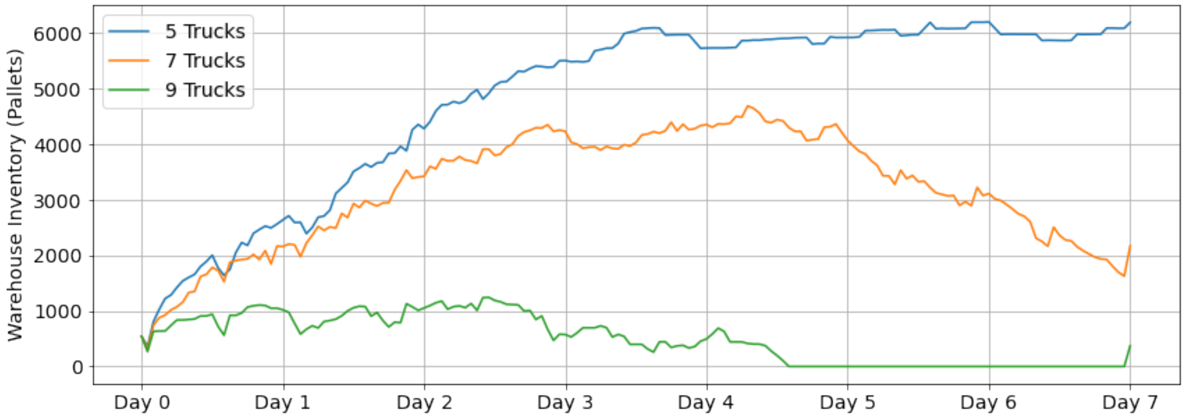


Figure 8.11: Run 6: warehouse levels

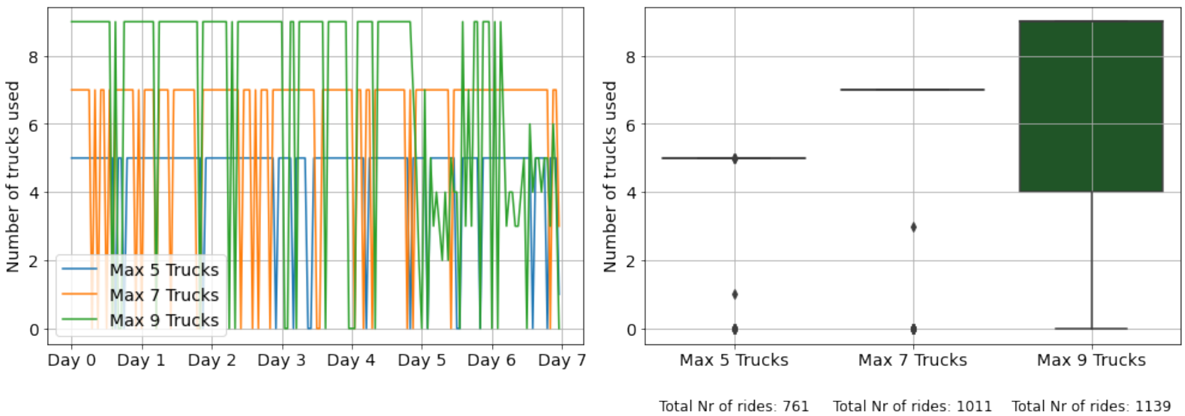


Figure 8.12: Run 6: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

8.4. Scenario 4: Real-Time Control

Lastly, this simulation has been used to simulate the Future State in which the data is considered real-time and the information asymmetries are eliminated. The results of Run 7 are visible in Figure 8.13 and Figure 8.14, and the results of Run 8 are plotted in Figure 8.15 and Figure 8.16. While Table 8.4 shows all results regarding the performance of the introduced KPIs.

Simulation		Max Trucks Available	Data	Accumulated Node Time (hours)	Truck Shuttle Deviation	Average Warehouse Level (pallets)	Peak Warehouse Level (pallets)
Scenario 4							
	Run 7.1	5	Average	10 619	0.23	850	1 959
	Run 7.2	7	Average	6 314	1.72	1	177
	Run 7.3	9	Average	5 731	2.03	1	177
	Run 8.1	5	Peak	14 209	0.31	4 567	6 241
	Run 8.2	7	Peak	10 442	0.89	1 120	2 154
	Run 8.3	9	Peak	7 946	2.45	94	685

Table 8.4: Scenario 4 Performance

Overall, the Real-Time Control runs perform better than the asymmetrical runs in the previous scenarios. It is observed that the *Accumulated Node Time*, *Warehouse levels*, and *Truck Shuttle Deviation* are lower. However, the truck deviation is still high if a maximum of 9 trucks are available, which has been made visible in Figure 8.14 and Figure 8.16.

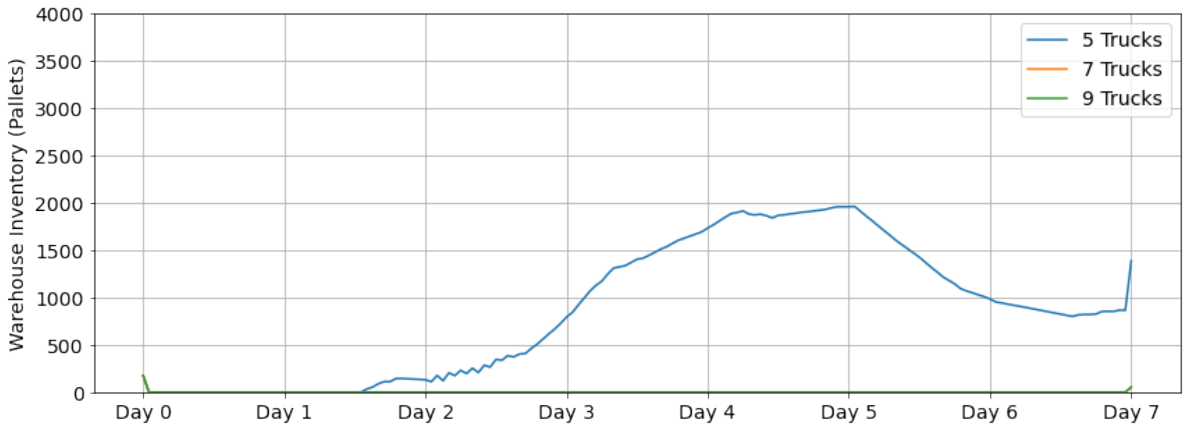


Figure 8.13: Run 7: warehouse levels

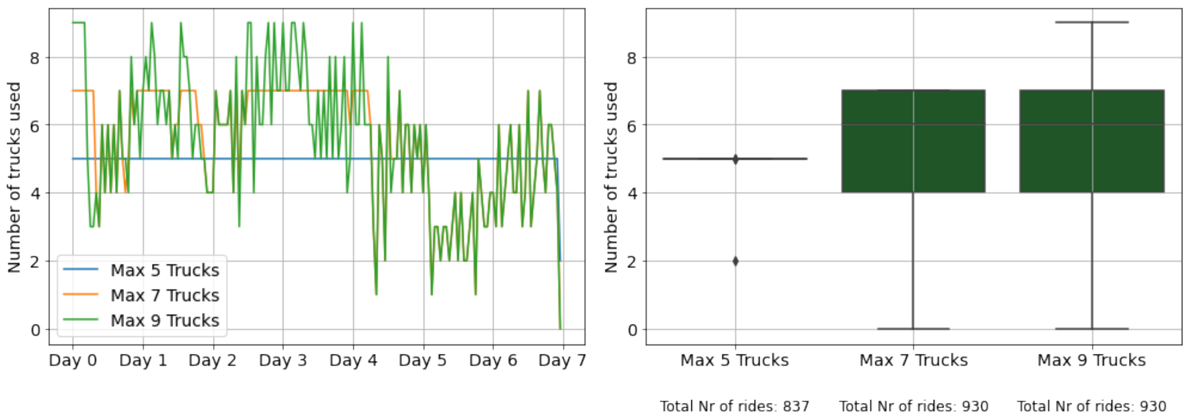


Figure 8.14: Run 7: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

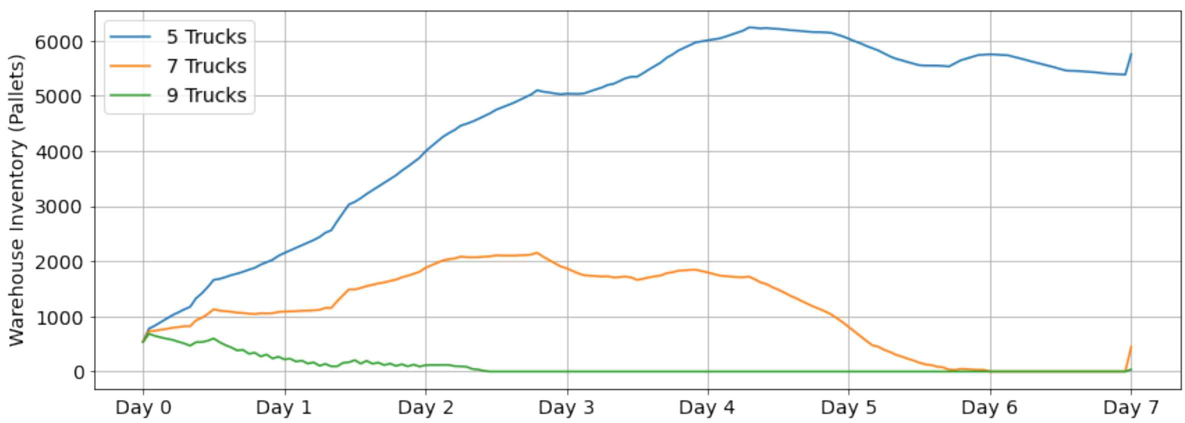


Figure 8.15: Run 8: warehouse levels

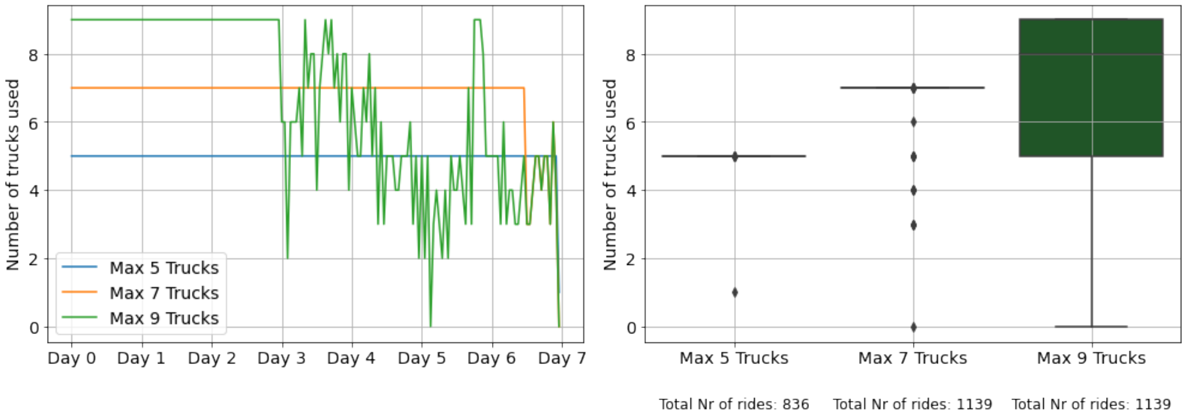


Figure 8.16: Run 8: Amount of trucks required per iteration visualized over the length of the prediction horizon on the left and box plots showing the deviation in trucks required on the right.

It can also be observed that with 7 trucks available, as many containers are being transported to the inland container terminal as with 9 trucks available. Also, the *Truck Shuttle Deviation* lowers with only 7 trucks available compared to 9 trucks. Therefore, 7 trucks would be the preferred number in these simulation runs if only considering the *Truck Shuttle Deviation* KPI. The *Accumulated Node Time* KPI is the leading performance indicator in this research. Therefore 9 trucks would be the preferred number of trucks due to the ability to move the products in the least amount of time through the network.

8.5. Altering Prediction Horizons

This section will briefly display the simulation results of varying the prediction horizon length. All previously shown results were computed in line with the operational planning horizon at Heineken of a single week. However, the effect of a specific prediction horizon has not yet been studied. Therefore, prediction horizons of 3,5 days and 14 days will be used to measure the effects of halving and doubling the current planning horizon at Heineken. The Real-Time Control model of Scenario 4 was again performed, accounting for 7 and 9 trucks available. The warehouse levels of these runs are visible in Figure 8.17 and Figure 8.18, respectively. The performance of the KPIs is visible in Table 8.5 and Table 8.6.

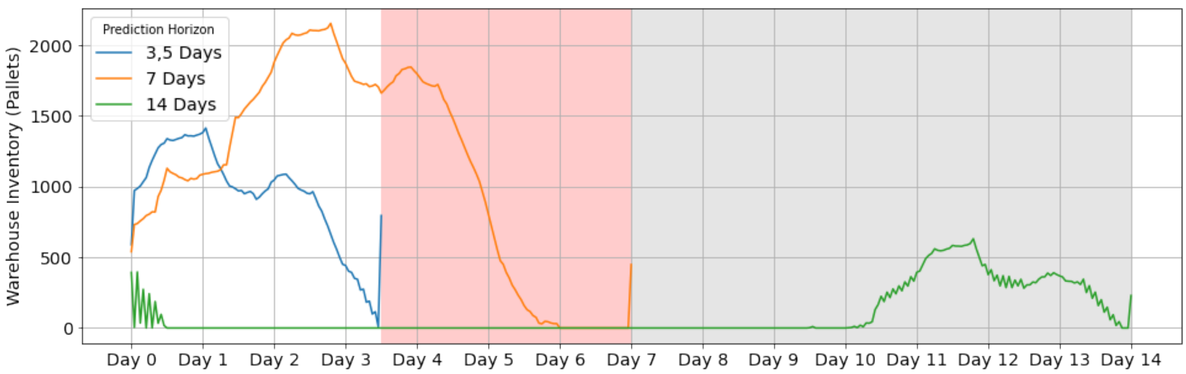


Figure 8.17: Real-Time Control Center Warehouse levels, where a maximum of 7 trucks are available, using peak data for prediction horizons of 3.5, 7, and 14 days.

Prediction Horizon	Max Trucks Available	Accumulated Node Time (hours)	Truck Shuttle Deviation	Average Warehouse Level (pallets)	Peak Warehouse Level (pallets)
3.5 Days	7	11 652	0.76	939	1 414
7 Days	7	10 442	0.89	1 120	2 154
14 Days	7	8 245	1.16	93	631

Table 8.5: Performance of varying prediction horizons with 7 trucks available while using peak data. The *Accumulated Node Time* is normalized to 7 days to make the numbers comparable with differing prediction horizons.

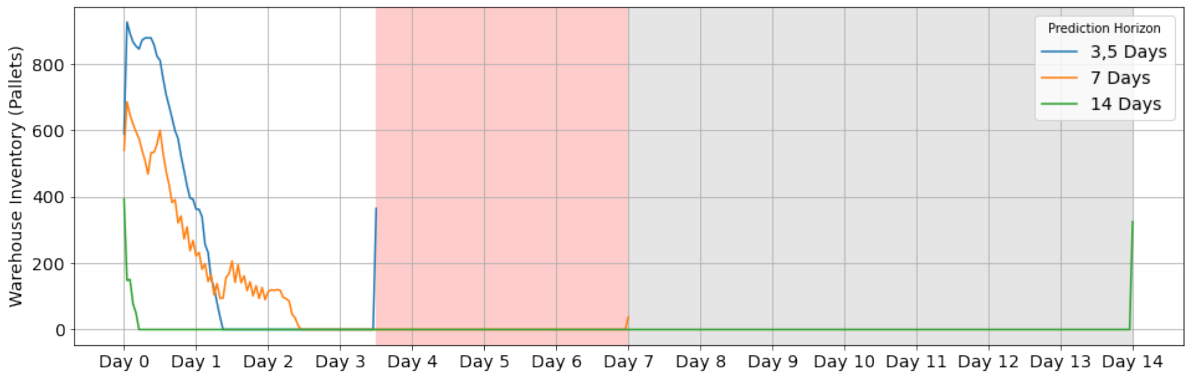


Figure 8.18: Real-Time Control Center Warehouse levels, where a maximum of 9 trucks are available, using peak data for prediction horizons of 3.5, 7, and 14 days

Prediction Horizon	Max Trucks Available	Accumulated Node Time (hours)	Truck Shuttle Deviation	Average Warehouse Level (pallets)	Peak Warehouse Level (pallets)
3.5 Days	9	9 982	2.38	228	926
7 Days	9	7 964	2.45	94	685
14 Days	9	6 944	1.86	3	392

Table 8.6: Performance of varying prediction horizons with 9 trucks available while using peak data. The *Accumulated Node Time* is normalized to 7 days to make the numbers comparable with differing prediction horizons.

It can be observed that the warehouse levels are easily kept close to zero when a longer prediction horizon of 14 days is considered. Also, the *Accumulated Node Time* KPI decreases steadily with a longer prediction horizon for all runs. Therefore, it can be concluded that a longer prediction horizon causes to model to predict the impact of the production output further in the future. As a result, the model can create a more sustainable loading planning based on the introduced objective function (Equation 7.1).

This objective formula was constructed to realize optimal flow, which is in line with the *Accumulated Node Time* KPI, which is the leading KPI within this research. Hence, decreasing *Accumulated Node Times* is a sensible outcome when the prediction horizon is elongated. On the other hand, the objective formula is formulated to minimize the *Truck Shuttle Deviation* KPI, as can be seen in the results. Regarding warehouse levels; overall, a decrease in stock levels is seen with increased length of the prediction horizon. In conclusion, it is observed that a longer prediction horizon causes the model to perform better in accordance with the objective formula.

8.6. Validation

After the model has been extensively verified in subsection 7.3.3, based on multiple feasibility and sensitivity scenarios, it was concluded to function in line with the designed model. The verification ensured the model was built right, while validation ensured the right system was built.

Here, the model is validated based on the representative level of the model compared to the real-world outbound logistic network at Heineken. Also, by feeding the model with historical data and considering different scenario's the validation of the model is performed. In chapter 6, several design assumptions were listed. Due to these assumptions, the simulation models represent a simplified model of the real-world scenario. However, based on the results of the scenario analysis, it can be seen that the model behaves very similarly to the real-world system. Where the most significant topics have been highlighted in the following enumeration:

1. **Average & Peak Production Data** First, the model's behavior was validated to align with the real-world system by testing the model with an average week production output and a week with peak output. The average and peak production simulation runs were feasible by varying the number of trucks available.

2. **Container Availability Uncertainty** By modeling the container availability as a probability distribution, the stochasticity of the real-world system is present in the model. Consequently, considering the container availability fluctuation, the MPC model is tested on the algorithm's adaptability.

3. **SKU Differtation** By differentiating between different SKUs, every container was restricted to carry a specific number of pallets. Therefore, as in the real-world system, this model could differentiate between different types of containers. Consequently, the number of containers and trucks required to transport the finished products aligns with the real-world system. And pallet flow is restricted by addressing the different SKUs. Finally, it was observed that based on the palletized production output, a realistic number of containers was being loaded daily. From the real-world scenario, it is known that a peak production day requires at least 10 trucks to transport containers between the brewery and the inland terminal. Similarly, in Figure 8.11, it is observed that the model is only feasible if 9 trucks are available.

4. **Binary Variable** Only the required truck rides were modeled by modeling a binary decision variable representing the number of trucks needed per iteration. As a result, the model's output can be analyzed on the deviating number of trucks necessary to transport the loaded containers from the brewery to the terminal. Therefore, the daily truck rides can be compared to the historical real-world truck rides.

5. **CMPC** Moreover, CMPC was found to be a suitable modeling strategy due to the adaptability and predictability of the model. Also, due to the ability to model the complete logistic network with a single control agent, the model's operational planning level is comparable to the real-world scenario by considering a rolling horizon of a week. Furthermore, CMPC considers all operational constraints and therefor the dynamics of the simulations models are comparable to the real-world system.

6. **Similarity** Lastly, based on the performance of the simulation results, it is observed that the model exhibits a similar behaviour as what has been analyzed in the current state analysis. It can be seen that warehouse levels are within a reasonable range while considering a limited amount of trucks available. Furthermore, by detailed modeling of the capacity constraints of the cross-docks, pallets only flow into the warehouse during moments of high throughput. Lastly, the number of pallets per container is modeled based on an extensive historical database. As a result, the daily number of containers required is in line with the real-world system.

In conclusion, in line with the verification, the validation process is an imported step in simulation modeling. Based on the results of the scenarios presented in this chapter, it was validated that the model produces outputs that are highly comparable to the real-world system.

8.7. Simulation Results Discussion

This section will compare the different simulation scenarios, emphasizing the simulated future control scenario (*Scenario 4*), which incorporates real-time data. The simulations conducted in *Scenario 1* and *Scenario 2* were crucial in determining the individual impact of warehouse and container availability asymmetry, respectively. A comprehensive overview of the simulation results, including KPI performance, is provided in Appendix B. The performance comparisons of *Run 2.1, Run 4.1, Run 6.1, Run 6.2* and *Run 8.1* are neglected due to unrealistically high inventory levels in the warehouse.

Comparing the first scenario to the Future State scenario in Table 8.7, it can be concluded that warehouse asymmetry has a limited effect on the performance of the *Accumulate Node Time* and *Truck Shuttle Deviation* KPIs. However, it is worth noting that the *Average Warehouse Level* and *Peak Warehouse Level* KPIs exhibit a reduction due to the real-time availability of the warehouse occupation data in the Real-Time Control Centre. In Table 8.7, the performance comparison between *Scenario 4* and *Scenario 1* in percentage is provided.

Simulation		**Data**	**Accumulated Node Time (hours)**	**Truck Shuttle Deviation**	**Average Warehouse Level (pallets)**	**Peak Warehouse Level (pallets)**
Scenario 4						
	Run 7.1/1.1	Average	103%	61%	81%	83%
	Run 7.2/1.2	Average	101%	100%	-	-
	Run 7.3/1.3	Average	100%	100%	-	-
	Run 8.1/2.1	Peak	101%	82%	100%	107%
	Run 8.2/2.2	Peak	100%	100%	84%	87%
	Run 8.3/2.3	Peak	98%	100%	70%	73%

Table 8.7: Comparison Scenario 4 with Scenario 1

Then, Table 8.8 visualizes the percentage differences between the performance of the KPIs between *Scenario 4* and *Scenario 2*. Where, *Scenario 4* represents the Future State, real-time Control Centre, and is compared to the asymmetric container availability Control Centre. It can be concluded that *Scenario 4* performs better on all 4 KPIs due to the absence of the container availability asymmetry. For the simulations of *Scenario 2*, a container availability of 89% was used. Furthermore, Table 8.8 shows that the absence of the asymmetry caused at least a 16% improvement on the *Accumulated Node Time*, 15% on the *Truck Shuttle Deviation* and warehouse levels were also lowered considerably.

Simulation		**Data**	**Accumulated Node Time (hours)**	**Truck Shuttle Deviation**	**Average Warehouse Level (pallets)**	**Peak Warehouse Level (pallets)**
Scenario 4						
	Run 7.1/3.1	Average	84%	15%	46%	56%
	Run 7.2/3.2	Average	76%	74%	-	-
	Run 7.3/3.3	Average	75%	70%	-	-
	Run 8.2/4.2	Peak	81%	41%	87%	61%
	Run 8.3/4.3	Peak	84%	85%	44%	86%

Table 8.8: Comparison Scenario 4 with Scenario 2

Lastly, the performance of the full *Asymmetric Control Centre* has been compared to the *Real-Time Control Centre*. The results are depicted in Table 8.9. It is observed that the *Real-Time Control Centre* causes a significant improvement regarding all 4 KPIs. Consequently, pallets flow faster through the network, with less deviation in the number of trucks required and lower average and peak levels in the warehouse. However, it should be noted that this reduction across the board is mainly due to the 100% container availability and not due to the availability of real-time inventory data.

Simulation		**Data**	**Accumulated Node Time (hours)**	**Truck Shuttle Deviation**	**Average Warehouse Level (pallets)**	**Peak Warehouse Level (pallets)**
Scenario 4						
	Run 7.1/5.1	Average	82%	14%	42%	54%
	Run 7.2/5.2	Average	77%	73%	-	-
	Run 7.3/5.3	Average	74%	67%	-	-
	Run 8.3/6.3	Peak	78%	73%	19%	55%

Table 8.9: Comparison Scenario 4 with Scenario 3

The comparison between Run 5.1 and 7.1 has been studied in more detail. Run 5.1 represents the full *Asymmetric Control Centre*, and Run 7.1 represents the *Real-Time Control Centre.* Figure 8.19 depicts the combined warehouse levels for an average production week.

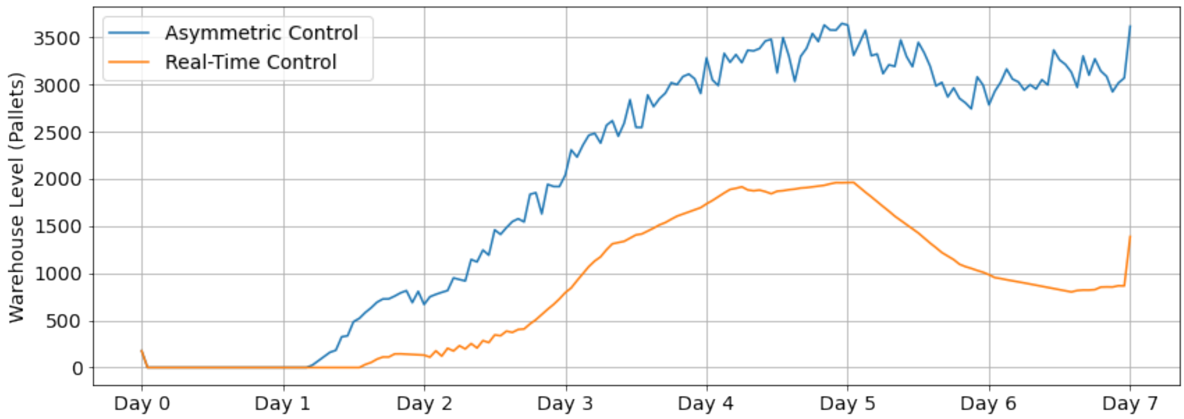


Figure 8.19: Warehouse levels of Run 5.1 and 7.1, where the Asymmetric Control Centre performance is compared to the Real-Time Control Centre. Parameters were set to a maximum availability of 5 trucks, and data of an average production week was used.

For both simulations, the warehouse level starts increasing over the course of Day 1. It can be concluded that the combination of trucks available and uncertainty in container arrival causes warehouse levels to rise. Over the complete horizon, in the Asymmetric model, 735 containers were transported to the inland terminal, while in the Real-Time Control model, 837 containers were transported. In conclusion, the Real-Time Control Centre performs better regarding average and peak warehouse levels and truck usage variation. Also, the *Accumulated Node Time* decreased from 12943 to 10619. Consequently, the Real-Time Control Centre can handle the fluctuating production output more efficiently by using less warehouse storage capacity and enabling efficient flow through the network while also considering steady-state truck usage.

Figure 8.20: Warehouse levels of Run 6.3 and 8.3, where the Asymmetric Control Centre performance is compared to the Real-Time Control Centre. Parameters were set to a maximum availability of 9 trucks, and data of a peak production week was used.

Figure 8.21: Box plots of trucks used per iteration of Run 6.3 and 8.3, where the Asymmetric Control Centre performance is compared to the Real-Time Control Centre. Parameters were set to a maximum availability of 9 trucks, and data of a peak production week was used. At the bottom, the total number of rides per simulation is displayed.

Similarly, the results of Run 6.3 and Run 8.3 have been compared and studied in more detail. The warehouse levels and box plots of truck usage have been displayed in Figure 8.20 and Figure 8.21, respectively. In Figure 8.20, due to the availability of 9 trucks, the warehouse levels of both runs decline to zero over time. The warehouse levels require more time to decline to zero due to the presence of the information asymmetries. Also, a lower standard deviation in the required number of trucks is observed in Run 8.3, as well as a lower *Accumulated Node Time* (visible in Table 8.3 and Table 8.4).

Furthermore, in Figure 8.21, it is observed that the Real-Time Control Centre moves as many trucks as the Asymmetric model, while less deviation in the number of trucks used is observed. Due to the declining warehouse levels in Figure 8.20, it is concluded that a sufficient number of trucks is available for the shuttle. Solely considering the *Accumulated Node Time* KPI it is concluded that a model with 9 trucks available performs best since it results in the fastest pallet flow through the network.

9
Conclusions & Future Research

To achieve competitiveness, companies are highly agile in improving the robustness of their supply chain system by being responsive to external events, especially after experiencing the effects of a macro pandemic on the global supply chain system. Similarly, the world's second-largest beer brewer Heineken, with major exporting production plants in The Netherlands, requires a robust and transparent supply chain. This research has investigated the effects of the current outbound logistic planning tool on the logistic export network at Heineken. Thereby considering all aspects of the network; production, cross-docking, warehousing, JIT container loading, and container transport. Based on the current state analysis, several information asymmetries were present between the centralized planning tool and the physical state of goods. These asymmetries consisted of a warehousing time delay and the inability to collect data on the container status at the inland container terminal, resulting in an inefficient information feedback loop.

This study contributes to the scientific literature by using the case study at Heineken to research the effects of centralized MPC with real-time data compared to centralized MPC with the current information asymmetries. Unlike the available literature on MPC models, this research incorporates an integrated, centralized MPC model which enables optimal flow through the multi-product supply chain by minimizing inventory levels and the accumulated time spent at the supply chain nodes while also measuring the impact of the logistic variance created by the fluctuating production output. An Asymmetric Control Centre replaced the existing planning tool to simulate the Current State. At the same time, a Real-Time Control Centre was used to represent the Future State based on multiple requirements. Furthermore, the multi-SKU production outflow is matched with a specific container type based on delivery-specific information in a JIT loading environment. Multiple KPIs were introduced to measure the flow through the network of nodes and the stability of the steady-state logistic performance. The main research question was formulated as follows:

1. *How can the outbound logistic information network be controlled to increase the performance of the physical flow of goods, and what is the impact of the information asymmetries?*

Firstly, in the literature review (chapter 2), the relevant academic research components of the logistic system were individually addressed. After this, recent studies regarding MPC application in the supply chain were highlighted. Then, based on data from 2022, the physical state of the current outbound logistic network was analyzed. Within chapter 3, it was concluded that the high weekly deviation in the palletized production output puts considerable strain on the outbound logistic network; warehouse levels are unpredictable, and palletized items being directly cross-docked into a shipping container are considered to be low. As a result, it has been found necessary to examine the current logistic planning and information structure at Heineken Zoeterwoude.

From the analysis in chapter 4, it was deduced that the current logistic planning is only considered on the operational level. Moreover, the production planning does not consider the impact of production fluctuations on the logistic system. Currently, a centralized logistic planning tool that depends on data from multiple systems is in place. However, the tool's effectiveness is limited by its inability to collect data on the availability of empty containers, leading to an information asymmetry between the planning tool and the physical state of goods. Additionally, the system requires human operators to bridge the gap between the planning tool and third-party logistics providers. Data regarding warehousing, deliveries, and production is unavailable in real-time, causing an information asymmetry between the physical state and the centralized planning tool.

In chapter 5, several requirements were listed to model the Current State and Future State of the outbound logistic network. Based on these requirements, CMPC was found to be a proper strategy to replace the current centralized planning tool. Due to its adaptive and predictive characteristics, CMPC is suitable for dynamically modeling a planning tool with a fluctuating production input. Furthermore, the prediction horizon can be set to match the rolling horizon of the current planning structure, and CMPC can account for all system boundaries in place in the real-world system.

The Current State CMPC model includes the information asymmetries between the introduced Control Centre and the physical status. In contrast, in the Future state, the information asymmetries are eliminated due to the availability of real-time data. In chapter 6, the MILP algorithm using a state space representation was presented, which forms the basis of the CMPC model. Then, chapter 7 was used to introduce the simulation parameters and objective, while also a thorough model verification was performed based on several feasibility and sensitivity analyses. Also, the simulation scenario analysis was presented in this chapter based on two distinct models representing the Current and Future State. The model's behavior was concluded to align with the intended mathematical design of chapter 6.

The performances of the Current State and Future State model were analyzed based on four introduced key performance indicators. These key performance indicators were constructed to measure the effectiveness of the pulling effect of the inland terminal node. Also, the *Accumulated Node Time* KPI can measure the time spent per SKU in the network of nodes aiming to reduce this accumulated time. The *Truck Shuttle Deviation* is a critical metric for measuring the logistic system variation. A system with a lower deviation is more steady-state; as a result, the logistic system is more robust and reliable. Also, the *Warehouse Levels* were measured to test the model's feasibility. In line with the operational planning structure at Heineken, the simulation runs were performed considering a prediction horizon of 7 days, which was necessary to make the Current and Future States comparable. In addition, this research also incorporated the effects of different prediction horizons; several simulation runs were performed for 3.5, 7, and 14 days to study the impact of varying planning horizons.

In chapter 8, it was concluded that the Real-Time Control Centre performs better on all four KPIs; the accumulated node time decreased while the average and peak warehouse levels declined. The Real-Time Control Centre enabled a reduction of the *Accumulated Node Time* of at least 18% over all simulation runs. Also, the Real-Time Control Centre enables a more steady state container transportation due to the lower deviation in required truck rides. Consequently, the Real-Time Control Centre copes better with fluctuating production output. It enables products to flow through the network more efficiently, decreasing the warehousing strain at Heineken. Furthermore, the scenario analysis concluded that the container availability asymmetry has a considerably more significant impact on the logistic network than the warehouse asymmetry. While the *Accumulated Node Time* overall decreased by 18%, 16% was due to eliminating the container availability asymmetry. In addition, it was concluded that 7 trucks were sufficient to transport all containers to the inland container terminal in the *Real-Time Control* model, and 7 trucks resulted in the lowest *Truck Shuttle Deviation*. However, the *Accumulated Node Time* KPI was introduced as the primary KPI and the simulation runs with 9 trucks resulted in the lowest *Accumulated Node Time* and therefore operates according to the minimal flow principle.

Lastly, the Real-Time Control Centre was modeled with different prediction horizons to research the effect of varying planning horizons. In line with the objective function, which opts to optimize the flow through the network of nodes, it is concluded that elongating the length of the planning horizons yields better performance in terms of the *Accumulated Node Time* KPI. Consequently, the warehouse average and peak levels decrease with an increasing prediction horizon. However, increasing the length of the prediction horizons, when plenty of trucks are present for container transportation, impacts the *Truck Shuttle Deviation* negatively. Therefore, an optimal solution obeying all KPIs cannot be computed due to contradictory objectives.

9.1. Future Research

The proposed solution applied to the Future State model is considered innovative due to the ability to predict the impact on the logistic process and adapt to changing circumstances such as fluctuating production output. While this study mainly focused on creating a suitable control model that eliminates the current information asymmetries, future research must be conducted in multiple fields to create a complete and optimal outbound logistic network. This section will address to most crucial future research opportunities that are built on the research conducted in this study.

Incorporating Larger Node Network

The modular construction of CMPC paves the way for complete supply chain integration. While this study only considered the logistic network from production to the inland container terminal, future research could elaborate on the current model by accounting for procurement, resource management, and production. Alternatively, the model could be extended to the container's arrival in the associated deep-sea ports. Therefore integrating more nodes into the network thus creating a fully visible supply chain for Heineken. Moreover, by incorporating more nodes into the network, the CMPC planning tool can make a production plan based on the logistics constraints to create a steady-state production output. Consequently, logistic planning has to deal with less deviation, which makes the system more robust and predictable.

Planning Horizons

Most simulations in this research were performed while accounting for a static planning horizon of 7 days, which aligns with the current planning structure at Heineken. In addition, several simulations were performed with varying prediction horizons to examine the effect of different planning lengths. These experiments showed that different lengths influence the model's performance heavily. Therefore, future research should be focused on identifying the optimal planning length. This research should also include the computational burden of the CMPC model with varying prediction horizons. Longer prediction horizon models might be too computationally heavy to create a logistic planning with the required time window.

Then, while this research only included the operational outbound planning level, future research could extend to creating long and mid-term planning based on historical data. It was already concluded in the study of Pigeaud (2015) that the planning of outbound logistics does not consider any forecasts based on historical data. At the same time, the knowledge of the logistic impact created by the production output would be instrumental in mitigating obstructions in the outbound network. In this research, production fluctuations are a stochastic input into the centralized MPC model. Implementing *Artificial Intelligence* (AI) could help develop a predictive model based on the logistic impact of historical production cycles. However, years of precise data collection would be needed to create an accurate model. Furthermore, implementing AI requires a standardized way of data computation and handling; currently, this process is not standardized and prone to many exceptions.

Also, this research did not account for changes to the production schedule within the prediction horizon, while in the real-world scenario, changes to the production plan do occur. Future developments could include testing the CMPC model with live production data, which will likely change within the prediction horizon. As a result, it is necessary to recompute the model based on the changes in the expected production output. It is also necessary to research the logistic effects of production schedule changes.

Truck Shuttle Deviation

Within this research, the availability of trucks for each simulation run was statically modeled. As a result, the number of available trucks for shuttling containers between the brewery and CCT is set over the length of the prediction horizon. Future research should incorporate an additional decision variable that can dynamically decide the number of trucks available for a certain number of iterations. In this way, the truck shuttle deviation can further be reduced, which causes significant cost reductions.

Truck Deliveries

Lastly, the scope of this research solely included the outbound deliveries that were loaded into shipping containers. However, at Heineken, it is known that deliveries being loaded into semi-trailers cause a significant impact on the warehouse inventory levels because they are not loaded over the cross-docks.

Not accounting for the exact effects of the truck deliveries causes this research to be a simplified version of the reality at Heineken Zoeterwoude. Also, within the long-term vision of Heineken, the number of truck deliveries will likely increase over time, thus creating a larger impact on the logistic network. Therefore, future research should not mitigate the effects of the semi-trailer deliveries on the container deliveries.

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A

Appendix A

A.1. Python Algorithm GitHub Repository

A general version of the Python algorithm written for this research is available in this GitHub Repository (https://github.com/Martijn-maker/academic_thesis.git).

A.2. Scientific Paper

This section provides the scientific paper, which is a comprehensive academic summary of this report.

A Centralized Model Predictive Control Framework for Just-In-Time Outbound Logistics under Information Asymmetries - A Casy Study at Heineken

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Abstract

This study entails the development of a planning model utilizing Centralized Model Predictive Control (CMPC) to optimize the flow of physical goods throughout a network of supply chain nodes, utilizing a Mixed-Integer Linear Programming (MILP) approach to determine the optimal decision variables. Specifically, a Current State CMPC model was created to reflect the current outbound logistic network at Heineken Zoeterwoude, where information asymmetries are known to impact the accuracy of the outbound logistic planning tool. The Current State model was compared against a Future State model, where real-time data is available, thereby eliminating the aforementioned information asymmetries. By assessing four key performance indicators, it was found that the Future State model enables considerably better performance of the logistic network, even during peak production.

Keywords: Outbound Logistics, Information Asymmetries, Model Predictive Control, Control Centre, Logistic Planning

1. Introduction

In today's globalized world, Supply Chain Management (SCM) is the operations strategy for companies to be organizationally competitive. SCM focuses on coordinating material, information, and financial flows, involving all stakeholders in the decision-making process, in order to fulfill customer demand requirements (Hipólito et al., 2022). To achieve competitiveness, companies are extremely agile to improve the robustness of their supply chain system by being responsive to external events. Recently, many companies have experienced the effects of the COVID-19 virus on the supply chain. These developments have put a massive strain on the industry; container shipping costs spiked due to a worldwide shortage of empty shipping containers. The need for advanced integration of SCM along the chain has been fast-forwarded as companies are more than ever willing to invest in robust planning systems to minimize future inefficiencies in their logistic network. Supply chain integration is the process that coordinates the products flow between supply chain partners, including transaction materials movements, procedures, and optimization processes by also considering the underlying information flow. Integration is regarded as an important step in improving supply chains. Supply chain members are not very keen on interchanging data, but multiple studies pointed out the effectiveness of data sharing (Datta and Christopher, 2011; Rossini and Portioli, 2018). Business uncertainty in supply chain management has posed a considerable risk to the entire process flow. Supply chain risk management is important because of the cascading effects an incident might trigger in a logistic network. The recent developments in the global supply chain have also affected the logistic process for Heineken, the second-largest beer producer worldwide by volume. Specifically, the Heineken Brewery in Zoeterwoude, the largest brewery in Europe, exports over 70% of the produced volume to oversea customers. Due to the vast container shortages in recent years, Heineken could not ship products in containers to all oversea customers.

1.1. Problem Definition

The long-term goal of Heineken is to be resilient to micro and macro uncertainties by enhancing its operational planning process regarding outbound logistics for export products. Despite efforts to optimize the process, the current system has proven to be insufficiently robust, especially concerning the container loading process of finished products at the brewery. This process is highly reliant on two physical characteristics - the availability of space in the finished goods warehouse and timely access to empty containers at the outbound docks to load palletized products. To facilitate a just-in-time (JIT) loading process, Heineken employs cross-docks at the end of the production lines, acting as a buffer for temporary storage to enable flexibility in the loading process, therefore, theoretically, the use of inventory space can be eliminated. However, the efficient functioning of these physical operations is dependent on the interconnected information management systems used for warehouse management, resource management, and loading planning. These systems are integrated with internal departments and third-party transportation companies (responsible for container shipments), creating a complex information network that suffers from delays and feedback loops. Consequently, logistic operators must often intervene manually to correct information asymmetries between the physical status and the available information in the enterprise software modules. Failure to address these information asymmetries on time can result in production stoppages and inefficient handling of goods. Currently, a centralized logistic planning tool that depends on data from multiple systems is in place. However, the tool's effectiveness is limited by its inability to collect data on the availability of empty containers, leading to an information asymmetry between the planning tool and the physical state of goods. Additionally, the system requires human operators to bridge the gap between the planning tool and third-party logistics providers and data regarding warehousing, deliveries, and production is not available in real time.

The goal of this research is to increase the performance of the physical flow of goods considering the control of the outbound logistic information network at Heineken Zoeterwoude. Therefore the aim is to propose a simulation model of the current state of the planning tool, which will incorporate the existing information asymmetries. In particular, the simulation will be used to model the impact of the information asymmetry related to the availability of empty containers, as well as the asymmetry related to the daily information update. Secondly, based on several future state requirements, a novel logistic control approach will be introduced considering the outbound logistic planning.

Then, the performance of the newly introduced control approach will be compared to the performance of the current state simulation model. This will be performed by introducing several key performance indicators (KPIs) to measure the performance of the planning tool. Therefore, the following research question has been formulated:

How can the outbound logistic information network be controlled to increase the performance of the physical flow of goods, and what is the impact of the information asymmetries?

In support of the main research question, several subquestions have been formulated:

1. *What are the relevant academic research components of the current logistic system?*
2. *In what ways does this thesis research contribute to the academic literature?*
3. *What is the current state of the physical flow of goods of the outbound logistic network, and what is the performance of the KPIs?*
4. *What is the current planning structure of the outbound logistics network?*
5. *What are the information asymmetries in the Current State?*
6. *What requirements should be considered regarding the supply chain model, and what modeling strategy is preferred?*
7. *How can the logistic network be modeled into an MPC framework with a single control node?*
8. *How can the general node configuration be arranged in a mathematical model using a state space representation?*
9. *What KPIs can be introduced to measure the performance of the outbound logistic network?*
10. *How can the general MPC model represent the Current and Future States?*
11. *What parameters should be chosen for the MPC simulation scenarios?*
12. *How does the Future State perform compared to the Current State when the information asymmetries of the Current State are eliminated?*

The structure of this research is based on the SIMILAR approach, which provides a structured approach to engineering contemporary systems. The SIMILAR acronym consists of *State the problem, Investigate alternatives, Model the system, Integrate, Launch the system, Assess performance, and Reevaluate*. Firstly, section 2 will outline this research's academic research components and relevance. Thereafter, in section 3 the physical performance of the logistic network is highlighted, while the information network is assessed in section 4. Also, in section 4, the current state information asymmetries are addressed. In section 5, the suitability of CMPC as a modeling technique in supply chains is argued while also the model requirements are listed. These requirements are used to construct a general CMPC design, based on a MILP state space representation. Then, the simulation parameters are listed in section 6, and the results are presented in section 7. In section 8, conclusions are drawn and future research topics are identified.

2. Literature Review

2.1. Logistic Planning

The supply chain can be defined as 'a system comprising organizations, decision-makers, and technology decision policies responsible for transforming raw materials into finished products delivered to end customers (Subramanian et al., 2013). Logistic planning is the forward-looking planning process in production and logistics that requires knowledge of the appropriate supply chain for the product. Supply chain management (SCM) involves three levels of planning and decision-making: strategic planning, tactical planning, and operations control. Strategic decisions are long-term and affect the overall competitiveness and growth rate of the company. Tactical decisions focus on resource utilization based on demand forecasts. Operational decisions involve the daily management of supply chain activities. These levels of planning and decision-making are essential to effective SCM.

According to Fleischmann and Meyr (2003), supply chain optimization has three recurring difficulties: multi-objective decision-making, combinatorial complexity, and uncertainty. Firstly, most supply chain optimization problems require the consideration of multiple objectives, which cannot be optimized simultaneously. As a result, planners must determine satisfactory levels for each objective. Secondly, due to the large number of variables involved, most problems contain a combinatorially large number of alternatives. This often requires heuristics to compute near-optimal solutions instead of exact solutions. Lastly, the biggest challenge in supply chain planning is dealing with uncertainty (see subsection 2.2).

2.1.1. Information Asymmetry

Information asymmetry can be described as an inefficiency in information supply, resulting in a lack of supply chain visibility. Information asymmetries occur when information is not visible, mostly because a certain metric is not being measured. In addition, information asymmetry is described as a supply chain actor having more, better, or complete information on a certain metric compared to another actor (Vosooghidizaji et al., 2020). Information asymmetry can be found in supply chains where stakeholders are unwilling to share information due to economic reasons. Another form of information asymmetry can be found within a certain stakeholder using multiple information systems. Information asymmetry can for instance occur when a single system takes more state updates into account than another system.

2.2. Supply Chain Uncertainty

Uncertainty is defined as the difference between the amount of information required to execute a task and the available information (Flynn et al., 2016). Two distinctions can be made in supply chain uncertainty. The first can be addressed as internal uncertainty, propagating from inter-functional inconsistencies. The second is external uncertainty, which is related to the supply and demand of third parties. Supply chain integration can be described as the response to uncertainty, according to Flynn et al. (2016). In an integrated network, the output of one entity is the input of the next. Motivation for supply chain members to share information can be low due to their interests. On the other hand, there will always be a likelihood that information sharing will benefit every member. This phenomenon is called the mixed-motive nature of supply chain relationships (Hult et al., 2010). Ultimately, properly integrated systems develop the capabilities to respond rapidly in a changing environment. The incorporation of information technology (IT) systems can enhance visibility, collaboration, and communication among supply chain partners, resulting in better coordination and a more responsive supply chain.

2.3. Just-In-Time

Just-In-Time (JIT) production is a production strategy that aims to minimize inventory and increase efficiency by producing goods only as they are needed. JIT production was first developed in Japan in the 1950s and 1960s by Taiichi Ohno, an engineer at Toyota (Ohno, 1988). In the automobile factory, just-in-time meant looking at the process in reversed order, therefore only producing a single part if it was requested further up the process.

JIT systems, on the other hand, also have other fields of applications rather than the production industry. JIT logistics can be applied to four main fields in the supply chain: (1) customer services, (2) order processing, (3) inventory management, and (4) transportation management. This study will apply JIT logistics in the transportation management field, where empty containers must arrive in a JIT manner to ensure efficient product flow.

2.4. Control Theory

Control Theory (CT) has become an important research field in operations and supply chain management. Control is an information science and the first applications of CT in supply chains were single input, single output (SISO) controllers, which were used to track inventory levels (Subramanian et al., 2013). Control of supply chains was first proposed in 1961. The use of control in supply chains gained traction when information technology was implemented to predict sales, keep track of products, and Just-In-Time production.

2.4.1. Model Predictive Control

Especially, Model Predictive Control (MPC) has undergone rapid development regarding supply chain applications. MPC is a control strategy that uses a mathematical model of a system to predict future behavior and optimize control decisions over a finite time horizon. It is well-suited to supply chain systems because it can integrate multiple sources of information, including demand forecasts, production schedules, and inventory levels, to make optimal decisions that balance conflicting objectives. One of the key advantages of MPC is that it can account for uncertainty in the system, such as demand variability, production disruptions, and supply chain disruptions. This is critical in supply chain systems, which are often subject to unpredictable events that can have significant impacts on performance.

Within supply chains, MPC can be implemented in a centralized and decentralized manner (Subramanian et al., 2013). In a centralized controller, there is one integrated system that needs information as input from all nodes involved in the supply chain. Whereas in a decentralized system, all nodes are responsible for their node optimization. Therefore, no integral system is needed and each node only uses the information that applies to its situation. In addition, MPC can also be used to control a part of a bigger, integrated supply chain. Decentralized MPC is mainly applicable to supply chains containing multiple companies or entities, which do not share information internally.

Several studies have emphasized the advantage of using MPC, which has the ability to be stable and robust even in the presence of disturbances and stochastic demand. The literature review by Ivanov et al. (2018) focused on control theory application in supply chain management. The author found that control theory approaches are well-suited for decision management and performance achievement. Hipólito et al. (2022) implemented a demand-driven MPC framework for a perishable goods supply chain, while Li and Marlin (2009) used robust MPC for optimization with significant uncertainties in a multi-echelon supply chain problem. Braun et al. (2003) used a two-node framework to translate information sharing in a supply chain setting into control terminology. Eventually, a six-node, three-echelon network was created for a case study on a semiconductors supply chain. Wang et al. (2007) also discussed the challenges of implementing MPC strategies, including the need for accurate models and real-time data, as well as the need for skilled personnel to design and maintain the control system.

Several studies have compared centralized MPC and global optimization to decentralized MPC and local optimization to reduce the bullwhip effect in a supply chain. Perea-Lopez et al. (2003) modeled a multi-echelon supply chain using Mixed-Integer Linear Programming (MILP) and found that the centralized approach overall outperformed the decentralized approach in terms of profit maximization.

Nabais et al. (2013) modeled a supply chain using hierarchical MPC and introduced variable weights based on volume in the cost function, and the results showed that the hierarchical model performed better in terms of computation times. Nabais et al. (2013) was also the first to model the supply chain as a flow assignment problem. A scenario-based model predictive control approach has been proposed by Schildbach and Morari (2016), which uses a scenario tree to handle uncertainties in the supply chain and outperforms traditional approaches in terms of profit and inventory levels.

Stochastic modeling has been implemented in a semiconductor supply chain by Schwartz et al. (2006) using MPC, and a fluid representation of the three-echelon supply chain was used. In the comparison of centralized MPC and global optimization to decentralized MPC and local optimization by Fu et al. (2014), the former was found to be more effective in reducing the bullwhip effect and improving supply chain performance. However, the authors note that implementing centralized MPC may be challenging in practice. Mestan et al. (2006) optimized a mixed logic dynamical system with an MPC algorithm, comparing a decentralized MPC model to a centralized version, and concluded that centralized MPC performed better on average compared to the decentralized model.

In summary, several studies have shown the potential benefits of MPC in supply chain management, such as stability and robustness in the face of uncertainty. However, there are challenges to implementing MPC, such as the need for accurate models and real-time data. Additionally, the effectiveness of centralized and decentralized MPC approaches depends on the specific supply chain context.

2.4.2. Gloabl Control Centre

In addition to the use of MPC, a central control node as the *Global Control Centre* was first introduced by Dreyer et al. (2009). *Global Control Centres* enable transparent information systems by an integrated and coordinated production and logistic planning control system. *Global Control Centres* are centralized hubs that provide end-to-end visibility and control of a supply chain network. They integrate data from multiple sources to provide real-time information on the status of inventory, transportation, and production. Global control centers, also known as Control Towers, allow for greater responsiveness by mitigating information asymmetries in managing supply chains and can help to minimize the impact of disruptions and uncertainties.

2.5. Academic Relevance

This study entails the development of a planning model utilizing Centralized Model Predictive Control (CMPC) to optimize the flow of physical goods throughout a network of nodes, utilizing a Mixed-Integer Linear Programming (MILP) approach to determine the optimal decision variables. Specifically, a Current State CMPC model was created to reflect the current outbound logistic network at Heineken Zoeterwoude, where information asymmetries are known to impact the accuracy of the logistic planning tool. The Current State model was then compared against a Future State model, where real-time data is available, thereby eliminating the aforementioned information asymmetries.

The academic relevance of this thesis research can be summarized as follows:

> Unlike the available literature on MPC models, this research incorporates an integrated, centralized MPC model that enables optimal steady-state flow through the multi-product supply chain by minimizing inventory levels and the accumulated time spent at the supply chain nodes. This includes the following topics:
>
> 1. Incorporation of centralized MPC in a network of nodes, where the current state is prone to information asymmetries.
> 2. Matching fluctuating, multi-SKU production outflow with specific container type in a JIT loading environment, prone to uncertainty.
> 3. Two scenario analysis; the as-is state with the current information asymmetries will be compared to a state where real-time data is used by an autonomous decision maker which is assumed to have complete visibility.
> 4. Multiple KPIs of supply chain nodes will be evaluated simultaneously while using company data to assess the feasibility of the model.

3. Current Physical Flow

A depiction of Heineken's current outbound logistic network is presented in Figure 1. Following the brewing production process (1), the items are packaged and loaded onto pallets, marking the final production stage at Heineken Zoetewoude. The finished palletized products will move on to the cross-docking lanes (2), which serve as buffer conveyors with limited storage capacity. Then, the pallets are directly loaded in an empty shipping container (4) or temporarily stored at the warehouse (3). The arrival of empty containers is the responsibility of CCT, the operating company of the inland container terminal (6). CCT's duty is to operate the truck shuttle (5) between the brewery and the inland terminal. CCT provides the brewery with empty containers as they are needed (Just-In-Time) while also transporting the full container back to the inland container terminal. At every moment, multiple trucks are used for the shuttle between the brewery and the inland container terminal. On average, a round trip takes an hour. The logistic process heavily relies on the warehouse's availability of space and timely access to empty containers at the outbound docks.

3.1. Production

As indicated, the palletized output of the production serves as the input for the planning of outbound logistics. A specific area of the brewery is dedicated to producing goods for export. Throughout the year 2022, a total of 47 163 containers were loaded at the production plant located in Zoeterwoude, resulting in the production of 1 080 466 pallets. This accounts for the loading of 130 shipping containers a day, with peak levels rising above 200 containers daily. By considering the average weekly production, the deviation in production output was calculated (see Table 1).

Production in pallets (2022)	
Total Produced	1 080 466
Weekly Mean	20 778
Weekly Standard Deviation	15,4%

Table 1: Weakly production deviation at Heineken Zoeterwoude in 2022.

Based on the figures presented in Table 1, it can be concluded that there is a significant weekly variation in production output, which creates a significant strain on logistics planning.

3.2. Warehousing

As a result of the fluctuating production output, the levels in the warehouse also fluctuate heavily. Ultimately, direct cross-docking of the palletized goods is preferred. However, in 2022 8% of the produced pallets had to be temporarily stored in the warehouse. Mainly due to the unavailability of empty containers. Table 2 shows the weekly performance of the warehouse over 2022.

Warehouse Occupation in Percentage (2022)	
Performance (Weekly Mean)	95%
Weekly Standard Deviation	28%

Table 2: Weekly Warehouse Performance (2022).

Based on a maximum capacity of 3 500 pallets, the warehouse is on a weekly basis occupied for 95%. As a result, it is often not able to absorb production fluctuations.

3.3. JIT Container Arrival

The number of empty containers necessary at the brewery is directly related to the production output. On average, 89% of the required containers were delivered on time per week during 2022. It is important to note that if a container is unavailable, not all pallets will be transported into the warehouse because of the buffer capacity of the cross-docking lanes. There are a total of 13 cross-docking lanes available, each with an average capacity of 40 pallets. As a result, only 8% of the pallets produced in 2022 were actually stored in the warehouse.

Information Asymmetry	**Effect (average)**
Production Output	12 hour delay
Delivery Information	12 hour delay
Warehouse Levels	12 hour delay
Empty Container Stock	89% timely arrival

Table 3: Current state information asymmetries

4. Current Planning and Information Networks

Due to the relatively high fluctuations in the logistic network's performance, it was necessary to examine the current logistic planning and information structure at Heineken Zoeterwoude. Based on the supply chain typology introduced by Meyr and Stadtler (2005), the planning horizons at Heineken Zoeterwoude have been analyzed. Currently, a distinction is made between the long-term, mid-term, and short-term planning levels. While procurement and production are forecasted in the long term, logistic planning is only considered in the short term. Based on a two-week production schedule and customer orders, the logistic planning is created with a rolling horizon timeframe of a week. Therefore, the planning is updated with a new production plan on a weekly basis. While the production planning does not take into account the impact on the logistic system, which is known as the decoupling between production and logistics.

In addition to the current planning layout, the daily loading planning process is responsible for coupling the palletized production output with the required container type. Therefore, the planning tool receives production, warehouse, and delivery data as input. The information flows regarding the planning tool are schematically represented in Figure 2. Here, it is observed that the current planning tool receives daily updated regarding production, deliveries, and warehouse levels. The planning tool is a centralized system due to the central information collection and global planning output. The daily planning output is shared with CCT (inland container terminal) to verify the feasibility of the loading plan regarding the available stock of empty containers at CCT. Thereafter, the feedback provided by CCT is implemented in the loading plan by an operator which causes daily rework tasks (see Figure 2).

The planning tool is currently a daily processing system, dependent on the data feedback provided by CCT. The daily information delay and the feedback loop (denoted by the red box in Figure 2) cause information asymmetries between the planning tool and the current state of the physical goods; any state change after the daily update within 24 hours is not captured by the planning tool. Furthermore, the planning tool functions based on the assumption that containers are available at CCT, without considering the actual stock. Assuming the production plant has a uniform output flow, the average daily information is 12 hours. Moreover, derived from CCT data, it was found that the average weekly container arrival performance is 89%. The quantifications of the information asymmetries are presented in Table 3.

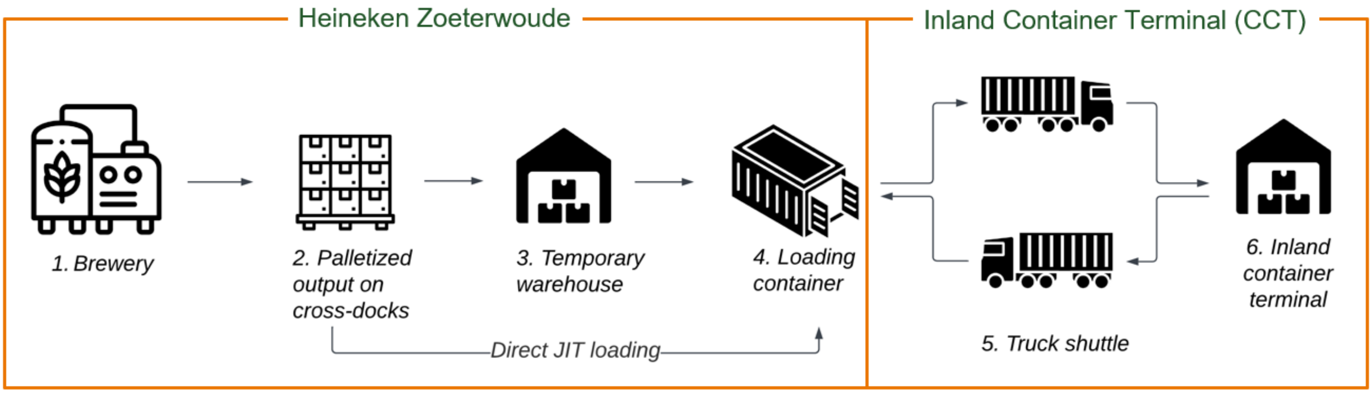

Figure 1: Outbound Logistic Network at Heineken Zoeterwoude

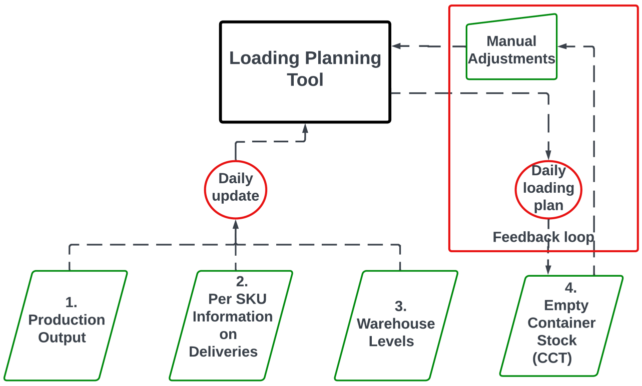

Figure 2: Centralized planning tool in current state

5. Model

Based on the *Current State Analysis* several requirements were determined to be necessary to model the logistic system to control the product flows and to measure the impact of the information asymmetries. Therefore, a Current State model will be compared against a Future State model. A distinction has been made between *General Requirements*, *Current State Requirements* and, *Future State Requirements*:

5.1. General Requirements

1. **Stochasicity** The model should handle stochastic input such as production variability and the uncertainty in the JIT arrival of empty containers at the brewery.
2. **SKU Differentiation** Model should differentiate between SKUs, including the number of products per SKU, to create a container loading plan for specific SKUs in specific containers.
3. **System Characteristics** Model needs characteristics of production output, SKUs produced, and constraints like truck and warehouse capacity and pallet movements per time unit. In this way, the model needs to be able to calculate the impact of the production on the logistic network.
4. **Real-World Data** Model needs real-world data on palletized output per SKU at the brewery, pallets per container, and container type for Heineken's logistic network.
5. **Centralized** Model should be centralized like the Current State planning tool, which collects data on a daily basis and creates a logistic loading plan considering input data of multiple modules.
6. **Planning Horizon** The model should be able to represent the length of the operational plannin horizon that is being used at Heineken Zoeterwoude.

5.2. Current State Requirements

1. **Information Delay** Model should have a time delay of 12 hours, on average, between the centralized planning module and the physical state of goods, in accordance with the real-world state.
2. **Feedback Loop** Model should consider effects on the logistic network caused by the information feedback loop between Heineken and CCT, which causes uncertainty in the timely availability of empty containers from CCT at the brewery. Historical data analysis found average performance over 2022 was 89%.

5.3. Future State Requirements

1. **Real-Time Data** Novel approach requires real-time state updates of physical goods and container availability at third parties to overcome information asymmetries. The model needs real-time data on the warehouse's physical state and the container availability at the inland terminal.

In section 2, multiple studies addressed the application of MPC in supply chains. Thereafter, MPC was found to be a suitable strategy to model the outbound logistic network at Heineken due to the adaptive and predictive characteristics of MPC; Heineken is constantly prone to a changing environment. Besides, MPC enables to model the complete logistic network. Moreover, the current state planning tool is a centralized system and can therefore be associated with a centralized MPC model. CMPC can simulate the current state of the outbound planning tool due to the centralized information gathering. Accordingly, CMPC enables to model the current time delays and feedback loops currently present in the system. Also, CMPC can be used to create a loading plan based on the production input and the associated constraints regarding cross-docks, truck availability, and container availability. Lastly, CMPC is used to model the Future State, in which the information asymmetries are omitted by assuming all data to be transparent and available in real-time.

5.4. Design

The MPC strategy is based on a mixed-integer linear programming (MILP) algorithm. This algorithm is constructed according to the flow assignment problem which was implemented by Nabais et al. (2013). Nabais et al. (2013) introduced a *Control Centre*, which is modeled as a central control agent, responsible for the flow assignment problem. The flow assignment is modeled as a sequence of events, where products are either stored at nodes or transported through a flow between nodes. Nodes can be modeled without a flow to represent a time delay in the network. The inventory level at each node is mathematically represented in Equation 1.

$$I_i(k) = I_{i-1}(k-1) + I_i(k-1) - \sum_{j \in Dn(i)} S_{ij}(k) + \sum_{j \in Up(i)} S_{ji}(k) \quad (1)$$

In which, $I_i(k-1)$ is the inventory level at node i at discrete time $k-1$, $I_{i-1}(k-1)$ is the state of the node I_{i-1} at $k-1$ (modeled as a time delay), $Dn(i)$ is defined at the set of downstream nodes to which the node supplies material, while $Up(i)$ is the set of nodes from which the node receives the material. Lastly, S_{ij} is the amount of material that flows from node i to node j.

Based on the flow assignment problem, the outbound logistic network at Heineken Zoeterwoude has been modeled as a set of nodes and flows visible in Figure 3. Here, the circular nodes represent a time delay in the network, while the rectangular nodes represent nodes with storage capacity. In Figure 3, the orange arrows depict the optimal path through the network of nodes. The first arrow depicts the fastest pallet flow, and the second arrow the fastest container flow. The flow is considered sub-optimal if goods do not follow this path in the minimum amount of time.

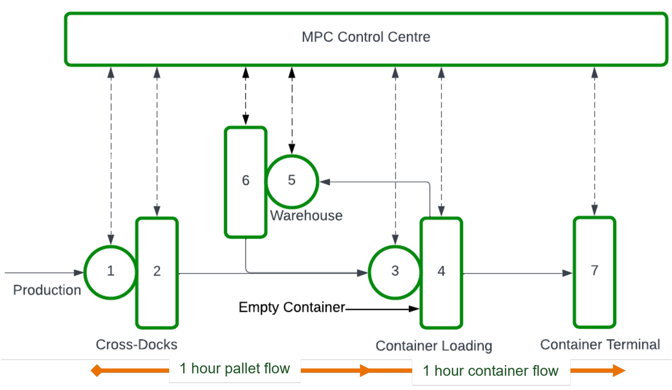

Figure 3: Flow assignment design of the logistic network, with the incorporation of a Control Centre.

Then, based on the listed requirements a mathematical format can be introduced using indices, sets, decision variables, and parameters.

Indices	
k	*index of discrete time instant*
j	*index of single product type (SKU)*
i	*index of supply chain node*
i'	*index of node upstream to node i*
i''	*index of node downstream to node i*
n	*index of number of trucks*

Sets	
X	*Network of supply chain nodes*
U	*Set of flows for palletized goods*
P	*Set of SKUs*

Variables	
x_{ij}	*Stock level of SKU j at node i*
$u_{i'ij}$	*Palletized flow of SKU j from node i′ to node i*
l_j	*Binary Container flow of SKU j for each truck n*

Parameters	
p_j	*Palletized Production output per SKU j*
c	*Binary value for container availability*
x_{max}	*Storage capacity for each SKU j at node i*
u_{max}	*Palletized flow capacity for each SKU j from node i to node i″*
X_{max}	*Total storage capacity at node i*
z_j	*Number of pallets of SKU j per container*
N_p	*Prediction Horizon of MPC model*

5.5. Dynamic State Space Representation

The general dynamic node equation, applicable to each SKU j for each node k is written as:

$$\begin{aligned} x_{ij}(k+1) = x_{ij}(k) + \sum_{j \in P} p_j(k) + \sum_{i' \in X} u_{i'ij}(k) - \sum_{i'' \in X} u_{ii''j}(k) \\ + \sum_{i' \in X} c(k) z_j(k) l_j(k) - \sum_{i'' \in X} c(k) z_j(k) l_j(k) \\ \forall i \in X, j \in P \end{aligned} \quad (2)$$

Subjected to the following non-negative constraints:

$$x_{ij} \geq 0 \quad \forall i \in X, j \in P \quad (3)$$

$$u_{i'ij} \geq 0 \quad \forall i \in X, j \in P \quad (4)$$

And subjected to the following container flow constraint:

$$\sum_{j \in P} l_j(k) \leq 1 \tag{5}$$

In Equation 5, the number of SKUs per container flow is limited to one. So, it is considered that every container can only hold a single product type. Lastly, the capacity constraints for the flows and nodes are presented in Equation 6, Equation 7, and Equation 8. Where, Equation 6 denotes the total capacity constraint for each node i for all products j, whereas Equation 7 is concerned with the capacity limits of each node i for each SKU j. Equation 8 represents the flow constraint of each SKU j from node i' to node i.

$$\sum_{j \in P} x_{ij}(k) \leq X_{max} \quad \forall i \in X \tag{6}$$

$$x_{ij}(k) \leq x_{max} \quad \forall i \in X, j \in P \tag{7}$$

$$u_{i'ij}(j) \leq u_{max} \quad \forall i \in X, j \in P \tag{8}$$

The general node equation presented in Equation 2 can be presented in a matrix representation where the characteristics per node will be set according to the design in Figure 3:

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}_u\mathbf{u}(k) + \mathbf{B}_l\mathbf{l}(k) + \mathbf{B}_p\mathbf{p}(k) \tag{9}$$

$$\mathbf{y}(k+1) = \mathbf{x}(k+1) \tag{10}$$

The output, $\mathbf{y}(k+1)$ of the model is equal to the state, $\mathbf{x}(k+1)$ of the system, therefore the supply chain is fully observable. $\mathbf{x}(k+1)$ is determined by considering the current state $\mathbf{x}(k)$, the actions $\mathbf{u}(k)$ & $\mathbf{l}(k)$ and, the production output $\mathbf{p}(k)$ is modeled as a disturbance to the system. In Equation 9, $\mathbf{A}$ is the state matrix for each node, while $\mathbf{B}_u$ represents the pallet flow characteristics. $\mathbf{B}_l$ represents the container flow property of each node. Lastly, $\mathbf{B}_p$ holds the production input details for each node. The matrix representation can be found in section 8.

5.6. Performance Indicators

Several Key Performance Indicators (KPIs) will be used to measure the performance of the simulations while considering the Current State and Future State of the model.

5.6.1. Accumulated Node Time

Building on the work of Hipólito et al. (2017) and Hipólito et al. (2022), whose research incorporated the expiration date of perishable goods in the supply chain, this research will incorporate the accumulated time per SKU spent in the network. This KPI will measure the optimal flow of goods through the network of nodes. This is performed by measuring the accumulated time spent in the network of nodes, longer than the optimal path. The optimal path is defined as the quickest route from the cross-docks directly to the container terminal, this has been depicted by the orange arrows in Figure 3. Goods following this optimal route will only be required to spend two discrete time steps k in the network. The equation for the KPI is shown in Equation 11. The goal is to minimize this accumulated sum.

$$\tau = \sum_{j \in P} p_j(k) - \sum_{j \in P} x_{ij}(k + len) \qquad \forall k \in N_p \tag{11}$$

τ, which represents the *Accumulated Node Time* over the course of the prediction horizon, is equal to zero if the products entering the network from the production lines are directly cross-docked and are not being stored in the warehouse. If products spend more time in the supply chain, the equation becomes larger than zero. *len* denotes the number of nodes part of the optimal path, which is two in this case.

5.6.2. Truck Shuttle Deviation

This KPI will measure the deviation in transportation needed from the brewery to the inland container terminal, based on the fluctuating production output. If the transportation deviation is considered high, it is hard to plan and predict future needs in terms of containers and trucks. If this deviation is low over time, the number of trucks and containers required per hour will be more steady state.

This deviation will be measured by monitoring the output of the container flow decision variable l_j. Within the simulation, this decision variable has a certain length which denotes the maximum number of trucks per iteration. Based on this capacity constraint, the decision variable chooses the most optimal number of trucks per iteration. The variance formula is depicted in Equation 12.

$$\sigma = \sqrt{\frac{\sum_{k \in N_p}(l_j - \mu)^2}{N_p}} \tag{12}$$

Where σ is the standard deviation and μ denotes the average number of trucks needed for container transportation for each iteration k the prediction horizon N_p.

5.6.3. Warehouse Inventory Levels

The average warehouse level can be measured over the prediction horizon N_p by Equation 13.

$$\nu = \frac{\sum_{k \in N_p} \sum_{j \in P}(x_{5j}(k) + x_{6j}(k))}{N_p} \tag{13}$$

Where, ν represents the average inventory level at node x_{5j} and x_{6j} (see Figure 3) for all SKUs j over the complete prediction horizon N_p. Besides the average level, the simulation run's peak inventory level (ρ) will also be measured. This formula is presented in Equation 14.

$$\rho = \max_{k \in N_p}(x_{5j}(k) + x_{6j}(k)) \tag{14}$$

6. MPC Simulation

The dynamic mathematical model presented in Figure 3 has been implemented in Python with the use of the Gurobi solver. All simulation runs were performed on a laptop with 16GB onboard memory, a 3.10GHz quad-core Intel Core i7 processor, and Gurobi Optimizer version 10.0.1. Determining the prediction horizon and discrete-time step is important, as the computational burden increases with smaller time steps and larger horizons. The supply chain dynamics, such as production output and truck shuttles, should also be considered when selecting a time step. A discrete-time step of one hour has been chosen, as it aligns with the changing dynamics of the system. The simulation parameters in Table 4 have been set based on the rolling production plan for the upcoming week.

Simulation Parameters	
Prediction Horizon (N_p)	1 week
Discrete-time instant (k)	1 hour

Table 4: Simulation Parameters

Furthermore, the simulation runs will be performed using historical production data of the Heineken brewery in Zoeterwoude. This data was preprocessed from batch processes in hectoliters to hourly output data in the number of pallets per SKU. This study uses two distinct datasets; an average production week and a peak production week (see Table 5).

Production Data	
Average Production Week	
Number of Pallets	21 220
Number of SKUs (j)	63
Peak Production Week	
Number of Pallets	24 075
Number of SKUs (j)	64

Table 5: Simulation Parameters

The capacity constraints are presented in Table 6.

Constraint Values	
x_{max}	[200, 200, 400, 400, 400, 5 000, 10 000]
u_{max}	[200, 400, 400]
X_{max}	[600, 600, 600, 600, 20 000, 30 000, 50 000]

Table 6: Capacity Constraint for all flows, nodes, and SKUs per node.

6.1. Simulation Objective

In line with the introduced *Accumulated Node Time* KPI, the objective is to optimize the flow for each SKU through the network of nodes. The *Control Centre* will be implemented as a central agent; therefore a linear objective function is introduced that will be minimized to simulate the required behavior. The objective implemented in the MPC model, and applicable to both the current and future scenario, can mathematically be represented in the following way:

$$J = min \sum_{i \in X} \sum_{j \in P} x_{ij}(k) * Q \quad \forall k \in N_p \tag{15}$$

In Equation 15, the number of pallets of each SKU j stored at each node i is minimized based on the associated weights **Q** for each i in the network of nodes. In order to align the mathematical expression in Equation 15 with the introduced KPIs, the nodes modeled as the warehouse nodes carry the highest weight in **Q**. The associated weights are presented in Table 7. Due to the lowest objective weight at node 7, a pull flow assignment will be created.

Objective Weights							
Node i	1	2	3	4	5	6	7
Weights Q	10	10	10	10	100	100	1

Table 7: Objective weight **Q** for each node

6.2. Current State & Future State

Based on the general layout visible in Figure 3, this section will provide the layout of the current state with information asymmetries which will be introduced as the *Asymmetric Control Center* (Figure 4). Whereas, the future state with real-time data will be introduced as *Real-Time Control Centre* (Figure 5).

6.2.1. Asymmetric Control Centre Model

In Figure 4, the schematic node representation of the *Asymmetric Control Centre Model* can be observed. Here, the information asymmetries are displayed in red. On the one hand, the delay between the control center and the physical state of the warehouse. On the other hand, the uncertainty of container availability. The information asymmetries are modeled in accordance with the quantification in Table 3. The delay regarding the production and delivery orders is assumed to be set and not further considered in this research. The state space of the asymmetric model differs from the one presented in section 8, and is presented in the full report of this thesis research. Furthermore, the uncertainty of the container availability is modeled as a probability distribution, where the probability of a container being available is set to 89%.

6.2.2. Real-Time Control Centre Model

Figure 5 represents the symmetric, real-time model where no information asymmetries are present. The state space representation can be found in section 8.

6.3. Simulation Scenarios

To compare the Current State model with the Future State model and, to measure the impact of the individual information asymmetries in the Current State model, four different simulation scenarios will be performed. All scenarios will be performed with the average production data and peak production data, as provided in Table 5. Also, each run will be performed

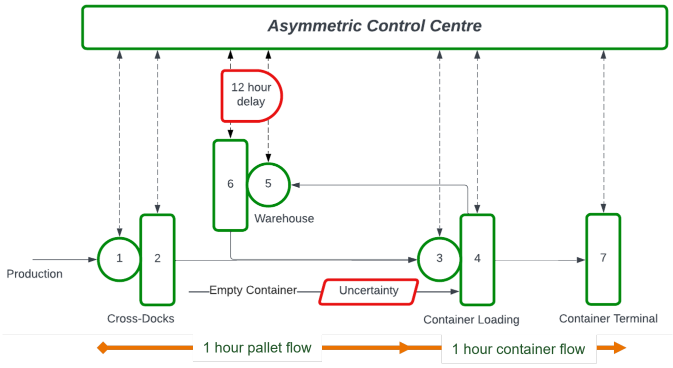

Figure 4: Node Network Configuration of asymmetric model

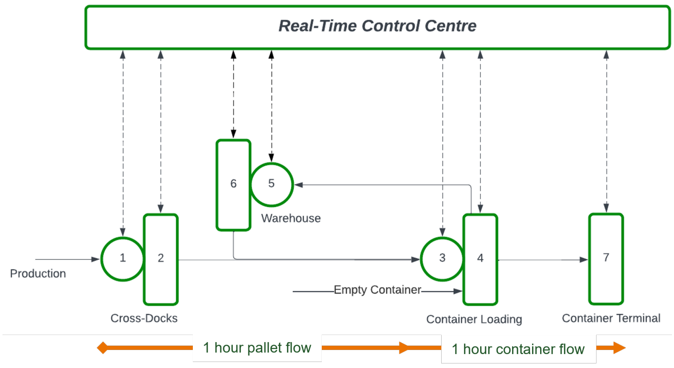

Figure 5: Node Network Configuration of symmetric model

three times, where respectively 5, 7, and 9 trucks are considered as the maximum number of trucks available. The first run will solely simulate the warehouse asymmetry in the Current State. Secondly, only the container availability asymmetry will be modeled in the Current State. Then, scenarios 1 and 2 will be combined into the full Current State Model. Lastly, the three aforementioned scenarios will be compared to the Future State scenario, in which the information asymmetries are eliminated and data is assumed to be real-time.

7. Results

7.1. Scenario 1: Warehouse Asymmetry

The simulations in this section will represent the current state model, which is solely prone to information delay regarding the inventory levels in the warehouse. The performance of the different runs considering the KPIs has been listed in Table 8, where the first runs are performed with the use of data from an average production week, and the second runs with peak production data. It is observed that the *Accumulated Node Time* τ decreases, with increasing available trucks for the transportation between the production plant and the inland container terminal. Also, it can be seen that Run 1.1 and Run 2.2 have no pallets running through the warehouse, due to the high number of available trucks for container transportation. The average inventory levels (ν) for the second runs are significantly higher compared to the first run.

	Data	**Trucks**	τ	σ	ν	ρ
Run 1.1	Average	5	10 291	0.38	1 055	2 374
Run 1.2	Average	7	6 271	1.72	1	322
Run 1.3	Average	9	5 744	2.03	1	277
Run 2.1	Peak	5	14 041	0.38	4 548	5 830
Run 2.2	Peak	7	10 493	0.89	1 330	2 479
Run 2.3	Peak	9	8 080	2.45	134	943

Table 8: Scenario 1 Performance. Where τ is the accumulated node time (hours), σ is the standard deviation of the required number of trucks per iteration, ν is the average warehouse inventory (pallets), and ρ represents the peak inventory level (pallets).

7.2. Scenario 2: Container Availability Asymmetry

In Scenario 2, the information asymmetry is simulated by setting the probability distribution regarding the container availability (c) to 90%. As a consequence, only 90% of the required containers will be available, in addition to the restricted number of trucks available for each simulation run. Furthermore, warehouse asymmetry is not considered in this simulation run. The results can be found in Table 9.

	Data	**Trucks**	τ	σ	ν	ρ
Run 3.1	Average	5	12 579	1.55	1 828	3 520
Run 3.2	Average	7	8 332	2.34	1	177
Run 3.3	Average	9	7 594	2.91	1	177
Run 4.1	Peak	5	15 169	1.43	5 250	7 260
Run 4.2	Peak	7	12 861	2.17	2 363	3 540
Run 4.3	Peak	9	9 514	2.88	215	799

Table 9: Scenario 2 Performance. Where τ is the accumulated node time (hours), σ is the standard deviation of the required number of trucks per iteration, ν is the average warehouse inventory (pallets), and ρ represents the peak inventory level (pallets).

7.3. Scenario 3: Combination Scenario 1 & 2

This scenario combines the previous two scenarios and shows the results if both information asymmetries are present in the system. It can be observed that scenario 3 performs very similarly compared to the KPI performances depicted in Table 9. Hence, it is concluded that the container availability with 90% has a more significant impact on the performances of the KPI in comparison the the warehouse asymmetry of 12 hours.

	Data	**Trucks**	τ	σ	ν	ρ
Run 5.1	Average	5	12 942	1.65	2 005	3 642
Run 5.2	Average	7	8 232	2.35	1	322
Run 5.3	Average	9	7 779	3.05	1	322
Run 6.1	Peak	5	14 834	1.45	4 825	6 198
Run 6.2	Peak	7	13 556	2.42	3 179	4 687
Run 6.3	Peak	9	10 128	3.35	496	1 243

Table 10: Scenario 4 Performance. Where τ is the accumulated node time (hours), σ is the standard deviation of the required number of trucks per iteration, ν is the average warehouse inventory (pallets), and ρ represents the peak inventory level (pallets).

7.4. Scenario 4: Real-Time Control

Lastly, this simulation has been used to simulate the future state in which the data is considered to be real-time and the information asymmetries are therefore omitted.

	Data	Trucks	τ	σ	ν	ρ
Run 7.1	Average	5	10 619	0.23	850	1 959
Run 7.2	Average	7	6 314	1.72	1	177
Run 7.3	Average	9	5 731	2.03	1	177
Run 8.1	Peak	5	14 209	0.31	4 567	6 241
Run 8.2	Peak	7	10 442	0.89	1 120	2 154
Run 8.3	Peak	9	7 946	2.45	94	685

Table 11: Scenario 3 Performance. Where τ is the accumulated node time (hours), σ is the standard deviation of the required number of trucks per iteration, ν is the average warehouse inventory (pallets), and ρ represents the peak inventory level (pallets).

7.5. Altering Prediction Horizons

In addition to the prediction horizon of a single week, the effects of a varying prediction horizon are accounted for. The *Real-Time Control Centre* with peak production data and 7 trucks available is modeled with prediction horizons of 3.5 and 14 days, in addition to the simulation runs performed for 7 days. The results of these simulations are visible in Table 12 and Figure 6.

Pred Horizon	Trucks	τ	σ	ν	ρ
3.5 Days	7	11 652	0.76	939	1 414
7 Days	7	10 442	0.89	1 120	2 154
14 Days	7	8 245	1.16	93	631

Table 12: Performance of varying prediction horizons with 7 trucks available while using peak data. The *Accumulated Node Time (τ)* is normalized to 7 days to make the numbers comparable with differing prediction horizons.

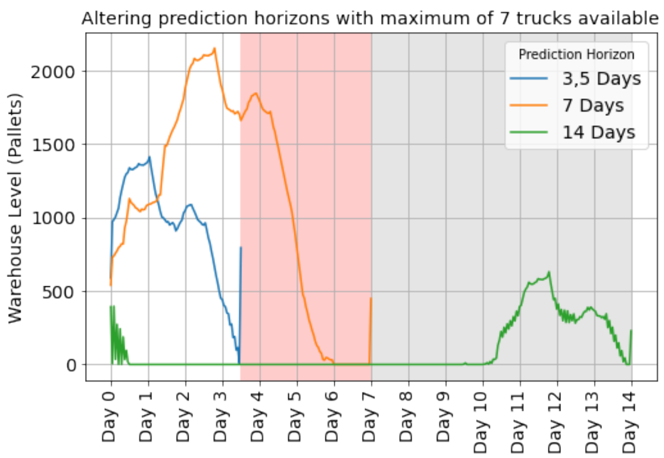

Figure 6: Real-Time Control Center warehouse levels, where a maximum of 7 trucks are available, using peak data for prediction horizons of 3.5, 7, and 14 days.

Due to the objective function, which enables optimal flow through the network of nodes, it is observed that the simulation with a 14-day prediction horizon allows for the lowest *Accumulatd Node Time*, while also the warehouse levels are the most optimal throughout the length of the horizon. Only the *Truck Shuttle Deviation* deteriorates with a longer prediction horizon.

7.6. Results Discussion

Firstly, it should be noted that the results of the peak warehouse levels (ρ) in Table 8, Table 9, Table 10 and, Table 11 with values above 4000 pallets show an infeasible solution since the warehouse would overflow in these cases. For these runs, it can be either concluded that the number of available trucks was not sufficient or the container availability percentage was too low.

Then, the most significant results will be compared. Firstly, Run 5.1 is compared with Run 7.1, in both runs a maximum number of 5 trucks per iteration were available. Also, Run 5.1 represents the full *Asymmetric Control Centre* and Run 7.1 represents the *Real-Time Control Centre.* Figure 7 depicts the combined warehouses levels for an average production week.

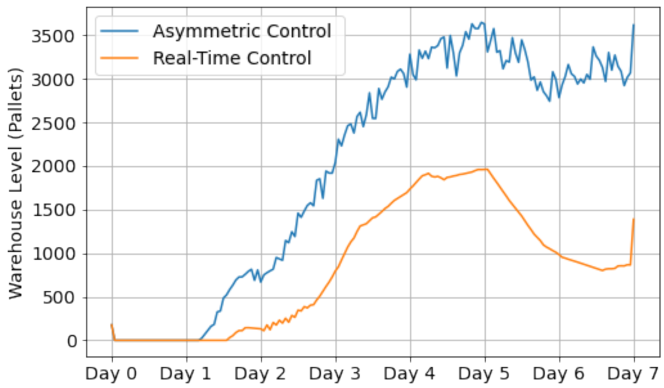

Figure 7: Warehouse levels of Run 5.1 and 7.1, where the Asymmetric Control Centre performance is compared to the Real-Time Control Centre. Parameters were set to a maximum availability of 5 trucks and data of an average production week was used.

It is observed that the warehouse level starts increasing for both simulations over Day 1. It can be concluded that the combination of trucks available and uncertainty in container arrival causes warehouse levels to rise. Due to the container asymmetry in the Asymmetric Control, only 735 containers were transported to the inland terminal. While in the Real-Time Control model, a total of 837 containers were transported. In conclusion, the Real-Time Control Centre performs better regarding average and peak warehouse levels and, truck usage variation. Also, the Accumulated Node Time decreased from 12943 to 10619. Consequently, the Real-Time Control Centre can handle the fluctuating production output more efficiently by using less storage capacity of the warehouse and enabling efficient flow through the network while also considering steady-state truck usage.

Similarly, the results of Run 6.3 and Run 8.3 have been compared. The warehouse levels and boxplots of the deviation in truck usage have been displayed in Figure 8 and Figure 9, respectively. In Figure 8, the warehouse levels of both runs decline to zero over time due to the availability of 9 trucks. This can also be seen in Figure 9, where both the Asymmetric and the Real-Time models move 1,139 loaded containers to the inland terminal. As a result, the warehouse levels deviate to zero over time. Due to the 90% container availability of the Asymmetric Control, the warehouse levels take longer to decline to zero. Also, a lower standard deviation in the required number of trucks is observed in Run 8.3, as well as a lower Accumulated Node Time (visible in Table 10 and Table 11). Lastly, the warehouse asymmetry has been found to have less impact on the four performance indicators than the container availability asymmetry. This is concluded by comparing Table 8 and Table 11.

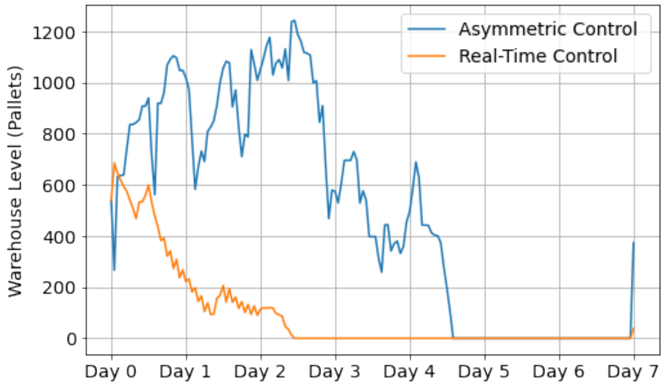

Figure 8: Warehouse levels of Run 6.3 and 8.3, where the Asymmetric Control Centre performance is compared to the Real-Time Control Centre. Parameters were set to a maximum availability of 9 trucks, and data of a peak production week was used.

Figure 9: Box plot comparison of Run 6.3 and 8.3, where the Asymmetric Control Centre performance is compared to the Real-Time Control Centre. Parameters were set to a maximum availability of 9 trucks, and data of a peak production week was used. At the bottom, the total number of rides per simulation is visible.

Considering all results, it can be concluded that the Future State control method enables increased decision support in the outbound logistic network of the Heineken brewery. Through real-time data, warehouse levels are lower, logistic movements are more steady-state, and pallets spend less time at the production facility on average. In addition, it is concluded that a longer prediction horizon yields better performance in terms of the *Accumulated Node Time*.

8. Conclusions & Future Research

To achieve competitiveness, companies are highly agile in improving the robustness of their supply chain system by being responsive to external events, especially after experiencing the effects of a macro pandemic on the global supply chain system. Similarly, the world's second-largest beer brewer Heineken, with major exporting production plants in The Netherlands, requires a robust and transparent supply chain. This research has investigated the effects of the current logistic planning tool on the logistic network at Heineken. Thereby considering all aspects of the network; production, cross-docking, warehousing, JIT container loading, and container transport. Based on the current state analysis, several information asymmetries were found to be present between the centralized planning tool and the physical states of goods. These asymmetries consisted of a warehousing time delay and the inability to collect data on the container status at the inland container terminal, resulting in an inefficient information feedback loop.

This study contributes to the scientific literature by using the case study at Heineken to research the effects of centralized MPC with real-time data compared to centralized MPC with the current information asymmetries present. An Asymmetric Control Centre replaced the existing planning tool to simulate the Current State, while a Real-Time Control Centre was used to represent the Future State. Considering the high weekly fluctuations in the production plants' output, CMPC was found to be a suitable strategy for planning outbound logistics due to MPC's adaptable and predictive characteristics. Based on four introduced key performance indicators, it was found that the Real-Time Control Centre, performs better on all four KPIs; the accumulated node time decreased while the average and peak warehouse levels declined. Also, the Real-Time Control Centre enables a more steady state container transportation due to the lower deviation in required truck rides. Consequently, the Real-Time Control Centre copes better with fluctuating production output. It enables products to flow through the network more efficiently, decreasing the warehousing strain at Heineken. Furthermore, it was concluded that the container availability asymmetry has a larger impact on the logistic network than the warehouse asymmetry. Lastly, by studying the effect of altered prediction horizons, a longer prediction horizon was found to be beneficial in terms of the *Accumulated Node Time*, also in terms of warehouse occupation, the longer prediction horizon showed the best results.

Based on this research, several suggestions for future research can be made. Firstly, this study assumed that production output was set and not changeable throughout the prediction horizon. However, in the real-world scenario, the production schedule can be changed if it causes obstructions in the outbound logistics. Furthermore, MPC can be used to plan the outbound logistics on a larger scale, therefore incorporating all network nodes till the deep-sea port, as was depicted in Figure 1. Future research should evaluate the possibility of enlarging the scope and include more nodes in the network, starting with the ability to alter production schedules based on the calculated logistic impact. Moreover, future research should incorporate the effects of varying prediction horizons. While this research incorporated models with different prediction horizons, more research should be computed in terms of optimal solutions with contradictory objectives. Lastly, the computational efficiency of the algorithm was not explicitly measured in this research; however, to construct an efficient planning tool that can replace the current planning structure at Heineken, the computational efficiency of the algorithm should be assessed.

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Appendix A. Model Matrix Representation

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{A.1}$$

$$\mathbf{B}_u = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \\ 0 & 0 & 0 \end{bmatrix} \tag{A.2}$$

$$\mathbf{B}_l = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ -1 & -1 & -1 & \dots & -1 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix} \tag{A.3}$$

$$\mathbf{B}_p = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{A.4}$$

B

Appendix B

B.1. Asymmetric Control Centre Model Matrix Representation

$$\mathbf{A} = \begin{bmatrix}
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
1&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&1&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&1&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1
\end{bmatrix} \tag{B.1}$$

$$\mathbf{B}_u = \begin{bmatrix}
0&0&0\\
-1&0&0\\
1&0&1\\
0&-1&0\\
0&1&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&0\\
0&0&-1\\
0&0&0
\end{bmatrix} \tag{B.2}$$

$$\mathbf{B}_l = \begin{bmatrix}
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
-1&-1&-1&\dots&-1\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
0&0&0&\dots&0\\
1&1&1&\dots&1
\end{bmatrix} \tag{B.3}$$

$$\mathbf{B}_p = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{B.4}$$

B.2. Real-Time Control Centre Model Matrix Representation

$$\mathbf{A} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{B.5}$$

$$\mathbf{B}_u = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 0 & 0 \\ 1 & 0 & 1 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & -1 \\ 0 & 0 & 0 \end{bmatrix} \tag{B.6}$$

$$\mathbf{B}_l = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ -1 & -1 & -1 & \dots & -1 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix} \tag{B.7}$$

$$\mathbf{B}_p = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \tag{B.8}$$

B.3. Simulation Parameters

B.3.1. Capacity Constraints Asymmetric Control Model

Constraint	Values
x_{max}	[200, 200, 400, 400, 400, 400, 400, 400, 400, 400, 400, 400, 400, 400, 400, 400, 5000, 10000]
u_{max}	[200, 400, 400]
X_{max}	[600, 600, 600, 600, 600, 600, 600, 600, 600, 600, 600, 600, 600, 600, 600, 20000, 30000, 50000]

Table B.1: Capacity Constraint Real-Time Control Model for all flows, nodes, and SKUs per node.

B.3.2. Capacity Constraints Real-Time Control Model

Constraint	Values
x_{max}	[200, 200, 400, 400, 400, 5000, 10000]
u_{max}	[200, 400, 400]
X_{max}	[600, 600, 600, 600, 20000, 30000, 50000]

Table B.2: Capacity Constraint Real-Time Control Model for all flows, nodes, and SKUs per node.

B.4. Simulation Data - 7 days

Figure B.1 and Figure B.2 depicts the palletized production output per SKU of an average production week and a peak production week, respectively. While, Figure B.3 and Figure B.4 show the accumulated palletized production output for all SKUs combined for both production weeks.

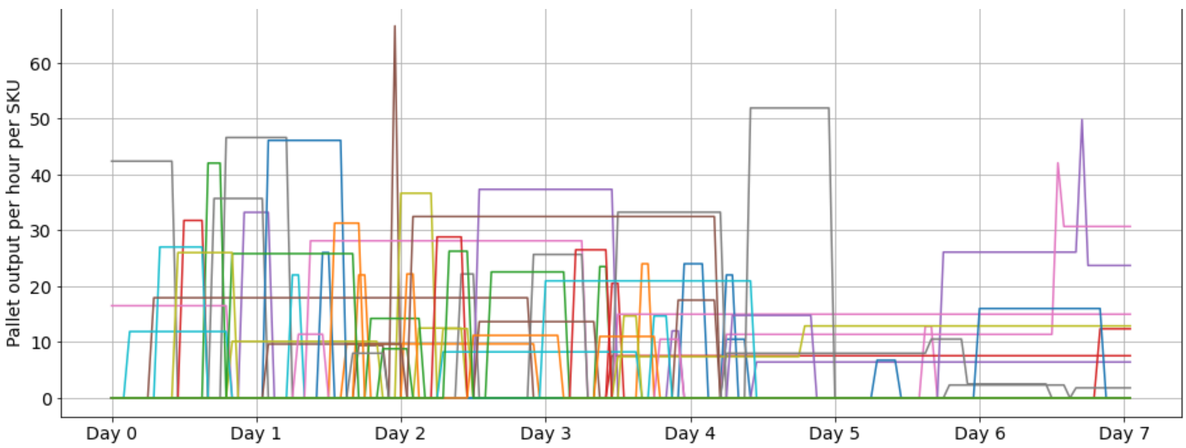

Figure B.1: Palletized production output of average week (2022) per SKU.

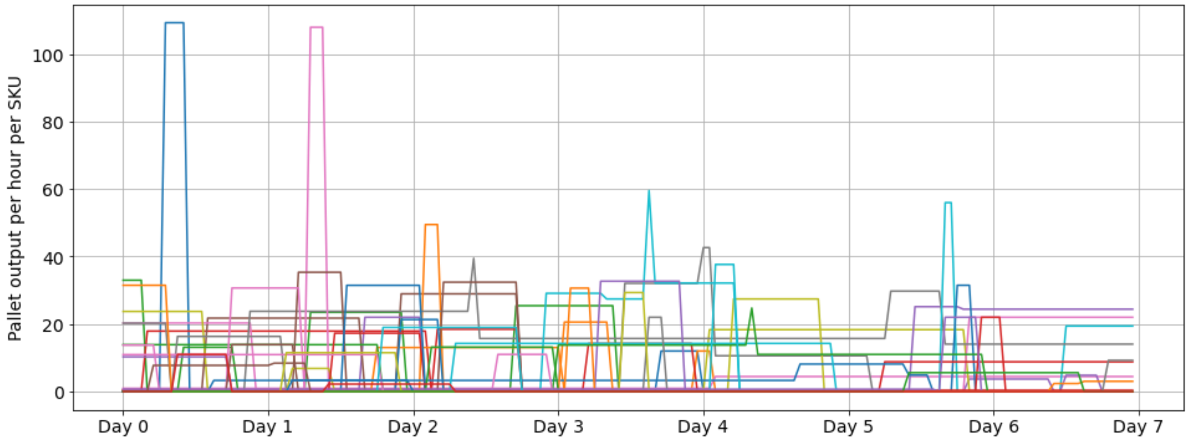

Figure B.2: Palletized production output of peak week (2022) per SKU.

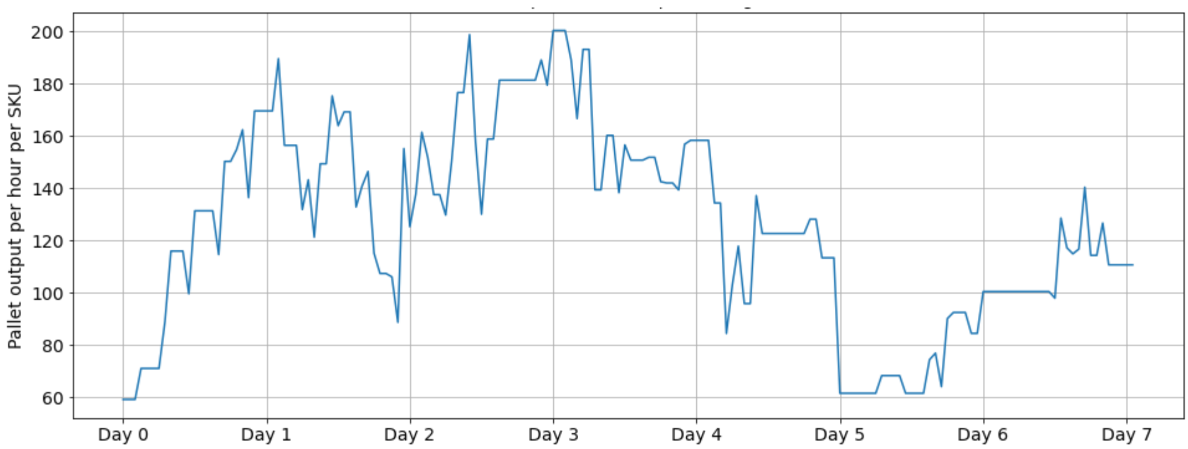

Figure B.3: Palletized production output of average week (2022).

Figure B.4: Palletized production output of peak week (2022).

Figure B.5, depicts the simulation constraints where the number of pallets per container is determined based on historical data over 2022. In 2022, 277 different SKUs were produced. For each SKU, Figure B.5 depicts the number of pallets per container. It is observed that mainly 22 pallets are loaded into a container, corresponding with a 40 ft container.

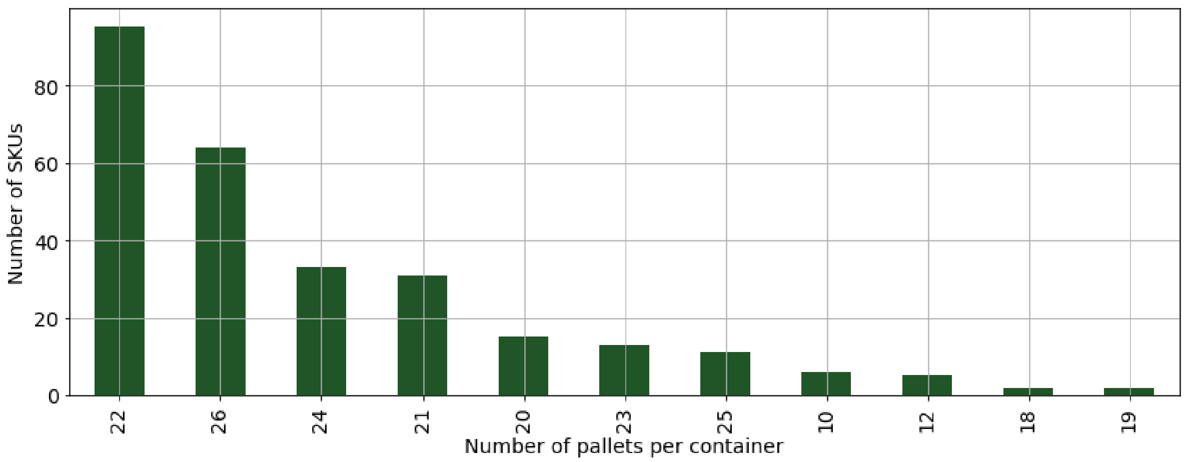

Figure B.5: Number of pallets per container per SKU used for the simulation, based on historical data over 2022.

B.5. Simulation Data - Altering Prediction Horizon

In addition to the simulation runs performed over seven days, different prediction horizons with 3,5, and 14 days have been used in the simulations. The datasets used for these simulations are compared to the peak week data used in the seven-day simulations. Figure B.6 depicts the accumulated production output over 3.5 days, while Figure B.7 shows to accumulated production output over 14 days.

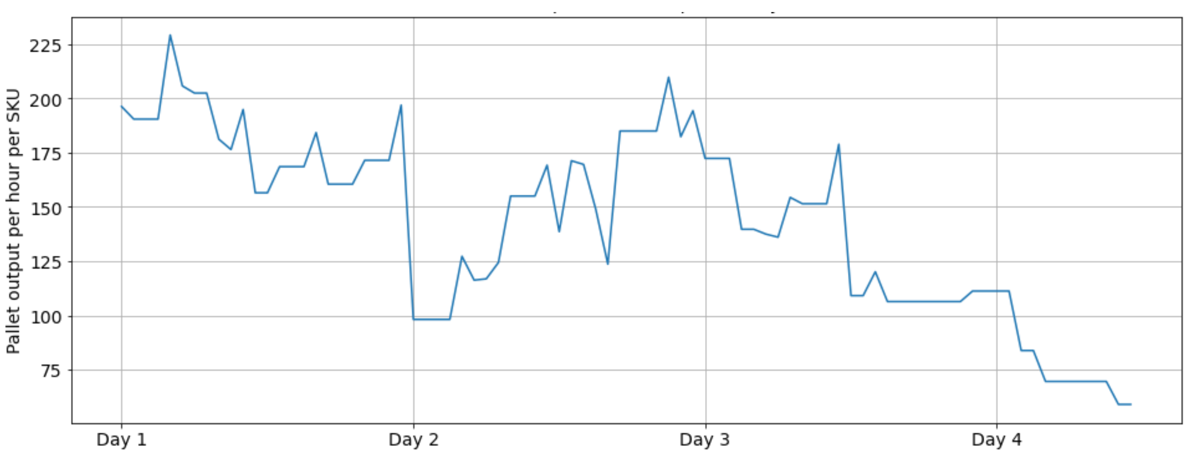

Figure B.6: Palletized production output for 3,5 days.

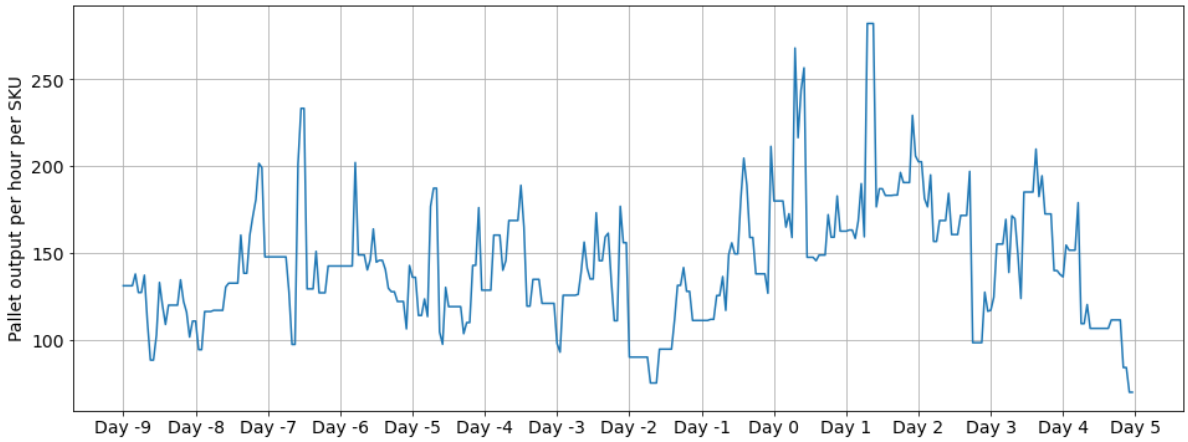

Figure B.7: Palletized production output for 14 days.

B.6. Results

Table B.3 displays the performance for each KPI per simulation run as presented in chapter 8.

Simulation		Max Trucks Available	Data	Accumulated Node Time (hours)	Truck Shuttle Deviation	Average Warehouse Level (pallets)	Peak Warehouse Level (pallets)
Scenario 1							
	Run 1.1	5	Average	10 291	0.38	1 055	2 374
	Run 1.2	7	Average	6 271	1.72	2	322
	Run 1.3	9	Average	5 744	2.03	2	277
	Run 2.1	5	Peak	14 041	0.38	4 548	5 830
	Run 2.2	7	Peak	10 493	0.89	1 330	2 479
	Run 2.3	9	Peak	8 080	2.45	134	943
Scenario 2							
	Run 3.1	5	Average	12 579	1.55	1 828	3 520
	Run 3.2	7	Average	8 332	2.34	1	177
	Run 3.3	9	Average	7 594	2.91	1	177
	Run 4.1	5	Peak	15 169	1.43	5 250	7 260
	Run 4.2	7	Peak	12 861	2.17	2 363	3 540
	Run 4.3	9	Peak	9 514	2.88	215	799
Scenario 3							
	Run 5.1	5	Average	12 942	1.65	2005	3 642
	Run 5.2	7	Average	8 232	2.35	17	322
	Run 5.3	9	Average	7 779	3.05	2	322
	Run 6.1	5	Peak	14 834	1.45	4 825	6 198
	Run 6.2	7	Peak	13 556	2.42	3 179	4 687
	Run 6.3	9	Peak	10 128	3.35	496	1 243
Scenario 4							
	Run 7.1	5	Average	10 619	0.23	850	1 959
	Run 7.2	7	Average	6 314	1.72	1	177
	Run 7.3	9	Average	5 731	2.03	1	177
	Run 8.1	5	Peak	14 209	0.31	4 567	6 241
	Run 8.2	7	Peak	10 442	0.89	1 120	2 154
	Run 8.3	9	Peak	7 946	2.45	94	685

Table B.3: Simulation results