MASTER

Vendor managed inventory optimization in an FMCG company
A case study at Mars

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Vendor managed inventory optimization in an FMCG company

A case study at Mars

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Abstract

This study explores the implementation of Vendor-Managed Inventory (VMI) in a large Fast Moving Consumer Goods (FMCG) company, addressing capacity constraints within an undefined inventory process. An inventory model is developed to improve the supplier-buyer relationship between Mars and its respective suppliers. The focus of this multi-item, multi-period inventory system is to determine cost-efficient bounds for Vendor-Managed Inventory (VMI) suppliers. The model uses a simulation-optimization approach to determine (near-)optimal inventory levels, addressing the challenges posed by the highly variable MRP (Material Requirements Planning) schedule. The cost-efficient bounds are found in a capacitated and uncapacitated inventory model and explorations for supply chain improvements for both supply chain partners have been established. Finally, potential process improvements are detected to reshape the collaboration approach and find potential next steps for further collaboration.

Keywords: *VMI, VMCI, vendor managed inventory, simulation-optimization, inventory optimization, capacitated, non-stationary demand, supply chain collaboration, information sharing*

Executive Summary

Introduction

In Vendor-Managed Inventory, the core idea is to have the vendor, in the case of Mars the supplier manage the inventory. Each supplier should perform this task to the best of their ability. However, the vendor might have conflicting interests with the buyer or the vendor does not know what the buyer expects. To address this, this research aims to perform a case study on how to manage a Vendor-Managed Inventory process from a buyer perspective to generate an implementable system based on three core components: the visibility of the process, setting the best bounds, and finally establishing a framework for continuous improvement. This analysis is performed on these three core components, the products and their respective properties, the supplier process, and the buyer process to improve synchronization between those aspects.

Problem statement

The issue at the core of the Vendor-Managed Inventory structure of Mars Raw and Pack is evident. The current inventory management approach results in suboptimal performance due to a lack of transparency in the supplier process, an inability to set clear targets for suppliers, and an inability to measure suppliers accordingly. Additionally, the rationale behind the relatively high stock levels, the prevalence of obsolete materials, the limited spare capacity in the warehouse, and the unsatisfactory service level the rationale remains unclear.

Research design

In light of the aforementioned problem statement, a research design has been devised, encompassing the various issues identified therein. Firstly, it is necessary to establish the root cause analysis, which will identify the key drivers for the high stock levels with the associated low service. This will also determine which suppliers perform well and which suppliers perform poorly, as well as establish what is being asked of suppliers. Subsequently, the root cause analysis also seeks to identify deficiencies within the inventory control system and to develop differentiated policies for different types of items. Finally, a simulation-optimization procedure has been established to identify the optimal bounds to share with the respective suppliers, to advance the capability maturity model integration from its current initial stage to a managed, defined, quantitatively managed, and finally a continuous improvement stage. The process involves proactively monitoring suppliers, defining improvement directions, and identifying optimal bounds for products and their suppliers. It transitions from a reactive method of raw and pack inventory control to a proactive and forward-thinking strategy.

Findings and Recommendations

The research identifies the critical factors for improving the Vendor-Managed Inventory process at Mars, with a particular emphasis on process redesign. In particular, it is necessary to determine how to manage a supplier, what targets should be set for the supplier, how to improve the relationship with the supplier, and what the next steps should be for more accurate stock level settings, integrated cost models, and better feedback. Based on this, the feasible opportunities for improving the overall parameters within Mars are described to establish which parameters influence the overall performance within the Vendor-Managed Inventory structure within Mars and to what extent. The key finding of the simulation-optimization model is the value of supplier synchronization for reducing inventory levels, improving fill rate, and reducing costs as given in Table 0.1.

Policy type	Fill rate	Inventory	Cost
Asynchronous suppliers	-	-	-
Optimization	+1.21%	+7.39%	-7.47%
Optimization including segmentation for Flexibles and Cartons	+2.09%	-18.63%	-8.86%

Table 0.1: The value of supplier synchronization

Framework

The framework for this process is based on four critical indicators, addressing the shortcomings of the previous approach. As shown in Figure 0.1, the pillars: capacity planning, inventory control, optimization, and feedback work collectively to elevate the process maturity from a managed stage to a fully scoped and transparent procedure. This transition enables proactive supplier management by incorporating new methods of information sharing. The resulting process is both manageable and quantitative, with the potential for continuous improvements.

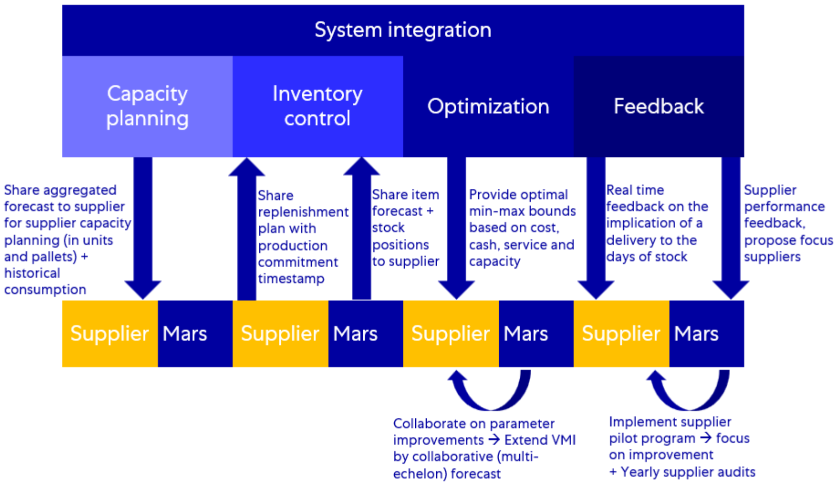

Figure 0.1: System Integration

Process redesign

The research identifies the transition required for Mars to evolve from a reactive inventory process to a quantitatively managed system. Insights from supplier pilots revealed the root causes of over- and understocking, leading to the implementation of supplier-specific processes for proactive inventory control. A feedback cycle has been established, enabling synchronized decision-making and measurable improvements in policy effectiveness. The model highlights that achieving higher fill rates requires either capacity expansion or item segmentation. These findings lay the foundation for a manageable and continuously optimized process to ensure the right inventory levels while supporting future scalability.

Parameter redesign

The research highlights several opportunities for improving inventory performance and cost efficiency. First, Increasing the service level to 97% is feasible within the current capacity, but it incurs significant costs, highlighting the need to evaluate trade-offs between warehouse expansion and more frequent setups. Second, optimizing Minimum Order Quantities (MOQs) offers limited inventory reduction but remains an area for improvement. Third, service segmentation can be enhanced with better data quality, resulting in notable outcomes: a 52.73% reduction in inventory costs, a 32.08% decrease in inventory levels, and a 3.85% improvement in fill rate through item-level segmentation. Additionally, reducing lead times, as informed by Supplier analysis, proves valuable for cost reduction and performance improvement.

Conclusion

This research establishes a comprehensive framework for managing Vendor-Managed Inventory (VMI) suppliers within Mars, addressing key inefficiencies in transparency, inventory control, and supplier performance. The findings demonstrate that segmentation and parameter optimization can significantly reduce inventory costs and levels while improving service levels. Achieving these gains requires structured data management to enhance insights into economic lot sizing and demand classification. Further refinement of the optimization model, integrating forecast accuracy and demand variability, will unlock additional potential for cost and inventory reductions, fostering a more proactive and collaborative supply chain strategy. Therefore it is advised to implement the supplier synchronization process, establish capacity planning with suppliers, close the feedback loop, and define optimal bounds for all suppliers.

Preface

This report is the result of my graduation project that has been conducted to fulfill the graduation requirements for the Master of Science degree in Operations Management and Logistics at Eindhoven University of Technology.

First of all, I want to thank Karel van Donselaar. This project would not have been what it is now without your guidance and knowledge about the topic. Although you guided the project in a sometimes challenging direction, I have learned a lot during the process. I appreciate that you always made time to answer my questions with great enthusiasm. Secondly, I would like to thank Melvin Drent for providing me with useful, critical feedback. I appreciate that you were always flexible and helpful.

Furthermore, I am grateful that I got the opportunity to conduct my project at Mars. I want to thank Mark Goorts for all his support and for getting me in touch with the right people and especially for remaining very invested in my project. In addition, I also want to thank Indraneel Roy Choudhary for guiding me in the last months of the thesis.

Finally, I want to thank my girlfriend, friends, and family for always being there for me and for providing the distraction that was often needed. Without you, my time as a student in Eindhoven would not have been as memorable as it is now. As this graduation project marks the end of my studies, it also marks the end of my time as a student. A journey where I have not only learned a lot but especially also had a lot of fun. I am grateful for everyone who supported me during this period.

Daan van Strien, December 2024

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List of abbreviations

Abbreviation	Definition
ADI	Average Demand Interval
ANOVA	Analysis of Variance
AFR	Aggregated Fill Rate
BOM	Bill of Materials
CO_2	Carbon Dioxide
CoV	Coefficient of Variation
CSV	Comma Separated Values
DOC	Demonstrated Output Capacity
EDI	Electronic Data Interchange
EOQ	Economic Order Quantity
EOI	Economic Order Interval
E2E	End-to-End
FG	Finished Good
FMCG	Fast Moving Consumer Goods
JELS	Joint Economic Lot Size
KPI	Key Performance Indicator
LA	Logistical Agreement
MEIO	Multi-echelon Inventory Optimization
MRP	Material Requirements Planning
MOQ	Minimum Order Quantity
OUTL	Order Up to Level
Q	Order Quantity
PO	Purchase Order
ROL	Reorder Level
SCR	Supplier Connectivity Report
SLA	Service Level Agreement
SOC	Scheduled Output Capacity
S&OE	Sales and Operations Execution
S&OP	Sales and Operations Planning
SKU	Stock Keeping Unit
VMI	Vendor Managed Inventory
VMCI	Vendor Managed Consignment Inventory
NL01	Mars Factory in Veghel, the Netherlands
FR08	Mars Factory in France
DE04	Mars Factory in Germany
GB18	Mars Factory in the UK
PL01	Mars Factory in Poland

Contents

1 | Introduction

This introduction offers an overview of the company and the challenges addressed in this master's thesis. The research focuses on optimizing inventory levels within a Vendor-Managed Inventory structure. To provide a clear framework for this study, the company is introduced, the problem statement is defined, and the research questions are formulated. Additionally, the methodology employed to address these research questions is outlined. Finally, the structure of the thesis is presented to guide the reader through the subsequent sections.

1.1 | Company Description

The company where the research will be conducted is Mars Wrigley located in Veghel. Mars Wrigley is the world's leading manufacturer of chocolate, chewing gum, mints, and fruity confections. Mars Wrigley employs approximately 30,000 associates globally and has operations in approximately 70 countries. Headquartered in Chicago, Illinois, USA, Mars Wrigley will distribute its world-famous brands including M&M's®, Snickers®, Twix®, Skittles® and Orbit® in more than 180 countries (MarsInc., 2024).

1.2 | Problem Statement

Mars is striving to improve its supply chain to become more data-driven and manage the supply chain end-to-end. Figure 1.1 depicts the complete end-to-end supply chain of Mars. This supply chain contains the demand planning and suppliers, the Materials and production planning, manufacturing, and supply. This research will concentrate on the section Materials & Production Planning to be managed in collaboration with respective suppliers. The current challenge lies in the inventories of packaging and raw materials due to a volatile market and unclear agreements with suppliers. Previously, inventory policies were managed by each local team at each production site whereas Mars has implemented a change to now manage nine production sites in Europe on a regional level, headquartered in Veghel. The objective is to create a method for optimizing inventory levels within the complexity of multiple suppliers, multiple sites, and a highly diversified product portfolio in a highly volatile market under limited warehouse capacity.

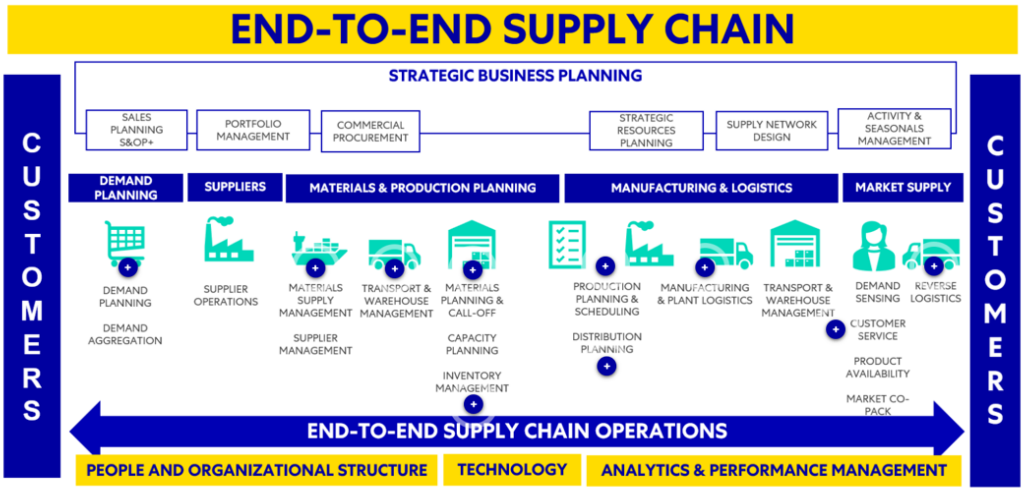


Figure 1.1: Supply chain Mars

Currently, the supply planning is asynchronous, with each site maintaining local policies to ensure sufficient stock is held for production. Furthermore, the supply planning is typically conducted with Vendor-Managed Inventory (VMI) or Vendor-Managed Consignment Inventory (VMCI), with a small part of purchase orders (PO) remaining but is likely to also shift to VMI or VMCI. This supply chain methodology provides supply chain collaboration to increase performance throughout the supply chain. However, no clear guidelines for suppliers have been established, thus resulting in no clear vision of performance leading to multiple stockouts and excessive stocks. Moreover, all Stock Keeping Units (SKUs) receive similar attention although some items provide much more value to the market or do not have very volatile demand, which removes complexity from the process. Therefore, a methodology has to be found to segment the SKUs further to be able to change from a reactive to a proactive approach.

1.2.1 | Supply chain analysis

The supply chain of Mars, in a Vendor-Managed Inventory (VMI) context, can be described from the perspectives of both information flow and product flow. From a perspective of product flow, demand is generated at the retailer, which requires finished goods and consequently raw and packaging materials. This is a general process found in several supply chains. Furthermore, the information also propagates in this manner, leading to a production forecast that is sent to the supplier due to the Vendor-Managed system Mars uses with its suppliers. Figure 1.2 shows the product flow and demand flow of items. Further deep-dive into this process is given in section 1.2.3. The subsequent sections of the problem statement aim to identify the key factors of data to be explained and to provide a more comprehensive understanding of the overall complexity of the problem.

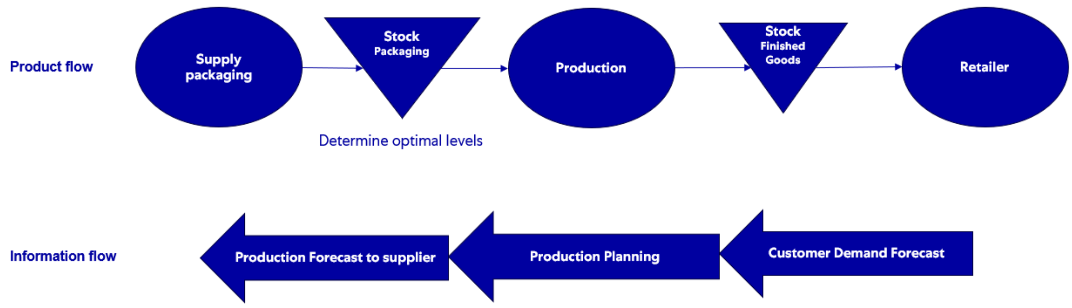


Figure 1.2: Product and information flow Mars

1.2.2 | Complexity

Mars Wrigley Europe oversees nine production facilities engaged in the manufacturing of either confectionery or gum. Collectively, these nine sites are supplied by 65 distinct suppliers, with approximately 20 of these suppliers specializing in flexible packaging and 45 specializing in carton packaging. Collectively, these suppliers deliver approximately 4,000 unique SKUs. Consequently, the complexity of items is considerable, and the types of suppliers are also diverse in terms of the number of SKUs delivered. The objective is to structure this complexity to reduce the difficulty of delivery. This will be achieved by improving information sharing and by measuring supplier performance to address any supplier that is underperforming.

Furthermore, the production of an end product requires the use of three or four distinct packaging materials. These can all be supplied by different suppliers. In addition, if one of those three or four materials is unavailable, the production of the product cannot be performed. Finally, the codes used to identify packaging materials frequently change, which reduces the ability to trace past demand. As a result, it is challenging to accurately determine the stock levels for new material codes.

1.2.3 | Current Process at Mars Packs

Currently, Mars operates under two replenishment principles, namely VMI and PO replenishment. The process for purchase orders is relatively straightforward, with Material Planners planning multiple weeks in advance based on the demand forecast of the production planning. This production planning works with two main parts, namely the Sales and Operations Execution (S&OE) and Sales and Operations Planning (S&OP+). The Sales and Operations Execution (S&OE), the business strategy, drives supply chain & performance excellence to deliver outstanding customer service through on-time and in-full delivery of the products of Mars. This planning process extends over the first three months, to reduce variability. However, as this process is difficult to manage as the aim for customer flexibility is high, the frozen period where the production is not permitted to change is only 1.5 weeks. As Mars is dealing with lead times of four weeks, the variability after this frozen period makes inventory management more challenging. The longer horizon approach is the Sales and Operations Planning (S&OP+) with the aim to look ahead from 3 to 18 months. This enables the company to align its supply chain with its long-term business goals. S&OP+ planning systems focus on the strategic promotion of products and the more detailed planning of the supply chain. Therefore, understanding this demand process is very important, and consequently how to adjust the inventory control policies to fit this production planning approach.

A significant portion of Mars's suppliers operate under a Vendor-Managed Inventory (VMI) system. In this system, suppliers receive demand forecasts from Mars, including total stock levels and a production planning forecast with a one-year weekly horizon. Based on this data, suppliers independently determine the quantities to deliver, following their internal methodologies. However, the current VMI process lacks a standardized approach to inventory management, with no established performance measures or limitations for suppliers.
Thus, Mars is presented with several challenges to improve the process. Firstly, the current production schedule must be analyzed in order to identify areas for improvement. Secondly, optimal inventories must be set as targets for suppliers by identifying a collaborative cost and service model, and thirdly, ways to help suppliers improve performance must be sought by means of information sharing. These measures will help to improve the inventory levels of Mars throughout its end-to-end supply chain.

1.2.4 | Conclusion

The supply chain system comprises a substantial number of items, which must be accommodated within the warehouse capacity of the respective Mars sites. Furthermore, the system is managed under a vendor-managed inventory, whereby suppliers are responsible for making replenishment decisions for Mars. Currently, there is no visibility on the performance of suppliers or the desired deliveries from suppliers. Finally, the demand forecast for Mars packaging material is highly volatile, which increases the complexity of the ideal inventory position for Mars. Consequently, a revised framework is necessary to align supplier performance with processes across all Mars sites, to enhance the fill rate of items while simultaneously reducing stock levels to align with warehouse capacity constraints. Within this framework, three key parts need to be established, the current ways of working and respective planning policies, a more optimal way of managing inventories, and finally, a way to implement these policies in a scalable way across the full regional supply chain planning team.

1.3 | Research Questions

It is evident from the situation at Mars that a new way of working is required. The company aims to optimize its VMI processes across its nine European factories and synchronize this process for all suppliers. Consequently, the primary objective is to determine the most effective inventory control systems under Vendor-Managed Inventory (VMI). This is to be achieved by providing clear targets for all suppliers to minimize the number of stockouts while adhering to warehouse capacity constraints. These targets can be defined based on different demand profiles, which will result in several categories with possibly different replenishment policies. However, within these categories, the targets are expected to be the same to keep the process manageable. Consequently, the subsequent section presents the primary research question derived from the aforementioned problem statement.

1.3.1 | Main research question

The following research question has been determined: *How can a near-optimal replenishment policy within a fast-moving consumer goods company be determined under high demand uncertainty within a Vendor-managed inventory structure?*

1.3.2 | Sub-questions

In order to address the main research question, a series of sub-questions have been formulated to facilitate a more detailed examination of the subject matter. These sub-questions have been classified into two categories: diagnostic (encompassing an analysis of the current situation and the underlying issues) and prescriptive (outlining potential strategies for enhancing inventory levels and associated processes). For questions 1 and 2 an explanatory approach has been chosen whereas questions 3 to 5 follow an exploratory approach. The main goal of sub-questions 1 and 2 is to determine the current process of suppliers and establish the current demand processes within Mars. In sub-question 3 the goal is to answer what replenishment policy fits the Material Requirements Planning (MRP) of Mars and provides the highest service level. Consequently, a bounded solution is provided when adhering to capacity constraints in sub-question 4. Finally, sub-question 5 encompasses the implementation of the replenishment process within each VMI supplier to combine the current methodology with an improved inventory control process. The sub-questions are given on the following page.

1. What are optimal methods for evaluating the performance of suppliers?
2. How can the demand forecast be interpreted more accurately based on the production planning? What segmentation approaches can be employed to enhance the interpretation of demand forecasts for various demand profiles?
3. How can near-optimal replenishment policies be found accounting for fast-moving consumer goods items upstream the supply chain?
4. How can these near-optimal replenishment policies be implemented under warehouse capacity constraints?
5. What are the best management strategies for this replenishment process under a vendor-managed inventory contract?

1.4 | Methodology

This section will elaborate on the research design. In this section, the scope of the research as well as the methodology will be discussed. The research will follow the problem-solving cycle proposed by van Aken et al. (2012) and given in Figure 1.3. The research consists of a problem definition, earlier described in the introduction section and further elaborated in Chapter 2. Furthermore, analysis will be conducted on both a quantitative and qualitative basis, with the objective of identifying potential areas for improvement. In the case of Mars, this may entail adjusting minimum order quantities (MOQs), identifying optimal stock levels, and analyzing the root causes of suboptimal performance. Based on this procedure, an optimal stock policy will be proposed, in combination with the required information-sharing methodologies. Based on these methodologies, interventions will be performed with suppliers, to test the performance increase over time. By repeating this process iteratively, insights gained from each intervention can be utilized to continuously refine the model, ultimately developing a universal model that can be applied to all suppliers.

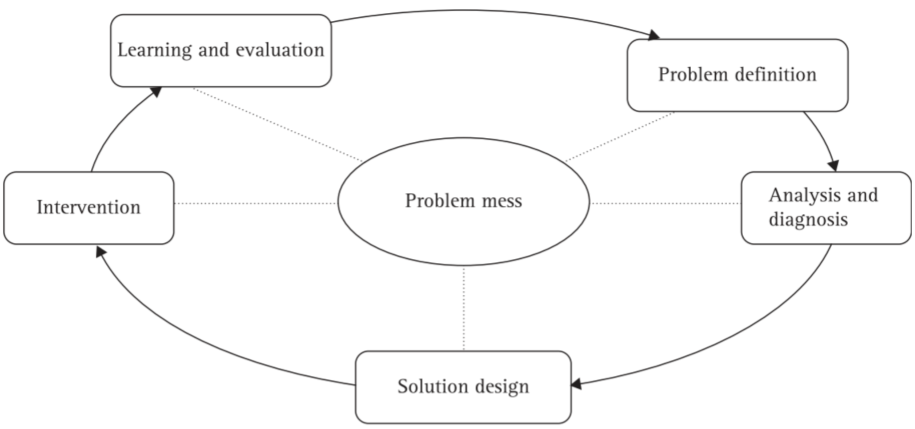


Figure 1.3: Problem Solving Cycle (van Aken et al., 2012)

Furthermore, the research also incorporates the steps of supply chain collaboration and uses the model of (Ho et al., 2020), see Figure 1.4, to classify the Mars supplier collaboration during the process of the research.

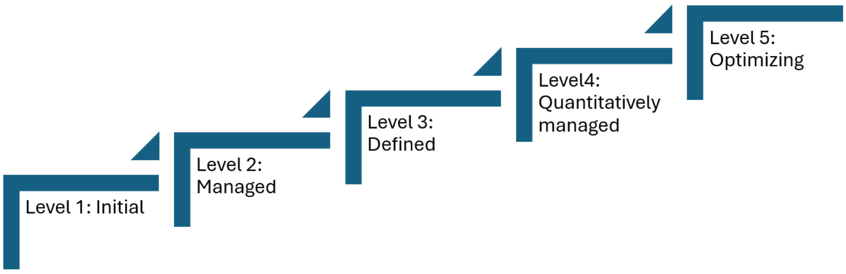


Figure 1.4: Capability Maturity Model Integration (Ho et al., 2020)

The following sections will outline the scope of the project within Mars, present the proposed quantitative and qualitative model, and finally, describe the approach to developing a decision support system for Mars. The following sections will describe the required steps to arrive at the final proposed model, as well as key assumptions or simplifications that are expected to be made.

1.4.1 | Scope

The objective of this research is to identify potential inventory optimization techniques within a vendor-managed inventory (VMI) contract. The focus is on the packaging materials of Mars, from the upstream supply chain of Mars. In section 1.2, the part of the supply chain that is the focus is highlighted. For optimizing inventory, min-max policies will be used to guide the VMI supplier. However, it is necessary to consider important constraints, such as warehouse capacity at Mars sites and supplier constraints, including lead times and minimum order quantities (MOQs). Furthermore, the supplier processes will be investigated to identify potential improvements that can be made at both supply chain partners. Finally, this new proposed policy will be simulated and compared to a naive policy that has currently been used by Mars.

1.4.2 | Qualitative model

The qualitative model is a survey-based approach that focuses predominantly on determining an optimal process for Mars and its suppliers. To identify potential bottlenecks in the process and to find potential solutions for reshaping the supplier process. Therefore, this model will also use the steps in the model of van Aken et al. (2012) to identify the current situation, analyze all aspects, and find a proper solution to implement within Mars. This has to be feasible and in line with the processes of both supply chain partners reflecting the problem diagnosis.

1.4.3 | Quantitative model

The objective of the quantitative model is to establish optimal reorder levels and order-up-to levels for suppliers of Mars, with the aim of creating an integrated optimal supply chain collaboration approach within a VMI context. The fundamental aspect of this model is the utilization of simulation-optimization techniques to ascertain these levels, intending to achieve cost optimization under constraints imposed by warehouse capacity and fill rates. The model employs a segmentation approach to identify item categories that respond differently to varying min-max levels, due to inherent item properties. Consequently, the model seeks to explain these item characteristics and provide a model fit for Mars, to optimize their inventories in a manner that is integrated with the cost optimization of both supply chain partners. In addition, the model of Danese (2006) is used for implementing the closed feedback cycle measuring the demand patterns and consequently providing insights into the supplier process.

1.5 | Outline

This thesis is built up as follows. At first, the problem context is drawn in combination with the detailed supply chain processes within Mars in chapter 2. This chapter highlights the core processes within Mars, its respective production planning, ordering system, and current challenges within the supply chain. Following this problem context, a literature review will enlighten further on the possible approaches to this problem as well as establish key findings in MRP, VMI, and inventory control processes throughout a multi-echelon supply chain scope given in Chapter 3. Consequently, a more in-depth analysis is given on all product types and different suppliers in Chapter 4 and 5. These chapters are explanatory in nature, primarily aiming to describe the current situation and prepare the input parameters and variables. This includes, but is not limited to, a segmentation approach for products and a supplier pilot and survey to enhance process knowledge across the supply chain bounds for the model described in Chapter 6. This chapter describes the conceptual and detailed design of the model and describes the simulation-optimization model implementation. Afterward, the implications of the quantitative analysis in the aforementioned chapters will be discussed on a qualitative basis in Chapter 7 to describe not only what values will return near-optimal results but also how to manage this model in a vendor-managed inventory structure. Finally, Chapter 8 provides the key conclusions and recommendations of this research.

2 | Problem Context

The following section provides a more detailed account of the Mars supply chain, focusing on the complex processes occurring within and outside the defined supply chain boundaries of Mars. Furthermore, it will explicitly elaborate on the supply chain processes, systems, and data, with particular attention to the demand patterns within Mars, its production process, and the replenishment process. Additionally, this detailed supply chain design will provide a comprehensive understanding of the problem context.

2.1 | Supply Chain Network Mars EU

2.1.1 | Rules and regulations

Following the regulations and directives established by the European Union, all food-related packaging materials are required to display the language of the country of origin in a legible and prominent manner EuropeanCommission (2024). Consequently, Mars is required to define the demand for each packaging material to all suppliers for a substantial number of different stock-keeping units (SKUs). Furthermore, Mars also strives to be as flexible as possible in their commercial strategy with regard to their customers. In this manner, Mars introduces further complexity into its supply chain by offering a variety of packaging options, including the 5-pack, 6-pack, and 7-pack. If one of these options is chosen the complexity can also be significantly reduced. Consequently, the regulations and directives of the European Union, coupled with the flexibility that Mars seeks to implement, have resulted in the creation of a complex system comprising a variety of elements, each dependent on its own market demand, production batching process, and other pivotal supply chain variables. This, in turn, has led to a heightened level of complexity within the supply chain.

2.1.2 | The Multi-echelon supply chain

The Mars supply chain is extensive, beginning with the sourcing of raw materials and concluding with the distribution of finished products to consumers. This chain involves numerous stages, including the production of products in Mars factories around the globe. It is therefore essential to provide a detailed description of this supply chain and to delineate the scope of the focus area under investigation throughout this research project. As the foundation of supply chain management is built upon the dynamics of supply and demand, it is of paramount importance to be familiar with these concepts when defining the scope of the supply chain. In the case of Mars as a core manufacturing company, the supermarkets serve as the primary source of demand for the company's products, which then propagate through the supply chain. However, the Mars suppliers view the requirements of the factory as their respective demands. Thus, Figure 2.1 shows the scope of the supply chain of Mars for this research project. The demand placed on a specific factory by the Mars market (e.g. Dutch or German market) is used as the demand driver and is immediately propagated throughout the supply chain, including the respective lead times, in order to ensure the timely availability of the product in line with the associated demand date. As shown in Figure 2.1, this requires several aspects within supply chain management such as demand forecasting, capacity planning, order batching, and production planning to make sure the supply chain runs as smoothly and cost-efficiently as possible. Subsequently, the inventory at all relevant stock points must be managed to ensure product availability within the specified constraints, including, but not limited to, capacity and cash flow. The latter will be discussed in greater detail in the subsequent section of this analysis, which will address the problem diagnosis. (section 2.2. The core focus of this research is to ascertain how these demand processes can be shared with the supplier to facilitate the development of optimal policies that are cost-effective for both Mars and the supplier, align with the respective capacity requirements, and ensure the delivery of an adequate level of service. Accordingly, section 2.1.3 focuses on the supplier collaboration process employed by Mars, to identify (near-)optimal solutions within the aforementioned categories.

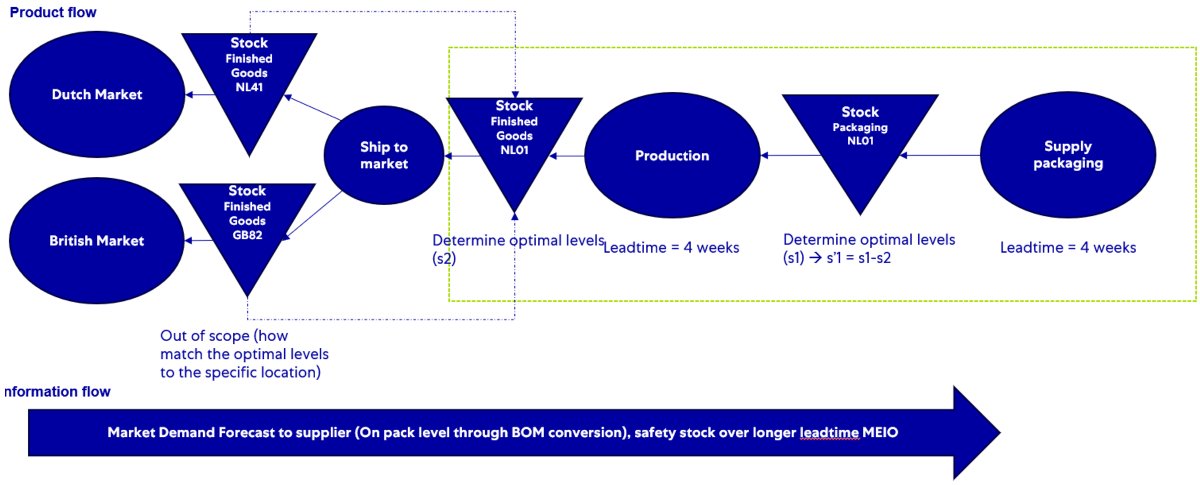


Figure 2.1: Multi-echelon supply chain

2.1.3 | The VMI supplier

The management of Mars' inventory by VMI suppliers presents unique challenges, particularly due to the lack of structured processes and clear accountability within the supply chain, as detailed in Chapters 3 and 5. In essence, the VMI supplier operates without the need for purchase orders. In this way, the supplier is responsible for the management of Mars' inventory, and thus for the potential consequences of stock shortages or surpluses of specific items. Nevertheless, this supplier is, in turn, highly reliant on the forecast provided by Mars. Consequently, suppliers may exhibit varying behaviors in response to these contractual arrangements. For instance, they may overstock items to ensure availability, despite the risk of obsolescence, which has to be paid for by Mars. Furthermore, modeling a VMI supplier is considerably more challenging than that of a regular purchase order requisition, given the lack of clarity surrounding the decision-making moments and the consequent inability to assume fixed lead times. These lead times are crucial for optimizing inventory control systems. Consequently, it is essential to provide the VMI supplier with greater visibility throughout the supply chain. However, this is contingent upon the implementation of the process. The delivery process of the supplier is not based on a clear-cut replenishment policy; rather, it is generally a manual plan where orders are placed when they are expected to be required. This results in a significant amount of ambiguity in the supply chain process. Mars does not have a clear view of this process and must manually address the potential stockouts. Furthermore, there is no closed feedback loop on who is responsible for costs associated with overstocked items. This ultimately places the financial burden on Mars.

2.2 | Problem Diagnosis

The performance of the inventory on Mars is evaluated according to three principal performance indicators. This includes cash, which is a measure of the business's liquidity and its capacity to invest in projects. The strategic goal is to avoid debt. Service is used for the relationship to the customer and attaining the highest possible service level. Finally, the cost is related to the cost of producing goods and for inventory purposes mainly focuses on reducing waste. In the VMI and VMCI processes, the cash component is managed by the supplier. The supplier retains ownership of the specific product until it is used by Mars or the product is in consignment stock for 90 days, after which Mars takes over the cash component. Therefore, the objective of this inventory control project is to reduce costs and associated waste while maintaining a high level of service. Figure 2.2, shows the performance pyramid used by Mars containing cash, cost, and service. The framework Mars uses has also been derived from the book on the Supply Chain Triangle by DeSmet (2018). Therefore, the penultimate goal of each company is to reduce the cash used for inventory and reduce the costs made for packaging due to waste, transportation, setups, holding, etc. Finally, the goal is also to maximize the service level while balancing all the constraints resulting from the cost and cash component. Therefore, this is a fully intertwined push and pull system and the goal is to arrive somewhere in the middle balancing all factors to reach an optimum. Thus, the following sections are dedicated to the cash, cost, and service components and to describe in more depth their interaction with the problem context.

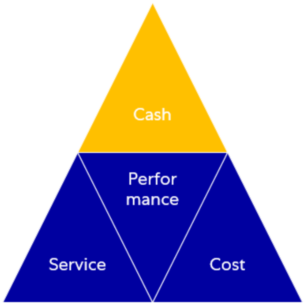


Figure 2.2: Performance Pyramid Mars

2.2.1 | Warehouse Capacity

The warehouse capacity of the Mars packaging material warehouses is relatively tight. All warehouses have a warehouse utilization of around 90%. Generally speaking, Mars wants to keep this level below 90% as shown in the target of Table 2.1. Consequently, reducing these stock levels is a primary objective for Mars, particularly given that exceeding the warehouse capacity necessitates the relocation to significantly more expensive overflow locations.

	Mars manufacturing site				
Warehouse metrics (↓)	GB18 (Slough)	NL01 (Veghel)	FR08 (Haguenau)	DE04 (Viersen)	PL01 (Janaszówek)
Capacity	5632	18275	7500	5000	2700
Packs Pallets Stored	4783	16010	4135	4847	2073
Utilization (Target<90%)	84.9%	87.6%	55.1%	96.9%	76.8%

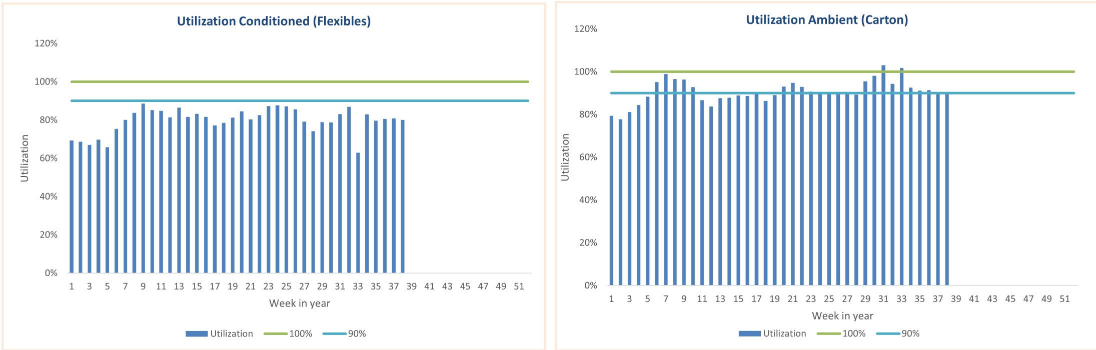
Table 2.1: Pallet capacity All chocolate sites

Furthermore, Mars categorizes its warehouse capacity into two distinct types: ambient and conditioned. The conditioned capacity has been allocated for items that require a temperature of approximately 15-18 degrees Celsius. The ambient capacity is intended for items that can be stored at room temperature. Table 2.2 shows the pallet capacity at the Veghel manufacturing site split between these two categories. As given in the Table the ambient capacity is much higher than the conditioned capacity. This is due to the fact that the ambient capacity is typically reserved for carton and corrugated materials, which require more space as fewer units can be accommodated on each respective pallet. However, it is important to note that this limited capacity cannot be shared among items.

Warehouse type	Pallet places
Warehouse Ambient Capacity (Carton)	13475
Warehouse Conditioned Capacity (Flexibles)	4800

Table 2.2: Number of pallets capacity in Veghel site (NL01)

Following this, Figure 2.3 shows the distribution of the ambient and conditioned items during the year. Especially in the ambient warehouse, some periods overflow locations have been used. This is undesirable as these overflow locations are significantly more expensive. Therefore, this is a factor that should be considered when developing inventory policies for suppliers of vendor-managed inventory, given that there is no infinite capacity. As section 2.2.2 will further describe, the level of service and stock holding is highly correlated. Therefore, the aforementioned cost, cash, and service matrix must be taken into account when attempting to optimize inventory levels.



(a) Utilization Conditioned (Flexibles) warehouse **(b)** Utilization Ambient (Carton) warehouse

Figure 2.3: Warehouse utilization Veghel (NL01) site

2.2.2 | Service level

The goal of Mars is to become the number 1 supplier of chocolate and confectionery. Therefore, the service level is very important for Mars. Mars aims to have a 98.5% pack availability to ensure production in almost all situations. This requires high safety stock levels to ensure this availability requirement. For normally distributed demand the formula for determining the safety stock and a reorder point for a given fill rate is given as follows:

$$s = \mu_{L+R} + SS$$

$$SS = Z_\alpha \cdot \sigma_{L+R}$$

where s is the reorder point, SS is the safety stock, μ_{L+R} is the mean demand during the lead time and review period, σ_{L+R} is the standard deviation of demand during the lead time and review period, Z_α is the Z-score corresponding to the desired service level or fill rate. Currently, the service level metric is not met for all items. However as Figure 2.4 clearly illustrates, increasing the availability target to levels around 98.5% causes the required safety stock level to become exponentially larger in a normally distributed demand situation. This already happens in a situation with a similar coefficient of variation. Within Mars, there is a considerable range of standard deviations among items, as well as a significant number of items for which demand is non-normally distributed, non-stationary, and dependent on various situations that are challenging to estimate. This further complicates the attainment of this ambitious availability requirement, potentially rendering it nearly impossible in a constrained capacity situation.

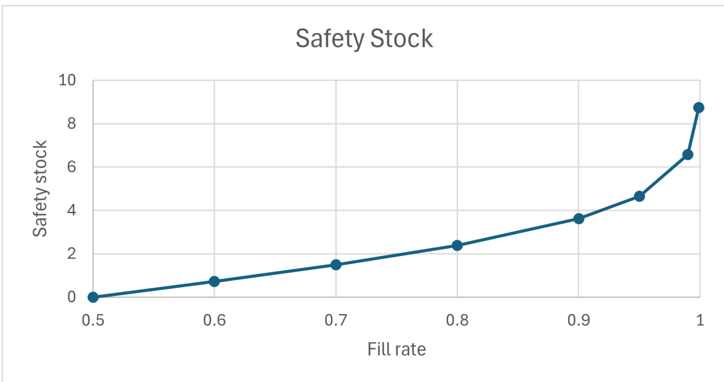


Figure 2.4: Safety Stock exponential increase

Moreover, an increase in service level does not only increase the inventory that is required to be held. Mars is also a company that experiences rapid change, with numerous item changeovers, new product introductions, and time-varying promotions. If products are faced out with the maintenance of an appropriate safety stock, this may also result in high obsolescence and, subsequently, high waste. The following section provides an elaboration on the sustainability goals and, consequently, explains why a high stock level ultimately also results in high waste.

2.2.3 | Sustainability Goals

In contrast to the service level objective set by Mars, the company also aims to minimize its waste output as much as possible. In particular, the risk of obsolescence is considerable for packaging materials. Furthermore, the high-safety stocks have a significant impact on the risk of obsolescence, given the aforementioned demand uncertainty. Consequently, the objective of Mars is to achieve an equilibrium between service and waste. In the Mars Net Zero 2050 roadmap MarsInc. (2023), a clear intention to reduce greenhouse gases, and waste, and to operate in an environmentally responsible manner is evident. This encompasses the following core areas: direct operations, agriculture, land use change, retail, logistics, and packaging. Of these, the latter is particularly relevant to the current discussion. Figure 2.5 clearly demonstrates that an increase in the fill rate has a considerable effect on the number of obsoletes that remain after an item has been phased out. The figure shows that having additional stock levels with decaying demand leads to higher leftover obsolete stock. In consequence, the safety stocks in a normal distribution situation are determined by the safety factor and the standard deviation. It thus follows that both these factors are the factors leading to obsoletes and thus packaging waste, which has a negative influence on the sustainability goals of Mars. It is therefore evident that the trade-off between fill rate and risk of obsoletes is of great importance, resulting in an urgent need for segmentation of items with different volatilities and different values for Mars. This would enable a more balanced approach to the fill rate and obsolete probability, rather than the current sole focus on achieving the highest possible pack availability. This presents a significant risk for items with high volatility and high required availability, as this will increase the chance of obsoletes significantly. Currently, the carbon footprint of the full scope

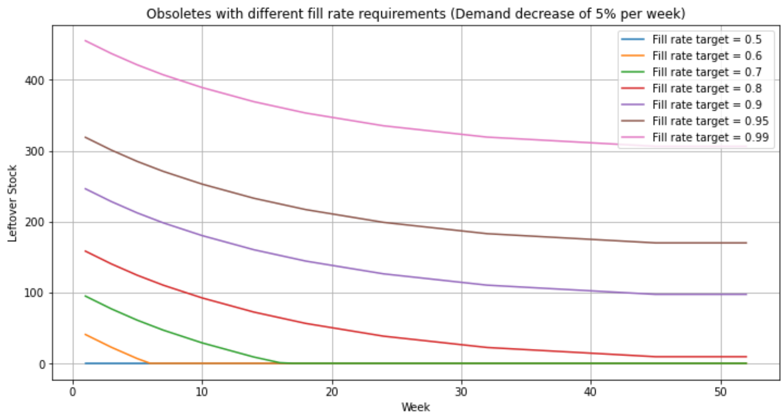


Figure 2.5: Number of obsoletes with respect to fill rate targets

of Mars regarding packaging is 1.4 megatons CO_2 which Mars wants to reduce to 0.6 megatons CO_2 by 2030. Therefore, the topic of reducing waste and increasing supplier collaboration is a major topic on Mars's agenda based on its strategic goals. Thus, the previous goals of increasing service level also have to be seen in perspective to the additional stock-build and possible increased waste.

2.2.4 | Under-performing forecast

The forecast of Mars appears to be highly volatile. This is caused by the bullwhip effect. As Mars wishes to be flexible in terms of demand and batch production, the magnitude of orders is amplified. Consequently, due to these demand patterns, it is more difficult to manage stocks and requires some safety stocks to cope with the variability in both demand and lead time. Figure 2.6 illustrates the squared coefficient of variation and average demand interval for all Mars items based on a weekly aggregated weekly production plan. This reveals a significant proportion of the data that is either intermittent or lumpy (Intermittent: 376, Smooth: 171, Lumpy: 106, Erratic: 25), thereby presenting significant challenges to inventory control (Boylan et al., 2008).

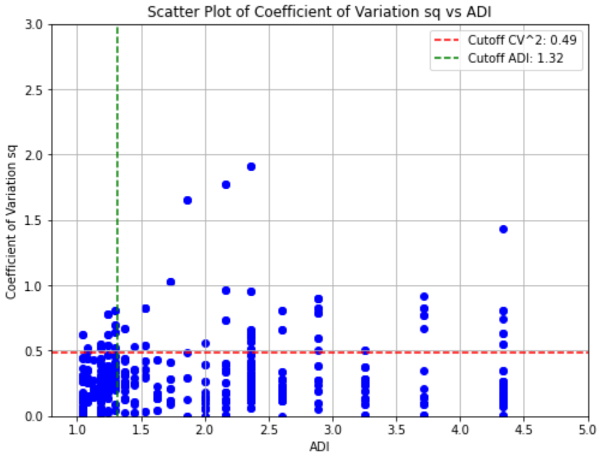


Figure 2.6: Forecast volatility Mars

In addition, the production performance is also not always 100% so the volatility can also be caused by the inability to produce exactly the planned production. In summary, both variations in customer demand and production performance make actual production difficult to predict. Given this inherent unpredictability of the forecast, it is challenging to identify the optimal policies for Mars items. Thus Mars is dealing with unstable demand, unstable forecasts, and a high forecast error.

2.2.5 | Commercially-driven MOQs

Currently, the minimum order quantities are driven by the commercial department within Mars in negotiating with the supplier. The focus is to drive a minimum order quantity that delivers the lowest price per unit. Therefore, this might result in relatively high holding costs and long inventory cycles. Moreover, the general cycle length for each product also has been determined every year. It can thus be argued that a double minimum order quantity (MOQ) situation may arise in which the MOQ is greater than the agreed cycle length, resulting in an increased stock of Mars. Similarly, a situation may occur in which the MOQ is less than the agreed cycle length, leading to the ordering of the agreed cycle length to reduce the number of setups from the supplier. Following from literature Mars employs both the EOQ (Economic Order Quantity) model and the EOI (Economic Order Interval) model for determining optimal cycles. Furthermore, the aforementioned cost models fail to account for holding costs at the Mars factories, resulting in MOQs and order cycles that may not be optimally efficient. Additionally, the MOQs and agreed cycles are established annually based on historical demand patterns, which may not accurately reflect the time-varying nature of demand. Using the basic EOQ calculation from (Nahmias & Olsen, 2015), holding and setup costs are critical factors in determining the optimal MOQ and cycle frequency. For instance, during high-demand periods, the optimal order quantity Q is significantly larger than in low-demand periods, even with identical cost parameters. This highlights the need to account for demand fluctuations and cost factors when determining the optimal Q. Relying solely on fixed annual demand patterns and excluding holding costs in the cost model, as is currently the case at Mars, should be avoided. Demand information at Mars is shared based on specific pack codes, which are grouped into material categories that influence setup frequencies and MOQs. This process, along with its implications, is further detailed in Chapter 4.

2.2.6 | Suboptimal stock level agreements

Presently, an SLA stock-level agreement that synchronizes suppliers has been set up for only 2 out of the 65 suppliers. Based on a rule of thumb it has been decided that the min-max for cartons is at least 10 days and a maximum of 7 weeks, for flexibles this has been established as 2 weeks and 10 weeks. However, this is mainly based on the varying lead times between the two items and general service agreements and proposed cycles for both items. In reality, these lead times and number of cycles still significantly vary between suppliers and items. Therefore, it is apparent that these limits are expected to be suboptimal as no segmentation has been used whatsoever and it purely relies on a one-size-fits-all rule using an educated guess for finding the most optimal bounds. Therefore, this problem leads to the requirement of an optimization system choosing the optimal bounds for each supplier, each item, and possibly varying service levels. Thus, this provides room for the model described in chapter 6.

2.2.7 | The supplier connectivity report

Mars has a strongly time-varying master production schedule. Each week the forecast changes significantly per item and this value is shared based on customer demand planned at the end of each cycle. However, the production cycles of the supplier and Mars do not match at all in the current situation. The Mars forecast is being followed and requires adjustments to the production schedule of the supplier each week. Furthermore, as described in section 1.2.3 on the current S&OP process, it is described that the plan is made for a very long-term horizon which should lead to sufficient capacity planning for suppliers. However, due to the changes during the leadtime of the suppliers, the master production schedule is a very reactive source for the planning of materials as it is impacted by numerous unaccounted reasons making it hard for the supplier to react without intensive manual labor. Furthermore, the suppliers are dependent on a weekly Excel export which the supplier has to manually interpret, and subsequently provide feedback, again manually, to Mars. Therefore, this report in its current format is potentially an obstacle for process optimization and is highly reliant on the experience suppliers have with working on this report. Based on the review on information exchange by Vigtil (2007) this puts the process of Mars in the lowest level of integration namely a disintegrated electronic update based on periodic sharing.

2.2.8 | Lacking visibility of Supplier process

The self-billing procedure employed by suppliers is based on the supplier connectivity report, which is received on a weekly basis. Consequently, the suppliers are responsible for billing all costs associated with the items in question, a process that Mars is unable to oversee effectively due to a lack of insight into the billing procedure. In this billing procedure, the supplier is responsible for determining the final costs and the final number of setups that have been used. Based on historical data, an expected number of setups is generated. However, in the event that fewer setups have been used, the supplier is free to bill the same costs per item. Furthermore, there are no identified processes available within Mars on the processes of each respective supplier. Consequently, there are no established efficiencies in changing the supplier or Mars process to match the consumers' needs at the lowest cost possible. Thus, the objective of this research is to provide more insight into these processes to explore the potential for enriched supplier collaboration.

2.2.9 | Planning Process gap

Suppliers typically receive feedback only when an item is identified as being out of stock. Therefore, a large firefighting structure is used to manage all materials to be available. Consequently, suppliers do not get feedback in their VMI replenishment process and do not know what target to aim for as these have not been agreed upon. To close this feedback loop as shown in Figure 2.7, two actions are undertaken

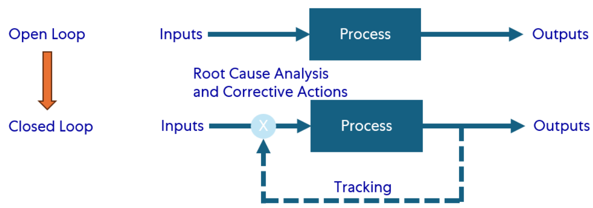


Figure 2.7: Performance cycle improvement

in this research design. Initially, a pilot study has been initiated with two suppliers to ascertain their existing procedures and identify potential optimal practices for guiding feedback loops. This is discussed in further detail in the subsection 5.3. Subsequently, the scope of this supplier synchronization project is expanded through a survey, which can be found in the supplier analysis chapter under section 5.4.

2.3 | Summary

The current VMI supply chain process faces three significant challenges. First, poor forecast performance reduces the accuracy of inventory decisions. Second, there is insufficient clarity regarding the number of setups required to optimally manage the process for both Mars and its suppliers. Third, Mars lacks the ability to effectively assess supplier performance and provide feedback to improve the process. These issues result in suboptimal service levels, excessive waste from obsolete items, and a disproportionate allocation of stock to less critical items, undermining the overall efficiency of the supply chain.

3 | Literature Review

This section of the master thesis research presents a summary of the existing literature on inventory control systems within a vendor-managed inventory structure by providing the key findings from the literature review of van Strien (2024). Additionally, it offers a background for the research questions and research design, thereby providing a foundation for the structure and methods used for this research. At first, the bullwhip effect, as described by Lee et al. (1997), is the primary driver of the aforementioned problem statement, due to the amplification of demand upstream of the supply chain. Furthermore, the bullwhip in combination with vendor-managed inventory is further elaborated on in Disney & Towill (2003a) and Disney & Towill (2003b). The subsequent sections will focus on the interpretation of demand, inventory control systems, and their respective applications within a vendor-managed inventory structure. In the literature review of van Strien (2024), the papers of Syntetos & Boylan (2005) and Syntetos et al. (2016) have been primarily used to identify the aforementioned demand patterns. These methods provide a framework for segmentation based on the demand interval and demand variability, which enables more effective inventory control. Moreover, Syntetos et al. (2016) provide further insights into research gaps regarding segmentation in the product, time, location, and echelon dimension. Furthermore, the fitting procedure of Adan et al. (1995) has been explained in order to fit distributions to the demand pattern as well as the identification of the χ^2 and Kolmogorov-Smirnov test by Syntetos et al. (2012). Consequently, these methods should assist in identifying the demand pattern and in fitting the relevant inventory control system to each demand category. In conclusion, forecasting demand within a supply chain is of significant importance for the effective management of inventory. By classifying demand patterns by fitting statistical distributions, a more realistic picture of the demand processes can be achieved, which is crucial for inventory management. Thus, based on these approaches a more general applicable policy can be determined based on methodologies from the upcoming sections. Implementing these policies and effectively managing stochasticity will allow Mars to transition to a more proactive approach, significantly reducing its reliance on the current reactive strategy. Finally, applying theoretical methods to real-world contexts may offer new insights for literature.

3.1 | Material Requirements Planning

The process at Mars focuses on material requirements planning (MRP) and its associated inventory control system. Therefore, it is essential to understand the key aspects of MRP. This includes examining the underlying assumptions and the established techniques that are predominantly referenced in the literature. Especially for handling uncertainty in MRP, Silver et al. (2017) provides solutions based on these systems and different demand types in Chapter 15 of the respective book. It also especially pinpoints the weaknesses in MRP which this research also tries to tackle. For example, fixed safety stock calculations are typically unsupported in MRP systems, leading users to estimate safety stock levels, often inflating them to prioritize stock-out protection. Moreover, data consistency is a common challenge in MRP systems, as inventory movements are often poorly tracked within organizations. Frequent design changes also lead to problems in the MRP as the component then changes slightly due to a change of the finished good which in turn provides difficulty in establishing lengthy time series of the same product. Due to the frequent changes in MRP systems, it is hard to establish a suitable inventory system for Mars.

3.2 | Inventory control

The core of the literature review of van Strien (2024) on inventory control is based on the four books of Nahmias & Olsen (2015), Axsäter (2015), Silver et al. (2017) and Vandeput (2020). The review identifies basic single-echelon models as well as multi-item models under capacity constraints. This consists of optimization problems under warehouse capacity constraints relevant to the earlier described case study of Mars. In addition, an explanation of the EOQ model found in Nahmias & Olsen (2015) has been elaborated on which shows relevance for determining the minimum order quantities that should be optimal for both supply chain partners which is also in line with the joint economic lot size model (JELS) by Banerjee (1985). Furthermore, an explanation has been provided on multi-echelon inventory control and especially assembly systems as proposed in Atan (2019). The assembly systems are relevant to the case study of Mars, as the process of Mars contains an assembly system structure where packaging and raw materials are taken into production, each containing different holding costs and lead times. Accordingly, the model proposed in Atan (2019) outlines a method for reducing the assembly system in question to a standard multi-echelon serial system. Furthermore, a method for solving the multi-echelon inventory system has been described in Atan (2019) using the heuristic proposed by Shang & Song (2003). Finally, in the literature review of van Strien (2024), a section has been provided on safety stock and safety leadtimes (Kampen et al., 2010), as for the case study of Mars it is relevant to consider the difference between fixed and dynamic safety stocks due to the high demand variability. In conclusion, based on the description of these processes, more optimal policies could be identified for the case studies within Mars. However, these optimal replenishment policies are expected to function effectively in an environment where purchase orders are prominent. In this case, the question arises as to how this can be made visible within a multiple supplier vendor-managed inventory situation. Further insights and literature on this topic can be found in section 3.3 and the literature review of van Strien (2024).

3.3 | Supply chain collaboration

In contrast to the earlier described inventory control methods, a significant body of literature has been written on collaboration within the supply chain. The case study of Mars is managed under vendor-managed inventory, which not only acts on the optimal inventory control system but is also highly reliant on the behavior of suppliers and the quality of the information shared by Mars. Lee & Whang (2000) identified the benefits of information sharing in a supply chain showing a reduction in average cost, inventory, and leadtime. Furthermore, the incorporation of MOQs has been introduced to identify the economic order quantity delivered by suppliers, thereby increasing the efficiency of suppliers to batch orders and reducing the cost per unit for Mars. However, for the case study of Mars, the optimal values have not yet been determined.

This research focuses on the VMI concept applied to managing replenishment in Mars' packaging materials warehouse. Firstly, the literature has shown that VMI and VMCI contracts are preferable to purchase order contracts because they help mitigate the bullwhip effect. (Lee et al., 1997)(Disney & Towill, 2003a). However, it is also noted that the positive effects of Vendor Managed Inventory structures are highly dependent on the correct implementation of the methodology. Marques et al. (2010) provide an overview of the key decisions, illustrated in Figure 3.1, necessary to establish an optimal logistical agreement (LA) with suppliers. In addition Zammori et al. (2009) provides an overview of KPIs suitable for both supplier and buyer in a VMI relationship. In the Mars case study, these decisions are not fully implemented, and the process is poorly documented. Therefore, it is important to create a newly defined process combined with the necessary best practices such as inventory optimization to optimize this process and achieve the positive factors described by Lee et al. (1997) and Disney & Towill (2003a).

Link	Associated question (s)/choice (s)
Type of VMI	Which type of Production and Dispatch process?
Periodicity of the LA	Which timescale? Which period of validity for the parameters defined by the LA?
Gross requirement expression	Are the supplier and customer planning processes synchronised? Where are the shared gross requirements defined?
Shared forecast	What is shared? What is the timescale? Which period of time?
Minimum/Maximum customer inventory level	How is it expressed: in pieces, in days?
Stock information	How is it expressed: in levels, in consumption? Periodicity: real-time, hour, day, week, etc.
Agreed minimal transport characteristic	What is defined: minimal lot size, minimal delivery frequency?

Figure 3.1: VMI Decisions (Marques et al., 2010)

In addition, the review of van Strien (2024) highlights several types of important issues related to Vendor Managed Inventory. The contracting has been discussed based on the paper of Dong & Xu (2002), performance measures used in a VMI system by Choi et al. (2004), optimization procedures using ABC categorization reviewed by Govindan (2013) and Govindan (2015), information sharing techniques proposed by Claassen et al. (2008) and finally a decision support system proposed by Achabal et al. (2000). This decision support system provides a framework for implementing a VMI system, focusing on vendor-retailer relationships and the necessary information sharing to address all aspects of VMI, including forecasting and inventory models under information-sharing conditions. These components of implementing the full scope of a VMI system are combined to determine the best possible framework for Mars. Furthermore, for cost identification the model of Glock (2012) has been investigated to provide the optimal number of cycles for both supplier and buyer. For further insight into these sections, refer to van Strien (2024).

This section has provided insights into the current VMI process, the well-established practices within VMI, and some directions for designing a VMI system. However, there are still several research opportunities to investigate regarding VMI systems. The research that has been performed is rather theoretical, whereas bringing the methodology into practice shows significant challenges based on what to share, how frequently to share, how to measure performance, and how to define optimality in situations where backorder costs are difficult to determine. This leads to the conclusion that a combination of methods should be applied in a practical supply chain environment. Based on these methods, the decision support system of Achabal et al. (2000) could be implemented in combination with new developments in inventory optimization theories to provide an applied (near-)optimal VMI system for FMCG companies with highly variable production schedules.

3.4 | Methods

This section provides a short overview of several methods containing optimization (Hillier & Lieberman, 2010), simulation (Boon et al., 2020), simulation of VMI models (Sari, 2007), segmentation (Syntetos & Boylan, 2005) and machine learning (Boute et al., 2022) which could be useful for solving the aforementioned inventory control problems. These approaches could be useful for improving the performance of the inventory control systems and consequently could be tested on the case study of Mars to provide more insights into the performance differences between certain methodologies.

3.5 | Integration Collaboration and (Multi-echelon) Optimization

For single-echelon optimization within assembly systems under VMI and VMCI contracts, van den Bogaert & van Jaarsveld (2022) provides a clear optimization approach with the objective of reducing inventory costs under a given fill rate. This approach has been implemented within Philips under a high configure-to-order environment. However, the limitation of this research is that it is unable to implement backorder costs or to implement supplier processes. Nevertheless, the value of supplier performance management and the setting of clear targets to enhance the fill rate of spare parts at Philips is clearly demonstrated. This case study provides a valuable basis for the case study at Mars, as it incorporates various previously described methodologies. The extension of the Mars case study could include multi-echelon inventory control, the incorporation of backorder costs, and an investigation of the demand pattern in an FMCG company compared to the demand process described at Philips.

Concerning multi-echelon inventory optimization, Eruguz et al. (2016) propose guaranteed service models for setting optimal stock levels. In the case of Mars, it would be beneficial to incorporate a structure of this nature to guarantee service levels for their customers. However, a potential research direction could be to incorporate VMI into this guaranteed service level model. In this way, the supplier is also expected to deliver a certain service level under fluctuating demand. Furthermore, it enables demand to be bounded for suppliers, thus ensuring that all general processes (stable demand situations) are managed using the guaranteed service model. Nevertheless, in the event of exceptional circumstances, such as a significant increase or decrease in demand, exceptional means can be used to ensure that demand is satisfied downstream the supply chain.

3.6 | Research gaps

The concluding section of this literature review summarizes the key findings from the discussed literature and highlights the research gap that forms the foundation of this study. Specifically, the identified gaps pertain to the Vendor Managed Inventory (VMI) literature, strategies for managing supplier performance, and inventory optimization models. The primary gap lies in the application of tailored inventory policies for varying demand patterns, aiming to develop a framework or guideline that enables suppliers to achieve optimal performance at minimized costs while meeting the specific requirements of Mars.

The fundamental concept of vendor-managed inventory is that the vendor is responsible for managing the inventory. Therefore, it might be counter-intuitive to determine the optimal stock levels for Mars, as this process is outsourced to the respective supplier. However, the supplier is only able to base their decision-making on the information shared by the manufacturer. This presents a potential research opportunity to explore how information sharing and collaboration can be enhanced to better address the significant forecast variability encountered upstream in the Mars supply chain. Furthermore, this concept has been primarily focussing on the finished goods materials.

Furthermore, the literature indicates the importance of measuring supplier performance to be able to act on VMI contracts. However, this performance can only be measured when Mars can clearly define the KPIs indicating high or low supplier performance. Consequently, there are no clear boundaries in the literature for minimum and maximum stock levels for multiple SKUs under warehouse capacity within a highly diversified product portfolio. Furthermore, in most cases, the capacity restrictions of suppliers have not been accounted for. Although a considerable amount of research has been conducted on safety stocks and safety times, relatively little research has been performed on other practical constraints for setting maximum stock levels. For SKUs with significant demand variation during the lead time, setting fixed safety stocks may be infeasible, particularly for newly introduced products with limited demand data. It can be concluded that there is a potential research gap in the area of setting clear targets for suppliers, thereby making the VMI process measurable and accountable.

Moreover, Mars has to be able to determine what stock levels would be optimal. The literature has shown that stock levels can be determined by several replenishment policies. However, replenishment policies appear to have suboptimal performance when managed within silos, both for upstream and downstream processes. The sharing of information within large multinational companies with multiple locations is not always as straightforward as anticipated. Furthermore, when considering the optimization of an entire supply chain, including suppliers in the process, minimal research has been conducted. While multi-echelon inventory control is a well-established phenomenon, there has been little investigation into controlling this inventory beyond the bounds of a single company, especially for assembly systems. Most of the literature on VMI contracts focuses on single-echelon inventory control or distribution systems, rather than on Mars' case study of assembly systems. It can be argued that a research gap exists in the implementation of a multi-echelon assembly system under vendor-managed inventory. Furthermore, it may be beneficial to compare different multi-echelon inventory optimization (MEIO) models, such as stochastic service models and guaranteed service models, to identify the most effective approach.

In addition, the literature has provided a wide range of methodologies for optimizing inventory control systems. Consequently, within optimization, several new (Machine Learning) methodologies have emerged. However, these methodologies have not yet been adapted to diverse supply chain environments. By using supervised segmentation, near-optimal levels can be determined. However, this process requires manual updating, which leaves a performance gap in periods where no update has been performed and communicated. Consequently, with these new methodologies, a continuous revision of optimal levels can be determined to create a more dynamic solution. The potential research opportunity identified from these methodologies is testing whether machine learning methods outperform more conventional statistical methods.

In conclusion, the research opportunity can be considered to be twofold. On the one hand, the objective is to create an optimal inventory control solution for Mars under high demand variability. On the other hand, the objective is to create a solution that is manageable and visible for the VMI supplier. In summary, the objective is to develop a feasible framework that does not require frequent adjustments, as this is not a viable process for suppliers. This approach enables the implementation of an accountable VMI system, which optimizes stock levels within Mars while maintaining flexibility for the VMI supplier. The roll-out of this VMI system has not been identified within a fast-moving consumer goods company in the literature. Therefore, the implementation of an optimal VMI system within a fast-moving consumer goods company provides a solution to the established research gap. In this way, a case study can be constructed on the methodologies described in this literature review, to combine scientific rigor with practical relevance.

3.7 | Summary

This literature review has discussed the problem caused by the bullwhip effect within supply chains. This bullwhip effect is the key driver for increased variability upstream supply chains. As this research aims to model upstream supply chain inventory, key components of the review are how to model demand at this stage, how to manage inventory best, how to collaborate with suppliers, and describe upcoming methods for the earlier mentioned questions. Following this, a section has been devoted to the integration of these core concepts and their respective applicability to the case study of Mars. This review establishes a foundation for a simulation-based optimization approach or the use of machine learning techniques to set optimal stock levels, assuming the stock is vendor-managed. This requires an in-depth examination of supplier processes to develop a near-optimal supplier management process in a case study.

4 | Product Analysis

The product analysis consists of two main components. The first involves collecting data on all relevant products, including setup and holding costs for each item and details about the supplier's production process. The second focuses on classifying various items and item groups. By analyzing the attributes of each item, differentiated inventory targets can be defined to optimize inventory management.

4.1 | Demand Analysis

The newly introduced planning system Kinaxis provides an End-to-end (E2E) planning solution for the described Mars supply chain. The demand propagates through the supply chain from market to supply also using the forecast for the supplier on packaging material. The following section will explain all the propagation steps to most accurately describe how the market forecast is propagated to a finished goods production planning and its respective BOM calculations to derive the planned consumption of packaging material demand forecast. In addition, the definition of demand is very ambiguous throughout the supply chain. For example, the material requirements planning is considered to be demand for the supplier however this is already a batched and agreed process while making a demand plan which in turn is based again on the independent customer demand forecast. Thus, this section aims to describe the different types of demand, the demand that will be sent to suppliers, and how to interpret all these demand types to answer subquestion 2. The production planning of Mars can be best compared to the Closed-loop materials requirements planning given in Figure 4.1, as proposed by Silver et al. (2017). The propagation of demand will be further explained in the subsequent subsections.

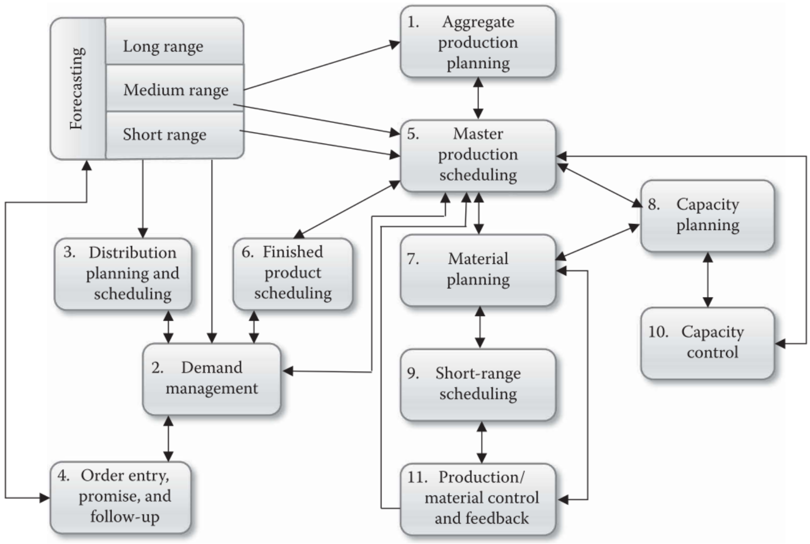


Figure 4.1: Closed-loop materials requirements planning (Silver et al., 2017)

4.1.1 | Consumer Demand

Consumer demand is independent and unconstrained. However, as this data relies on supermarket sales, it is challenging to estimate the actual demand for Mars. This is because supermarkets' actual sales data is highly dependent on considerations within retail, such as promotions, substitute products, and other key factors influencing this demand. Each respective market of Mars attempts to estimate these demands and formulate a plan accordingly so that it can be matched by supply.

4.1.2 | Market Demand

In response to consumer demand, there is a consensus that all markets must deliver to their respective customers. This constrained demand plan represents the fundamental requirements that are transmitted to the manufacturing facility and recorded as the anticipated date of material arrival in the market warehouse. The demand accumulates the consumer demand but already creates a demand plan based on the feasibility within the respective factories of Mars. This demand does not take into account the implications of different batching cycles that factories may wish to employ to optimize their processes. This demand accounts solely for the date on which the product is to be located at a market warehouse with a specified shelf-life requirement. In Chapter 6, the demand is employed for the multi-echelon forecast. The finished goods demand is converted to packaging material requirements following the rule elucidated in Section 4.1.5. This demand type is devoid of batching and consequently exhibits a greater number of non-zero demand periods than the subsequent factory demand.

4.1.3 | Factory Demand Finished Goods

Ultimately, the network capacity planner develops a long-term plan for all items based on the demand plan. This plan is designed to align with the production planning cycles. The demand plan reflects the supply to the market, indicating the desired number of items available at the system log-in date. This date should precede the market demand to ensure the availability of the required finished goods. Additionally, the demand plan incorporates a batching procedure to meet the production planning requirements.

4.1.4 | Production planning (Cyclic demand patterns)

In response to the factory demand for finished goods, the factory demand for raw and packaging materials is also generated within Mars. All items are processed through the bill of material (see reference 4.1.5 ultimately culminates in the supplier connectivity report, which represents the aggregated demand forecast of all suppliers. Subsequently, the suppliers are only privy to the data at this echelon following the completion of a batching procedure. It should be noted that no stocks of finished goods (packaged material) are shared with the supplier and that any service level misses are not included. It is only when planned production is no longer feasible that the supplier will become aware of an error. This demand appears to be highly volatile in terms of both quantity and timing, as a relatively short period has been frozen. This period is much shorter than the supplier lead times, increasing the difficulty of decision-making for suppliers. The remainder of this chapter will focus on this particular demand and identify groups with similar demand patterns.
In addition, Mars' production planning employs a DOC/SOC framework, integrating varying levels of capacity planning to ensure robust operational performance. This approach incorporates Scheduled Output Capacity (SOC), which represents the upper 15% of the factory's production output. By including this additional capacity, the planning process builds a buffer to safeguard against demand variability and supply disruptions. Conversely, Demonstrated Output Capacity (DOC) reflects the factory's expected output under typical operating conditions, serving as a baseline for realistic production expectations as illustrated in 4.2. The utilization of these distinct levels significantly influences the forecasts shared with suppliers. The inclusion of SOC in the planning process leads to inflated demand projections, resulting in higher stock levels. Effectively, this creates an implicit safety stock based on forecasted requirements. However, this methodology introduces a systemic bias, as suppliers must adjust to overestimated demand forecasts. Consequently, this often results in overstocking of raw materials, increasing inventory holding costs and potentially leading to inefficiencies within the supply chain.

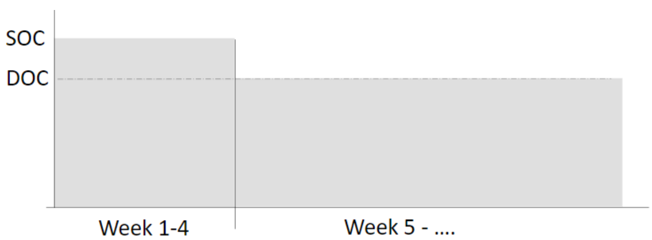


Figure 4.2: DOC/SOC

4.1.5 | Bill of Materials

The previously mentioned bill of materials conversion is being used to calculate the number of required packaging materials. The formulas for these conversions are given below.
Packaging material is in one finished good:

$$Q_S = Q_P \times q_{PS}$$

where:

- Q_S is the total quantity of the packaging material.
- Q_P is the quantity of the finished good to be produced.
- q_{PS} is the quantity of the packaging material required per unit of the finished good.

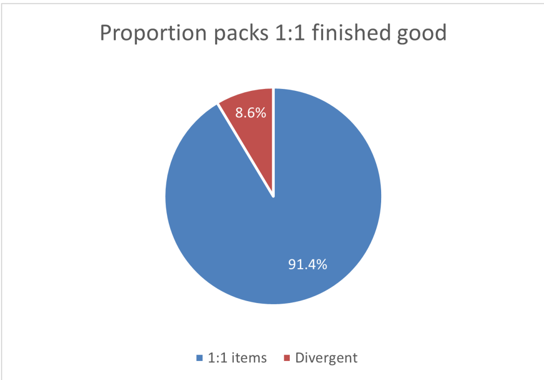
Packaging material is in multiple finished goods:

$$Q_S = \sum_{i=1}^{n} Q_{P_i} \times q_{iS}$$

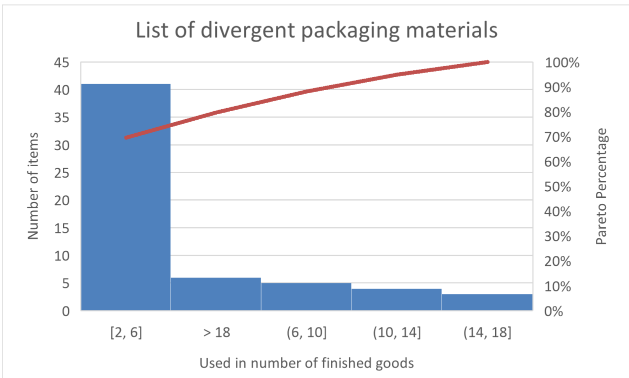
where:

- Q_S is the total quantity of the packaging material.
- Q_{P_i} is the quantity of the i-th finished good to be produced.
- q_{iS} is the quantity of the packaging material required per unit of the i-th finished good.
- n is the total number of finished goods.

For the current status of Veghel, there are around 686 active packaging material parts, of this list 627 items have a one-on-one relationship with a finished goods code. Figure 4.3 shows the relationship of 1:1 items as well as a Pareto chart for the number of items having more than a 1:1 relationship. Generally, the divergent items are for 70% only used in 2-6 finished goods items, and a few more codes are used in a significant number of finished goods items.



(a) Proportion of Packs 1:1 FG

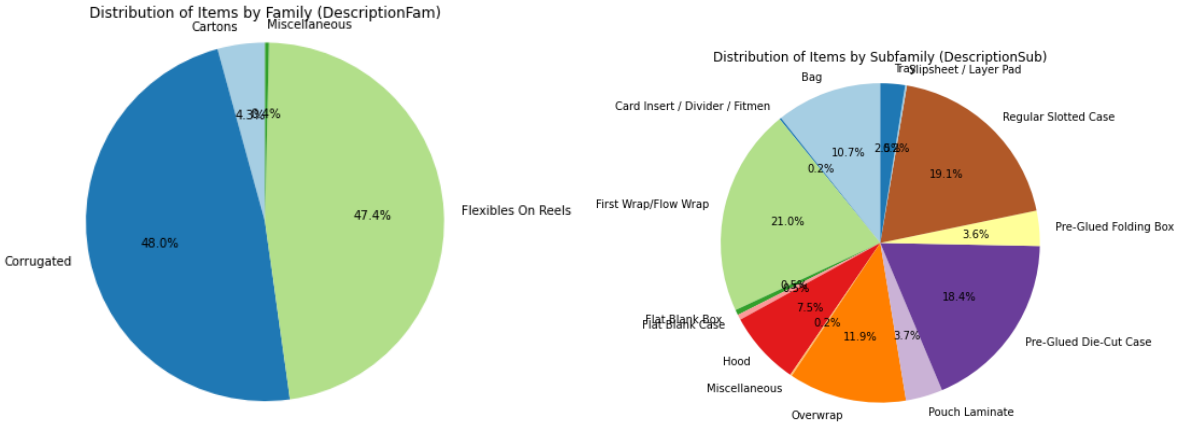


(b) Distribution divergent items

Figure 4.3: BOM descriptives

4.1.6 | Material Types

As outlined in the bill of materials, a range of material types have been identified as the source of a group of finished goods of Mars. The composition of a chocolate bar is constituted by the ingredients used to create the bar itself, as well as the complete wrapping procedure. In general, the chocolate bar will be wrapped in a preliminary layer. Subsequently, the product may be wrapped in a multipack or stored in a presentation box, which may also represent a certain multipack. Ultimately, all items are placed in their corresponding corrugated boxes, which are then transported to the appropriate market warehouse, supermarket, and ultimately, the end consumer. However, due to the considerable diversity of packaging materials and the multiplicity of suppliers involved, it is of paramount importance to gain familiarity with the properties of these products, with particular emphasis on the production process. Accordingly, to optimize the supply chain, it is essential to optimize the batch sizes in collaboration with the respective supply chain partners. However, due to the diversity of these products, it is necessary to perform an extensive data collection to ascertain the setup costs for each respective process. Furthermore, the setup costs can vary significantly within the same supplier, making the overall situation more complex. in Figure 4.4, all item types are given. These material types are very important to determine the associated setup costs for each material type. Furthermore, each material type has different properties such as the setup costs, and the holding costs for some items a lot more units fit on a respective pallet but also properties regarding forecast detail, different suppliers, and different requirements in the aforementioned bill of materials. In the later section on product segmentation (section 4.2), insights will be given on the



(a) Item family distribution

(b) Item type distribution

Figure 4.4: Item types

different assumptions these different items provide to finding optimal replenishment policies, both a one size fits all policy as differentiated policies which might improve cost performance, improve service levels and therefore aim to reduce costs while improving service which as mentioned in the chapter 2 is the key trade-off which is accounted for in this research.

4.1.7 | Demand Descriptive Analysis

The demand data is tested for normality, stationarity, and intermittence. Due to the short time series, the majority of items are non-normal, non-stationary, and intermittent. However, for items with longer timeseries it is usually also hard to fit a normal distribution.

Normality
For the normality test, the Shaprio-Wilk (SW) test has been used. Based on this analysis no items were normally distributed when not excluding the zeros. Furthermore, when excluding the zeros in demand only 11.47% of the items were found to be normally distributed over their respective time horizon.

Stationarity
For the stationarity test the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test has been the chosen method to identify which and how many items are stationary (Hobijn et al., 2004). Based on this test only 17.01% of the items were found to be stationary and if excluding the zeros only 9.15% was found to be stationary.

Intermittence
Using the earlier mentioned ADI used by Syntetos & Boylan (2005) where the cutoff value has been used as 1.32. Based on this 85.3% has been classified as intermittent items. Therefore, the demand patterns of the items in scope with the relatively short time series can be classified as non-normal, non-stationary, and intermittent in most situations. Therefore, it is very hard to fit a distribution to the demand instances for which the empirical research on demand and forecast has been chosen with a focus on the associated inventory management.

4.1.8 | Item Changeover process

Due to the frequent changes in items at Mars, the company faces the challenge of working with relatively short time series, making accurate demand prediction difficult. In the majority of instances where a changeover occurs, the item code is discarded and the same settings are selected for planning purposes. This is based on the assumption that the behavior of the subsequent code is identical to that of the previous code. Nevertheless, no investigation has been conducted to determine whether this assumption is indeed valid. Moreover, as the preceding packaging code is not retained, relatively short time series make it increasingly challenging to forecast the demand for individual materials. Therefore, this research project is concerned with monitoring the forecast that has been propagated throughout the system. In addition, this changeover process also results in a large obsolescence rate as all leftover stock after a certain changeover date becomes useless and is not fit for any further production. Therefore, the changeover process provides two main challenges, a high risk of obsolescence by not using the leftover stock and difficulties in the analysis as the data is not logged for changed-over items reducing the length of respective timeseries for each material code.

4.1.9 | Summary

The non-stationary and non-normal nature of the demand patterns, coupled with the high number of changeovers, makes it challenging to determine the suitability of the distribution fit for the demand distribution. Furthermore, especially for the MRP forecast it is hard to determine the underlying assumptions for planning the supply chain as it is based on the earlier mentioned demand propagation to the respective material codes. Therefore, the BOM translation combined with the enclosed forecasting method of finished goods in several systems causes it to be very challenging to make a stochastic estimation of both these variables. Thus, by simulating over an extended empirical time-series, the most effective method can be determined to optimize the reorder and order-up-to levels for each product, based on its specific item characteristics, demand patterns, and forecast behavior. Therefore, for subquestion two it is very hard to find the optimal interpretation of demand due to the fast-changing environment of different material products within Mars. However, it is good to evaluate the forecasting metric of the Mars supply chain and couple the value of information sharing to the process of the supplier. For now, it is most important to consider the MRP as-is and compare it to potential other demand propagation methods to ensure the best information sharing within a VMI supply chain for a production company.

4.2 | Product Segmentation

Furthermore, for Mars, it is valuable to establish a segmented method for managing inventory. As for the short time series for the products, it is hard to determine all item characteristics. Especially when running the optimal policy for each SKU independently to achieve the most optimal solution. Therefore, it is important to establish groups for Mars that could independently be used for item segmentation based on various properties. The following section describes an overview of the possible segmentation methods but for the shorter time series of Mars and distinct SKU classifications which are difficult on the material level enhanced segmentation as proposed is a limitation of the research and should be further investigated based on the identified priorities proposed in the subsequent sections. In Table 4.1, the levels of aggregation that can be segmented within each category are given.

Aggregation Level	Groups (Active)
Manufacturing site	1
Product Family	2 {Carton and Flexibles}
Product Sub Family	15
Specification group	169
Material Group	199
SKU	~600

Table 4.1: Levels of aggregation Mars

4.2.1 | Method

This section examines demand segmentation to establish differentiated target fill rates. Items are categorized by attributes such as demand volume and volatility, enabling tailored replenishment policies. A primary focus is adjusting the minimum reorder level within the min-max policy to align with segmented attributes. Volatility and volume are key decision factors, but certain packaging materials, critical for multiple finished goods, may warrant higher priority due to their impact on production continuity.
Different markets also require varying availability targets based on minimum shelf-life requirements. Packaging stockouts reduce production flexibility, necessitating re-planning. As Mars products have defined shelf lives and markets differ in their requirements, segmentation by importance and volatility is explored through ABC analysis. This method groups items to adjust fill rates, prioritizing Group A items with higher availability while reserving space for critical stock.
The most likely segmentation method would be based on volumes combined with forecast variability. Forecast variability can as mentioned before be split into the four groups proposed by Boylan et al. (2008) using the squared coefficient of variation and ADI. The hypothesis is that this would result in high-volume items with low variability, high-volume items with high variability, low-volume items with high variability, and low-volume items with high variability. When compared to the proposed min-max model, the high variability items may have a larger bandwidth, while the high run items may have a larger initial (min) stock. The exact classification cut-offs are yet to be determined and might be tuned to be able to satisfy demand in the best possible way. The methodology in the paper of Godsell et al. (2011) will be used to classify the SKUs based on their variability and volume. This is because the aforementioned paper proposes a lean and agile approach for newly introduced and steady-state items. Furthermore, the case of Mars also contains a significant number of changeovers to new item codes and newly introduced seasonal products, which may require a different replenishment policy approach concerning vendor-managed inventory compared to stable products all year round. Once the demand groups have been identified, a range of policies can be formulated to meet the identified demand most suitably. In addition, multiple criteria for further item segmentation for Mars have been identified and are presented in the following subsections.

4.2.2 | Waste priority

Highly volatile demand should sacrifice service levels as they contain the highest probability of obsolescence. (New product introductions should start with a lower service level, aim for ordering MOQ, and shorter cycles, which result in higher costs per item but lower risk of obsolescence). This is in line with the XYZ of the ABC XYZ analysis where high-risk items receive a lower target fill rate to combat both the waste and the overstocking risk and balance this more evenly compared to items with frequent production cycles.

4.2.3 | Production priority

As described in the Bill of Materials (section 4.1.5), some items are used in multiple finished goods items. Therefore, a stockout of this item poses a much larger risk to a supply chain disruption than an item that is used in one finished good only. This makes it apparent that considering that weighing this in a segmentation model is a good option to achieve fewer system disruptions. In addition, only considering the volume and volatility of items as in the ABC XYZ analysis causes high consumption items to have high fill rate targets whereas items with much lower volume but much more frequent use are considered unimportant as the final finished good is still not made if not all items in the bill of materials are available. Thus, it is apparent to weigh this criterion for a segmentation approach.

4.2.4 | Market priority

Mars delivers to different markets with different requirements for each respective market. Especially the requirement of minimum shelf-life for finished goods products per market is considered a key factor for having packaging available from an end-to-end perspective. When flexibility is required for production the out-of-stock risk should be as small as possible. Consequently, when the permitted shelf-life is very long, the room for delaying orders or already pushing productions if packaging is available is less of an issue as this market has relatively lower requirements. Thus weighing the importance of a final product to the respective markets is already important when considering packaging as for very tight supply chain planning more flexibility is required and thus more (safety) stock to ensure availability with the required shelf-life at any time.

4.2.5 | ABC XYZ analysis

In an ABC XYZ analysis, it is possible to factor items into different categories. For the sake of simplicity in Mars, it is worthwhile to identify items on item characteristics such as the flexible and carton material and focus on within-group segmentation for certain items based on their respective demand behavior. The flexible and carton materials are hard to normalize due to the lack of one unit of measure and especially the lack of value of a finished good to convert to the value of the usage of a particular item within this finished good.
From the perspective of relevance, this split appears to be the most cost-effective method for determining reorder and order-up-to levels within Mars. This approach employs a cost-based segmentation strategy, utilizing the relative holding costs associated with the number of goods stored on a pallet and the lead time for each item or item group. As has been identified, these item groups have similar lead times and holding cost ratios, which leads to the possibility of segmentation based solely on the demand type. In particular, the split between carton/corrugate and flexibles is the most practical and relevant, maintaining a simple stocking system for Mars. However, within these groups, further segmentation can be performed based on demand type, volatility, and value of each respective SKU.
Therefore the following Figure 4.5 shows the differences for the two core categories within Mars namely flexibles and cartons/corrugate. These groups are easily identified as these have totally different suppliers, different product types, and different production processes as earlier described in this Chapter. Also identified in Lovell et al. (2005) and Ploos van Amstel (1986) the product density of an item is important for determining the criticality of an item within a capacitated inventory control model.

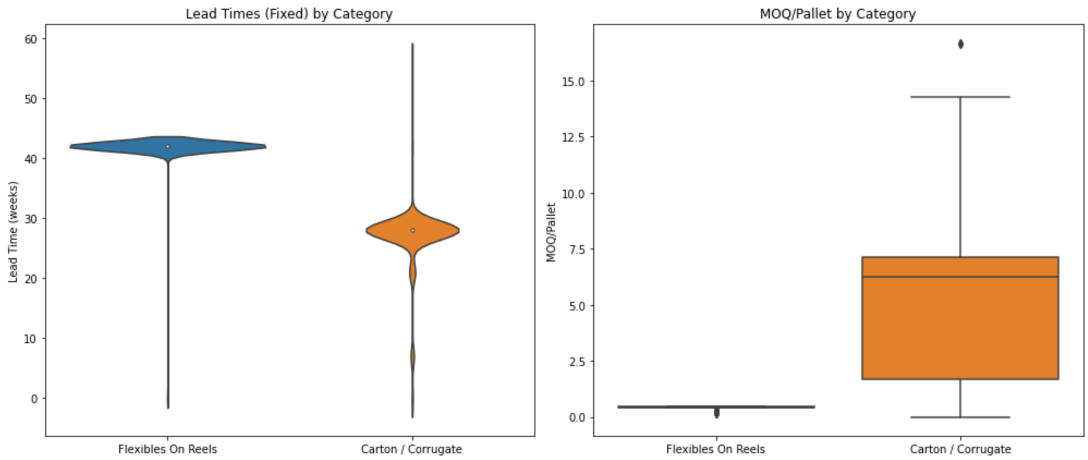


Figure 4.5: Flexibles and Carton / Corrugate Leadtimes and MOQ/Units per Pallet

4.2.6 | Summary

Items can be categorized on several criteria to establish an optimal inventory system. Based on value density the number of cycles can be increased for items as increasing the number of cycles for items with low value density holding costs can be reduced finding an optimum for holding and setup while adhering to similar fill rates. Based on the relative importance of items based on the aforementioned criteria a decision can be made to decrease fill rate requirements for certain groups to reduce required warehouse capacity even further. In the later described simulation-optimization model (see Chapter 6), the different models are tested to see the potential cost improvements from splitting the item categories into these different categories.

5 | Supplier Analyis

This chapter focuses on detailing all suppliers, including the materials they produce and their respective production processes. Based on these processes, an inventory control framework is collaboratively developed with Mars. Additionally, this chapter identifies the main differences between suppliers, outlines the current situation, and explores potential improvement directions. The description of the current situation serves as the foundation for the model presented in Chapter 6, while the proposed improvement directions inform the process redesign discussed in Chapter 7.

5.1 | Supply chain process Mars Supplier

Mars uses two different types of packaging material suppliers: carton and flexible materials, each with unique processes. Carton suppliers are typically chosen to be closer to Mars warehouses, as cartons are bulky and expensive to transport. These suppliers process raw board material by cutting it and printing the required artwork, though their changeover efficiencies are limited. In contrast, flexible material suppliers produce wrapping materials stored as rolled basefilm, which is less bulky and requires less pallet space. These suppliers are generally located further from Mars manufacturing sites, and costly and time-intensive material changeovers significantly influence their lead times. Therefore, maintaining higher stock levels for flexible materials is often more cost-effective than carton materials.

5.2 | Collaboration Mars and Supplier

Mars collaborates in two ways with the supplier. These collaborations are Purchase Order (PO) and Vendor Managed Inventory (VMI). The following section shows the respective differences between both methodologies.

5.2.1 | Purchase Order (PO)

The Purchase order process is relatively straightforward. Based on SAP proposals the material planner plans orders for different materials to maintain optimal stock levels. This process is shown in Figure 5.1. The SAP system proposes and each week the material planner schedules orders in the SAP system which are in turn requested from the suppliers and after confirmation the order and delivery are scheduled. Furthermore, the material planner monitors the stock levels and contacts the supplier if it is deemed necessary to postpone or delay an order.

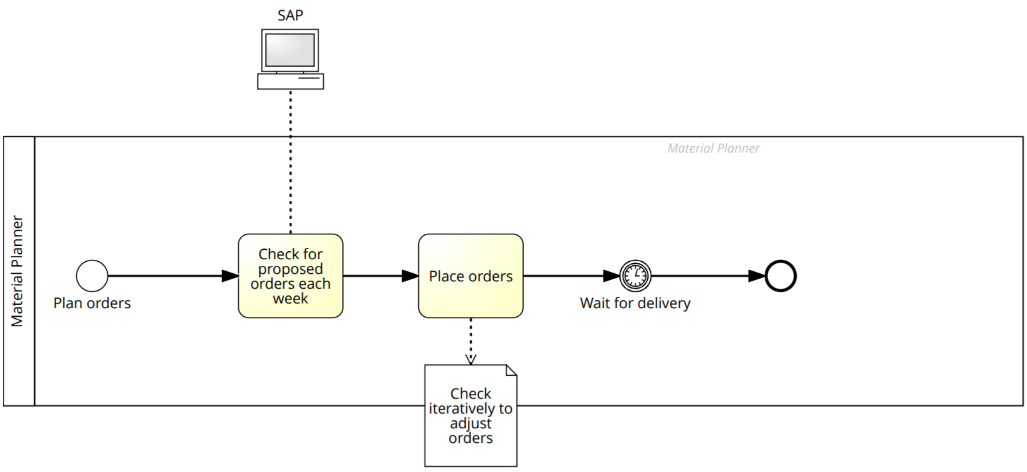


Figure 5.1: PO Process

5.2.2 | Vendor Managed Inventory (VMI)

Currently, Mars uses the supplier connectivity report to share the current stock levels and current forecast for the packaging materials at Mars. The sharing of information is based on the Material Requirements Planning (MRP) of Mars. This propagates the finished goods forecast to a material-deducted production planning. Each supplier receives the stock position and forecast of their materials and makes decisions based on what the supplier deems most suitable. However, this process cannot be optimal as for certain demand patterns different stock levels are required. Therefore, this research section aims to investigate the dispersion between supplier replenishment decisions, find potential best practices in information sharing, and finally find the best replenishment decisions and guidelines for the respective VMI suppliers. As shown in Figure 5.2, the VMI process is more complicated compared to the purchase order process. This is important for Mars to maintain in control of the respective stock levels at its manufacturing site. The process shows numerous manual interaction points with the supplier to maintain proper stock levels including a lot of manual information sharing, conformations to be made frequently, and several manual uploads to ensure data quality. Furthermore, the SCR is generally based on a CSV output file which is

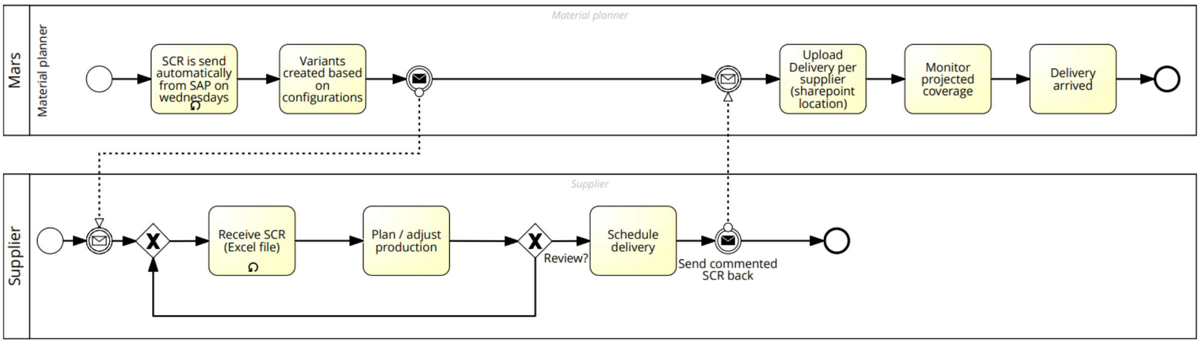


Figure 5.2: VMI Process

handled in several different ways by all suppliers, there are only 36 (around 2%) instances of Electronic Data Interchange (EDI) transmissions out of a total of 2,206 variants, and the remaining 98% is all based on sharing of excel workbooks extracted from the SAP system. The supplier generally receives data for the first 7 days in daily buckets following data for 8 to 12 weeks and finally, some demand aggregated on period (4-week bucket) level.

5.3 | Supplier Pilot

In this section, 2 suppliers have cooperated tremendously to pilot a new way of working regarding the vendor-managed inventory process. The goal of this pilot has been to gather information on the reasons for over and understock and establish possible solutions to stock reductions and service improvements.

5.3.1 | Performance measurement

During this thesis, a tool has been developed using Python to measure these key performance indicators. The tool calculates the expected stockout moment if no replenishment is made. In this way, each item can be categorized in an understocked, risk for production push, within SLA (in target), and overstocked region. Furthermore, Table 5.1 shows the stock regions each item can have. The measuring process is similar to the performance monitoring system approach proposed by Danese (2006). Figure 5.3 shows an example of the stock regions for each item over time. In the case study of Mars, the stock levels have been checked over the course of 5 months to provide proper root cause identification for not meeting the stock regions. The following section explains the implementation of this performance measurement within Mars.

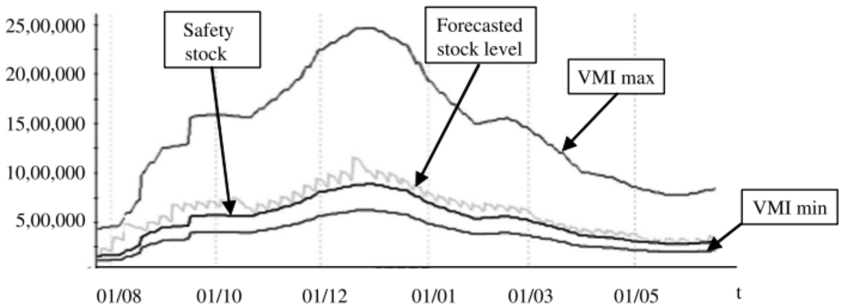


Figure 5.3: VMI min-max (Danese, 2006)

5.3.2 | Supplier performance measurement KPI

The implementation of supplier performance measurement requires specific information. This includes the supplier connectivity report for each respective site and the VMI supplier report, which details material codes and their associated suppliers. Additionally, units per pallet data are needed to calculate the volume within the specified stock regions. Finally, the performance measurement also requires the bounds for each item. In this case, the stock regions as described in Table 5.1 have been used. Based on these stock

	Carton / Corrugated	Flexibles
Item at risk	0-10 days	0-14 days
Risk Production Push	10-28 days	10-28 days
In target	28-49 days	28-70 days
Overstocked	49-999 days	70-999 days
Excess overstock (Stock >Demand Forecast)	>999 days	>999 days

Table 5.1: Stock regions suppliers

regions there are two performance metrics to measure the performance in the respective stock regions based both on the number of items and number of pallets in each respective region.

$$\text{Item-Performance} = \frac{\text{Number of items in the stock region}}{\text{Total number of items}} \times 100\%$$

$$\text{Volume-Performance} = \frac{\text{Total volume of items in the stock region}}{\text{Total volume of all items}} \times 100\%$$

Furthermore, the evaluation of supplier performance is based on the total volume of items in pallets, as opposed to the item-based performance metric, which may yield an inaccurate representation if smaller items comprise the majority of the metric. However, the classification of the items is consistent, and thus the percentages may change due to a different weight per item. In addition, the implementation is created using a Python script with the pseudo-code given in algorithm 1 (See appendix F.1). This report has been implemented within Mars from the start of July and has been used to keep track of inventory performance from all suppliers, and Mars factories both volume and item-based.
Following from this some patterns have been discovered in supplier processes between different suppliers. Figure 5.4 clearly shows that one supplier holds substantially more stock than the other. By identifying these different behaviors it is also necessary to see why this result is happening and what assumptions each supplier makes in its replenishment process. Section 5.4 further elaborates on this survey and its respective outcomes.

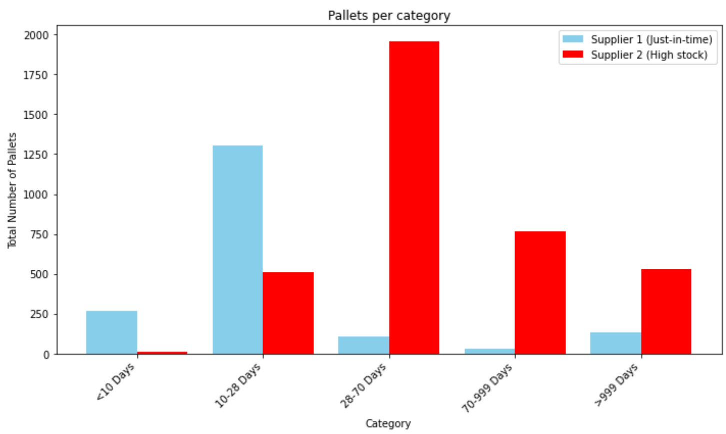
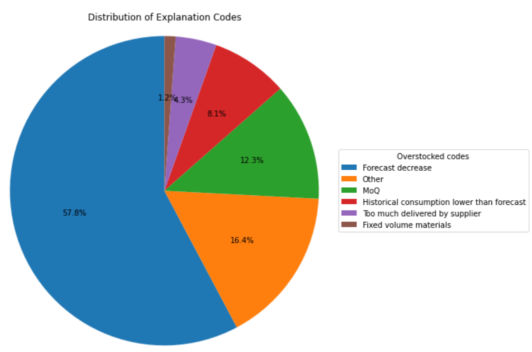


Figure 5.4: Different supplier behavior (Both Carton suppliers)

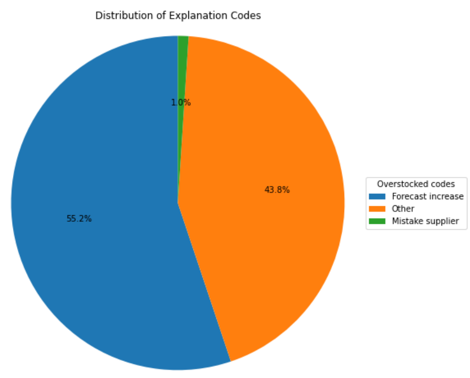
Based on these stock regions, the performance of all suppliers is measured on an item and volume basis, and for two specific suppliers taking part in the pilot, each week all items are shared in their specific stock regions and data has been collected on the reason codes for being in one particular undesirable stock region. The reason codes are defined by the expert knowledge of the senior material planner where the senior material planner checks the associated demand pattern and MOQ to label the most suitable reason code. This method has been set up to keep track of suppliers' progress, identify different supplier behaviors, and find root causes for being in respective stock regions to find solution directions such as MOQ reduction or forecast improvements. The next section focuses on the results of this method.

5.3.3 | Root cause analysis

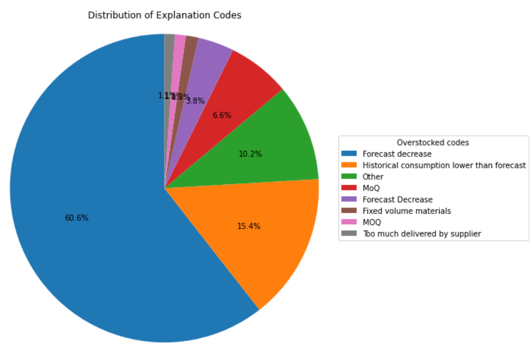
As mentioned before, the pilot with suppliers has also been used for root cause analysis. As shown in Figure 5.5, the primary root cause for understocked materials is the significant forecast increase. Additionally, other classifications are often associated with item switchovers. In this context, Mars typically aims to complete the last remaining stock in production planning before product changeover. This sometimes results in a small rounding error where the planned consumption is slightly higher compared to the available stock in which the items are flagged as at risk but due to the insignificant production loss classified as not an error by the supplier and shown in the other category. Rarely a mistake of the supplier has been addressed and the underlying reason codes are generally based on having a full capacity and thus being unable to produce all the items. Although in the overstocked reason codes the forecast is still a key indicator for being in this stock region, MOQ and too much delivered by the supplier become more prominent in this analysis. Therefore, based on these problems, a scientific model is created in Chapter 6 to be able to simulate what suppliers should have done in every situation according to replenishment decisions and what would happen if suppliers have the same replenishment process under different demand forecast or replenishment rules. This shows that a large proportion of the mistakes are caused by the forecast



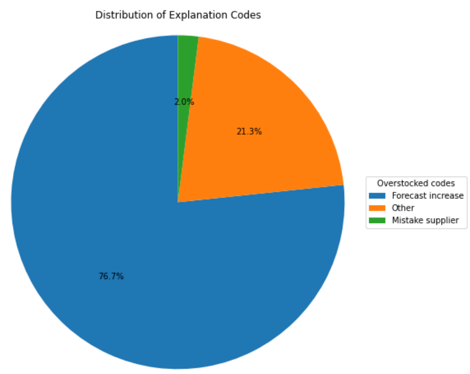
(a) Overstocked Flexible materials



(b) Understocked Flexible materials



(c) Overstocked Carton materials



(d) Understocked Carton materials

Figure 5.5: Reason codes of senior material planner for suppliers not meeting SLA bounds

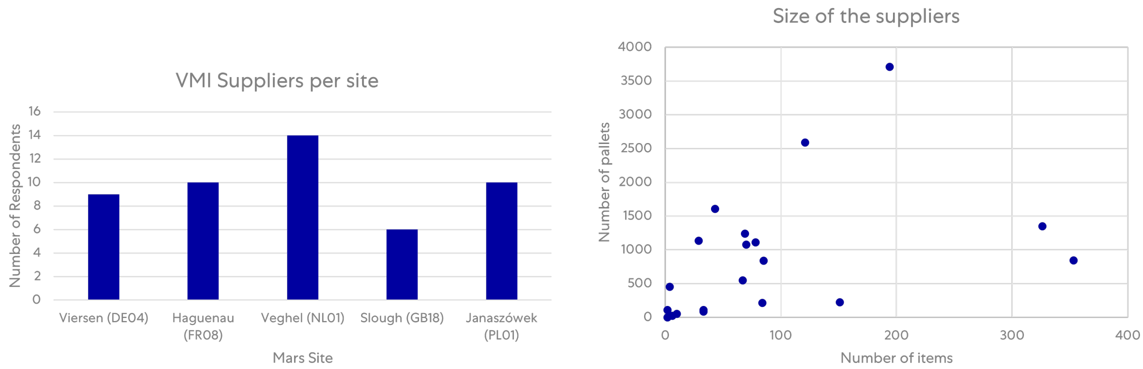
volatility during the leadtime. Therefore this is the key to dive further into the forecast to establish why the forecast is this volatile. However, the SLA bounds currently used could be suboptimal resulting in the possibility that the performance could deviate when other boundaries are set. The problem identification has been derived from 1 flexible supplier and 1 carton supplier investigating 5 Mars production sites. These analyses have been performed over the course of 5 months containing 1663 overstocked carton items, 2219 overstocked flexible items, 150 understocked carton items, and 194 understocked flexible items.

5.4 | Supplier Survey

To evaluate the current performance, a survey has been designed for distribution to suppliers. The survey is comprised of two principal sections. The first objective is to define the current supplier replenishment process, while the second is to establish potential avenues for improvement. The objective of section 5.4.2, is to determine the reorder and order-up-to-level levels currently utilized by the packaging material suppliers that deliver to the Mars manufacturing sites, whether these suppliers account for safety stock, their respective lot sizes, and delivery frequencies to factories. Moreover, it determines whether suppliers maintain inventory at their facilities, reserve safety stock for raw materials designated for Mars, and the current handling of the shared document (Supplier Connectivity Report) of Mars, including the level of automation of this document. This data is used to benchmark the replenishment policies employed by suppliers, to incorporate these into the scientific model presented in Chapter 6. The later sections are on improvement. The questions posed are designed to determine the flexibility of suppliers in meeting the agreed lead time, whether they encounter difficulties with the current process, and whether they have established best practices with other customers.
The results of the supplier survey are shown and the key implications for the subsequent simulation model (Chapter 6) are elaborated on. The survey received 25 responses from the 38 VMI suppliers delivering to Mars. The associated questions used for the survey are given in Appendix A.

5.4.1 | Descriptive statistics

The 25 suppliers exhibit a relatively diverse range of characteristics, including the materials delivered by each supplier, the size of the suppliers, the sites to which they deliver, and other descriptive statistics that identify multiple supplier types. For all, please refer to Figure 5.6. Furthermore, the respective number of items and pallets are provided. In terms of the size of the suppliers, there are a few relatively small suppliers with holdings of less than 100 pallets of stock across all sites and deliveries of less than 10 items. Furthermore, a medium-sized supplier group can be identified, delivering approximately 50 items with the number of pallets ranging from 1,000 to 2,000. Finally, two large flexible suppliers and two large carton suppliers have been identified. The flexible suppliers deliver a relatively higher number of items while having a large number of pallets to deliver, and the two large carton suppliers hold over 2,500 pallets at the respective Mars sites. As previously stated, carton suppliers typically offer more substantial items than flexible suppliers, who provide a greater number of rolls for packaging. These differences can be reflected in the pallet-to-item ratio.



(a) Supplier Deliveries to Mars site

(b) Supplier Size

Figure 5.6: Supplier Descriptives

5.4.2 | Benchmark Order Policies

This section is concerned with the quantitative aspects of the supplier survey, to identify the replenishment policies employed by suppliers, including their respective reorder and order up to levels. Subsequently, the flexibility of their production plans is investigated, to determine the potential for lead time reductions or additional stock holding at supplier locations. Furthermore, it identifies the different policies that are used for different Mars sites, and their respective implications for the supplier synchronization goal of Mars, namely the integration of all working practices among all sites and all suppliers.

Delivery cycles

In this section, the order cycles of all suppliers to each site are given, as for inventory management it is important to see how frequently deliveries arrive. For example in a monthly delivery pattern, if a delivery has just arrived there is a risk period over the next month. In Table 5.2, the delivery cycles of suppliers are given for the respective sites. The table shows more frequent deliveries for Veghel compared to the other sites which can be explained by the Veghel site being the largest production site.

Mars site		Viersen (DE04)	Haguenau (FR08)	Veghel (NL01)	Slough (GB18)	Janaszówek (PL01)
Delivery cycle	Daily	0	1	3	1	2
	Twice a week	4	3	6	2	0
	Weekly	1	3	2	1	5
	Twice a month	2	1	1	0	0
	Monthly	2	2	2	2	3

Table 5.2: Delivery cycles suppliers

Order policies

This section displays the results of the reorder level and order up to level in weeks given by the supplier as shown in Figure 5.7. For the Veghel (NL01) site, these levels are used to benchmark against the simulated policy in Chapter 6. However, it clearly shows distinct policies between Flexible and Carton/Corrugate suppliers where the extended reorder level is most likely lead time-based and the order quantities most likely are due to different cost structures. However, in both material types, a large dispersion is observed between the respective suppliers.

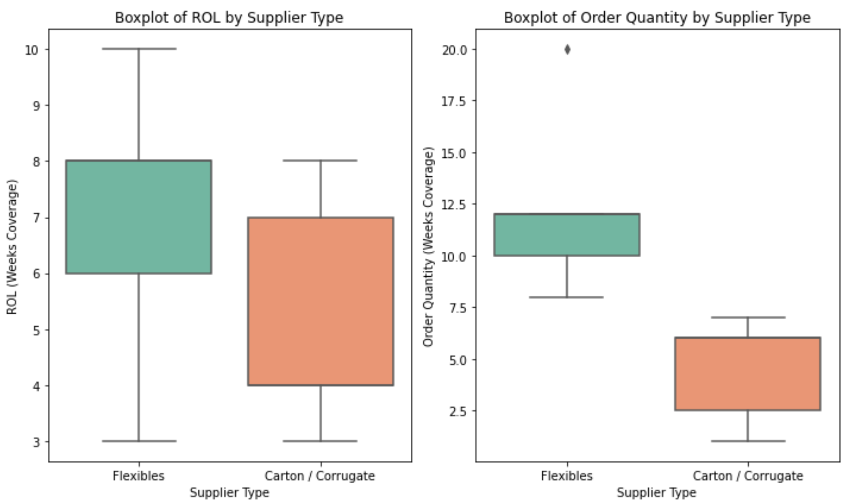


Figure 5.7: Order policies for the Veghel site

Review Period

The review period for all suppliers has turned out to be 1 week as the supplier connectivity report is reviewed each week. However, for suppliers, the review moment can be on different days, for the largest group of suppliers this is on Wednesday but differs for a group of suppliers also impacting the used supplier forecast.

Safety Stock

Regarding the safety stocks at the respective sites, (almost) no suppliers keep safety stock at the Viersen (DE04) and Haguenau (FR08) warehouses. However, for the other sites around half of the suppliers hold safety stock for the suppliers. Figure 5.8 shows the exact number of suppliers from the survey per site and the consequent percentage of suppliers holding safety stock additional to the reorder level and order up to level targets.

Figure 5.8: Safety stock of suppliers

5.4.3 | Asynchronous suppliers

This section will demonstrate the discrepancies between suppliers, thereby establishing how asynchronous the suppliers actually are in their respective policies. The initial example pertains to a supplier that provides goods to multiple Mars locations, each of which has its distinct policy. Furthermore, Mars has numerous suppliers operating from multiple locations. For some suppliers, the responses from these various sites have been collated. This section also considers the different approaches within the same supplier. As previously stated, Mars aims for supplier synchronization, therefore a uniform policy across the entire European Mars supply chain is preferable.

Different policy for each Mars site

Of the 15 suppliers that deliver to multiple Mars sites, 11 suppliers have different targets for the different Mars sites. Only 4 suppliers all deliver VMI while adhering to the same targets. Furthermore, for the suppliers delivering the same method the target varies from 8-12 weeks and the reorder level varies from 6-8 weeks. For example, this should in turn impact the pack availability at the respective sites as well as the stock coverage level impacting the warehouse capacity.

Different approach regarding VMI or PO for each Mars site

In addition, several Mars suppliers follow a different approach regarding delivering VMI or PO, especially using different approaches for different Mars sites. Table 5.3 shows the suppliers delivering to multiple Mars sites and consequently Table 5.4 shows the respective distribution of VMI and PO among the mixed suppliers. These results clearly indicate a very asynchronous supply chain process.

Full VMI	Full PO	Mixed
8	1	6

Table 5.3: Number of multi-site suppliers delivery type

Supplier	VMI Percentage	Number of sites
Supplier 2	50.0%	2
Supplier 6	80.0%	5
Supplier 7	33.3%	3
Supplier 8	50.0%	2
Supplier 9	50.0%	4
Supplier 10	50.0%	4

Table 5.4: Distribution of VMI/PO over the mixed suppliers

As shown in this overview, the Mars network is very asynchronous based on three dimensions, there is not the same policy regarding VMI or PO for each supplier delivering to different sites. The same supplier has different policies regarding delivery to different sites and the same site has different delivery procedures. This mismatch creates an unbalanced and asynchronous structure within the Mars supply chain, potentially disrupting the adoption of best practices. It also results in a significant double workload. Mars must either take responsibility for managing a large portion of their inventory or delegate control to vendors. Meanwhile, suppliers face the challenge of accommodating different delivery patterns for each Mars site they serve.

5.4.4 | Segmentation of SKUs

A key factor in this research is the use of segmentation for different items with different characteristics. Therefore, the survey looked at whether suppliers were segmenting their policies for different items based on some sort of priority rule, such as choosing high volumes over lower volumes or, if the forecast is very volatile, countering this for certain items by reserving more stock. However, in the survey, only 1 out of 25 respondents stated an item segmentation approach had been used, specifically based on forecast volatility and volume. All other suppliers indicated that no item segmentation was used for their respective SKUs supplied to the respective Mars sites. As mentioned in the benchmark ordering policy section, policy segmentation across Mars sites is quite common. This is even though relatively few suppliers supply multiple Mars sites.

5.4.5 | Adjustments during the leadtime

The survey found key implications regarding adjustments being made during the leadtime. This is also the key difference between a VMI and PO process as earlier described. However, for modeling and performance indicators it is paramount to see on which shared information the decision for a certain replenishment is made. Therefore, the simulation-optimization model in Chapter 6 describes the use of the provided leadtime by Mars as well as providing sensitivity analysis for increasing or decreasing the leadtime due to the decision-making of suppliers. Table 5.5 shows that there is a high level of flexibility for suppliers, especially regarding the delivery moment there appears to be a high level of flexibility during the leadtime. Moreover, Flexible suppliers tend to have more flexibility during the leadtime which can also be explained by the supplier processes in section 5.1. The adjustments during the leadtime provide more flexibility but are however flagged to only be performed if it is possible in the respective planning of the supplier. Finally, it complicates both the modeling and performance tracking progress as there is no clear-cut commitment with suppliers on their delivery quantity and time.

	Delivery moment	Delivery quantity
All suppliers	70.37%	55.56%
Flexible	88.89%	66.67%
Carton / Corrugate	66.67%	50.00%

Table 5.5: Adjustments during the leadtime

In addition to the flexibility in the leadtime, suppliers also tend to make their final production schedule relatively just-in-time to be able to plan their respective productions. The suppliers generally plan their production between 2 and 6 weeks in advance. Especially for flexible suppliers, production is planned around the 2 to 3 weeks mark which is much shorter compared to the agreed 6 weeks leadtime. Therefore, a possible leadtime reduction might be feasible. Chapters 6 and 7 further elaborate on the implications of these reductions based on the relative cost components and the associated process change.

5.4.6 | Supplier Preference (VMI vs PO)

The survey investigates the suppliers and what type of suppliers prefer which process. Figure 5.9 shows the tendency of most suppliers regarding VMI. Moreover, generally flexible suppliers tend towards VMI a bit more which could be in line with the flexibility during the leadtime associated with a VMI process. However, statistically testing using the chi-square and ANOVA, no significant results regarding the type of suppliers and their respective preferences have been found.

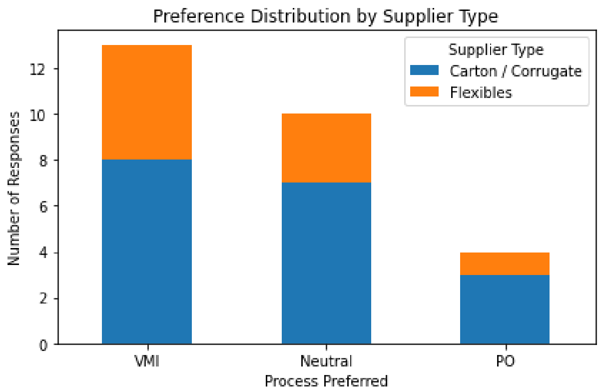


Figure 5.9: VMI vs PO

5.4.7 | Process automation

As defined in the problem context (Chapter 2), the automation of processes might be currently lacking. In addition, the supplier process description mentioned earlier in this chapter in section 5.1 describes the current supply process and already explains the number of suppliers receiving EDI messages compared to the manual Excel file. However, in addition to this expected process, the survey also targets to get a view on the handling of the SCR information. This part of the survey is mainly qualitative and the results show that a weekly review is performed based on the SCR. Following from this a manual Excel tool has been incorporated for 20 suppliers and 7 suppliers have built an automatic tool for SCR and VMI handling. Therefore, it can be concluded that additional steps can be taken to synchronize this process optimally over the Mars supply chain.

5.4.8 | Summary

The supplier survey provides Mars with great insights into the asynchronous behavior of all suppliers where different delivery cycles are used, suppliers use different order policies, safety stock is known at some sites but not at others, and finally, there is a difference in the VMI or PO planning process across suppliers and sites. Furthermore, suppliers do not segment for SKUs that are delivered to Mars. In addition, suppliers do make significant adjustments during the lead time leading to difficulty in performance measurement but also performance improvement by being more flexible. Finally, the process automation for suppliers is relatively low as a lot of manual Excel files are being used to process the SCR. In the following chapter (see Chapter 6), the simulation-optimization model is introduced. This model implements the results of this survey to establish the current situation of the policies employed by the suppliers established in section 5.4.2. Moreover, an in-depth examination of the model will be conducted to ascertain the potential for improvements in lead time and minimum order quantity (MOQ) with suppliers. The resulting gains will be quantified in the sensitivity analysis section.

6 | Simulation-Optimization Model

This chapter is organized into six main sections. The first section introduces the conceptual design, outlining the full scope of the model. The second section details the simulation model, including all variables, parameters, and their respective data sources, with an overview of these sources provided in Appendix E. The third section benchmarks the model against current policies. Next, the optimization model is explained, followed by a section on model validation. Finally, the chapter presents the model results and concludes with a sensitivity analysis, exploring the impact of varying key parameters.

6.1 | Conceptual Design

The goal of the simulation-optimization model is to determine the optimal reorder levels and order up to levels for suppliers. As there is a dynamic nature of the demand patterns as described earlier in the detailed supply chain analysis a simulation optimization procedure has been chosen. The goal of the simulation model is to model the current situation based on a current min-max procedure proposed by Mars, the situation based on the supplier's replenishment policies gathered utilizing the supplier survey in Chapter 5. Following this, an optimization model has been created to find the optimal replenishment bounds based on the weekly forecasted demand significantly reducing the runtime for items as the weekly aggregation delivers for a smaller state space. These optimal replenishment bounds (ROL,OUTL) are based on minimizing the total inventory costs while meeting a fill rate and warehouse capacity target constraint. The policy requires several different models, as such the following models will be created:

- (R,ROL_w,$OUTL_w$) policy current situation proposed by Mars, ROL_w representing a reorder level in forecasted demand weeks and $OUTL_w$ representing the order up to level in forecasted demand weeks.
- (R,ROL_w,$OUTL_w$) policy supplier situation, ROL_w representing a reorder level in forecasted demand weeks and $OUTL_w$ representing the order up to level in forecasted demand weeks with the different suppliers having their respective reorder and order up to levels.
- Optimization: (R,ROL_w,$OUTL_w$) policy optimization algorithm for (R,ROL_w,$OUTL_w$). This optimization provides three different optimization scenarios:
  - This uses the non-segmented optimization proposal indicating the ROL_w and $OUTL_w$ in a one-size-fits-all solution
  - This uses the optimization proposal splitting for Flexibles and Carton / Corrugate materials
  - This approach also shows a segmentation based on all items showing a theoretical reduction

In Figure 6.1, the conceptual design of the simulation optimization model is given. This model shows the different options that are being tested to collect valuable results within the Mars supply chain. This is tested on the items within the NL01 factory.

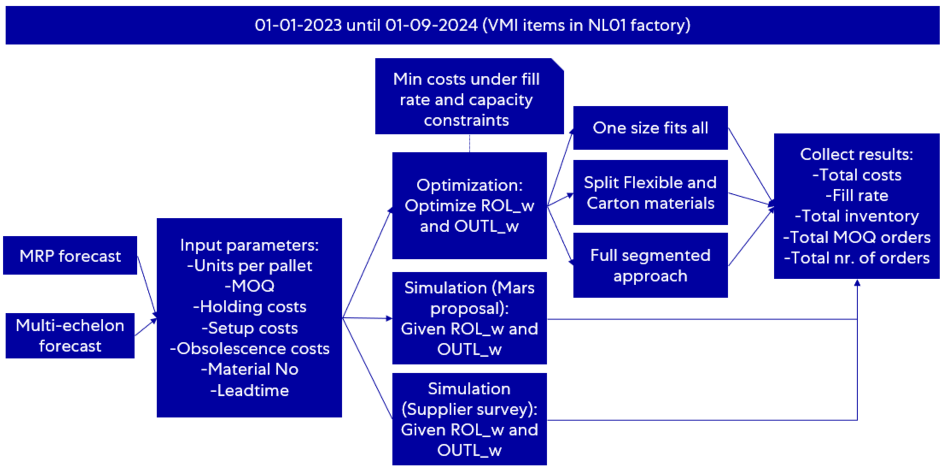


Figure 6.1: Conceptual design simulation-optimization model

6.1.1 | Overview of notations

Notation	Description
	Sets
N	Set of items
K	Set of policies for optimization
T	Set of weeks in the simulation
	Input Variables
$D_{i,t}$	Actual demand during period t for item i (in units)
$F_{i,t+w}$	Forecast for item i at time t for weeks $t+1$ to $t+26$ (in units, for $w = 1, 2, \ldots, 26$)
R_i	Review period for item i (in weeks)
L_i	Lead time for item i (in weeks)
MOQ_i	Minimum Order Quantity for item i (in units)
δ_i	Units per pallet for item i (in units)
$C_{\max}$	Warehouse capacity for manufacturing site (in pallets)
$P_{2,target}$	The target fill rate for the system
c_i	Cost of goods sold per inventory unit for item i
NQC_i	Obsolete costs for item i
A_i	Cost of a setup for item i
h_i	Cost per pallet for item i for 1 week inventory
MFI_i	Manufacturing frequency index for item i
$MatTime$	Maturation time for all items which is equal to one week
	Decision Variables
ROL^*_w	Reorder level in weeks
$OUTL^*_w$	Order-up-to level in weeks
Min^*_w	The min in weeks is defined by the ROL_w - L_i
Max^*_w	The max in weeks is defined by the $OUTL_w$ - L_i
y_k	Binary decision variable. It is 1 if the solution for policy k is selected in the optimal system, and 0 otherwise, where policy is (ROL^*_w, $OUTL^*_w$).
	State Variables
$\text{ROL}_{i,t}$	Reorder level for item i (in units) in week t
$\text{OUTL}_{i,t}$	Order-up-to level for item i (in units) in week t
$\text{IOH}_{i,t}$	Inventory on hand for item i (in units) in week t
$\text{IP}_{i,t}$	Inventory position for item i (in units) in week t
$\text{B}_{i,t}$	Backorder at start for item i (in units) in week t
$\text{Q}_{i,t}$	Order quantity for item i (in units) in week t
$\text{IOO}_{i,t}$	Inventory on order for item i (in units) in week t
	Model Output
$P_{2,i}$	The fill rate for item i over the simulation period
$TC(\text{ROL}_w, \text{OUTL}_w)$	The total costs under policy (ROL_w, OUTL_w) with setup, holding, and obsolete cost
IOH^{avg}_i	The average inventory level for item i over the total time horizon
$IOH^{avg}_{i,pallet}$	The average inventory level in pallets for item i over the total time horizon
nO_i	Total number of orders placed for item i over the simulation period
$nMOQ_i$	Total number of MOQ orders placed for item i over the simulation period

Table 6.1: Overview of Notations

6.2 | Simulation Model

Due to the high demand volatility, it appears reasonable to test the proposed policy on the (empirical) actual consumption data used in production. Therefore, a discrete event simulation will be created for this model, in which the demand and stock levels will be simulated over time. This will demonstrate the actual fill rates derived from the simulation process. Therefore, the assumptions regarding fitting demand distributions will be tested on actual data to check whether the new replenishment policy holds or is too general for specific types of items. In addition, the general policy will be tested against the segmented policy or subsequent policies to evaluate the performance of each respective policy. Moreover, an assumption can be made regarding the possibility of process adherence to additional complexity resulting from categorizing several groups. This will be tested to also test the sensitivity of increased and decreased process adherence. To provide a short example, a certain optimized model might perform well when the adherence of the supplier is over 50%, however in other cases the simpler model might be preferred. These tests are very relevant as the supplier performance appears to be highly diverse among suppliers. Consequently, the simulation model is comprised of two distinct elements. Firstly, the demand distribution assumptions are subjected to empirical testing using actual data. Secondly, supplier performance is incorporated to assess the impact of specific deviations from the proposed models on the inventory position of Mars. The associated pseudo code for the simulation is given in Appendix F.2.

1. ROL and OUTL calculation
In the simulation, the reorder level and order level in weeks are inputted. These levels are the same for each item during the full simulation. However, are updated on the respective forecast based on a rolling horizon approach.

$$ROL_t = \sum_{w=1}^{ROL_w} F_{t+w}$$

Where ROL_w is the reorder level in weeks and F_{t+w} is the forecast for the upcoming weeks

$$OUTL_t = \sum_{w=1}^{OUTL_w} F_{t+w}$$

Where $OUTL_w$ is the order up to level in weeks and F_{t+w} is the forecast for the upcoming weeks. For each week this procedure is run to determine the dynamic reorder and order up to levels.

2. Update the inventory position

$$IP_{i,t} = IOH_{i,t} + IOO_{i,t} - B_{i,t}$$

3. Determine the Required Order Quantity

$$Q_{i,t} = \begin{cases} \max(OUTL_{i,t} - IP_{i,t}, MOQ_i), & \text{if } IP_{i,t} \leq ROL_{i,t} \\ 0, & \text{if } IP_{i,t} > ROL_{i,t} \end{cases}$$

4. Calculation of inventory on order

$$IOO_{i,t} = \sum_{k=t-L+1}^{t} Q_{i,k}$$

5. Update Inventory On Hand (IOH)

The delivery quantity is always added to the beginning of the period and the demand is consumed during the period:

$$IOH_{i,t} = (IOH_{i,t-1} + Q_{i,t-L} - D_{i,t})^+$$

6. Update Backorder (B)

The delivery quantity is always added to the beginning of the period and the demand is consumed during the period:

$$B_{i,t} = (D_{i,t} - IOH_{i,t-1} - Q_{i,t-L})^+$$

The notation x^+ is formally defined as:

$$x^+ = \max(x, 0)$$

This formulation represents the nonnegative part of a variable x. It ensures that x^+ takes the value of x if $x \geq 0$ and assigns 0 otherwise.

6.2.1 | Demand data

For the demand data, the actual consumption of each material by the Mars factory has been used. Based on a week running from Sunday-Saturday the consumptions for each material code have been aggregated and exported from the datalake. This dataset contains the material code, the plant where it is used, and the start date of the week. The dataset has been cleaned for outliers and the time series has been complemented with the intermittent weeks containing no demand to ensure the smooth handling of the information during the simulation.

6.2.2 | Forecast data

The following section contains information regarding the forecast data for Mars and the choices made in this area. The Mars forecast can, as explained in Chapter 4, be considered as the MRP forecast and the associated Mars demand forecast.

Naive forecast MRP Mars
The naive forecast of Mars displays the current situation of the VMI suppliers best. This forecast comprises the existing material requirements planning for Mars. For each week, the MRP, which is also transmitted to suppliers, is executed, containing the weekly forecast for the forthcoming 26 weeks. The data has been collated for each SKU within the specified scope, from the commencement of the SKU's phase-in period to its phase-out date within the simulated timeframe. For each SKU, the data set comprises a maximum of 80 weeks' worth of information, including the demand for the respective 80 weeks as previously mentioned, as well as 80 forecast points. In each of these 80 weeks, the forecast for the subsequent 26 weeks is extracted, resulting in a notable expansion of the data set. Moreover, the data is refined to exclude absent data points by postulating that no forecast updates have occurred, thereby employing the preceding forecast. This process entails the adjustment of the temporal scope by a week, with the missing data point for the subsequent week's forecast based on the preceding forecast time point shifted one week.

Multi-echelon forecast
In the multi-echelon approach, apart from different forecast data an additional production leadtime has to be considered to get the desired echelon stock levels. This can be used to optimize the inventory levels not only based on the current stock of packaging materials but also consider the stock of packaged materials and provide the actual forecast of packaging requirements without including the order batching created in the material requirements planning. For this increased leadtime, the following formula is used to estimate the production leadtime for packaging materials. Furthermore, the maturation time is defined as 1 week as the item has to be in stock for one week before the item can be sold.

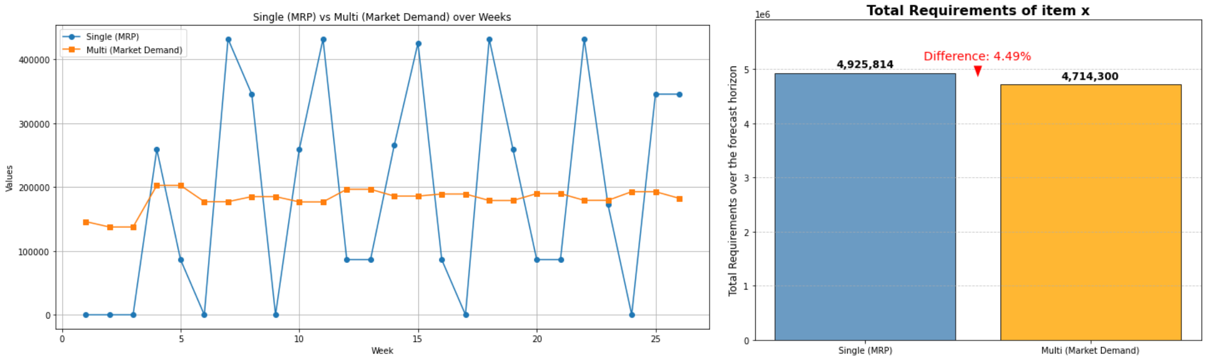
$$\text{Production leadtime} = R_i + \frac{1}{2}\left(MFI_i - 7\right) + MatTime$$

The total leadtime is given below.

$$\text{Total leadtime} = L_i + \text{Production leadtime}$$

In accordance with this production leadtime, it is expected that the simulation will adjust the reorder and order up to level according to this additional leadtime providing the optimal results on the same bounds. For establishing the min-max, the aforementioned leadtime should be subtracted to provide the supplier with a more realistic overview of the demand. This extension does not incorporate the effect on the finished goods production and its respective stock position which could be further elaborated on and mentioned in further research. The forecast data is retrieved from the Kinaxis due date of a packaging item as elaborated in Chapter 4.1.2. The key element of this is using the direct market demand forecast instead of the MRP forecast as mentioned before. Based on the earlier described bill of materials (see section 4.1.5), the demand is multiplied by the quantity used per item to find the gross requirements of each packaging code. The overall structure and assumptions are similar and the data is interpreted as a given without elaborating on the statistical nature of how this forecast has been generated within Mars. Finally, the same cleaning procedure has been applied as for the naive forecast mentioned earlier.
The largest difference between the two forecasts is given in Figure 6.2. This analysis demonstrates that the total requirements across both 26-week forecast horizons are approximately the same, as anticipated. However, the demand fluctuations in the MRP procedure are significantly high due to batching, which introduces additional volatility. This, in turn, affects the timing of deliveries from suppliers, increasing the

variability in supply chain operations. The market demand forecast shows a much more stable pattern asking for similar requirements for each week. This significantly influences the associated delivery decisions and makes the MRP approach much more sensitive to timing.



(a) Forecast pattern **(b)** Requirements difference

Figure 6.2: MRP forecast compared to market demand (multi-echelon) forecast for item x

6.2.3 | Cost data

As the model's objective function relies on minimizing the total costs within a supply chain, the following section is devoted to the extraction of setup and holding costs within Mars. Where the holding costs are relatively easy to gather as Mars maintains a weekly cost per pallet stored in the Kuehne and Nagel warehouse. The extraction of setup costs is much harder due to restricted data sharing between the suppliers and Mars on the costs per setup to determine the optimal costs per item. The following two sections will provide more detail on the cost buildup.

Setup Costs (A)
The setup costs include the data required for a setup at the suppliers' site. The setup costs are controversial within Mars and could thus not be shared fully for each supplier for each item. Therefore, a cost estimation has been made to find a general baseline for the magnitude of the setup costs which are undisclosed for confidentiality reasons. Accordingly, these costs will be deviated to measure the impact on the model. As a result, based on three cost models with suppliers, the average setup costs have been determined for the corrugate, carton, and flexible suppliers. These estimations have been applied and will generally impact the results in the sensitivity analysis as in general, the costs of setups for all suppliers are relatively similar.

Holding Costs (h)
The holding costs per item are aligned with the holding costs for a single pallet, which is generally €1.50 per pallet per week but can vary depending on the number of items per pallet. Therefore, a conversion factor is applied to the number of units per pallet for each material, as costs are incurred per pallet rather than per item. Hence the inventory has to be recalculated to the number of pallets on hand per period to find the total costs for each item by aggregating all costs over the respective time horizons the items are held.

Obsolescence costs (NQC)
In addition, during the simulated period, items are also subject to phase-out. The remaining stock of each item for which no forecast remains is defined as obsolete inventory. Consequently, the costs associated with this obsolete inventory can be calculated as follows:

$$\mathrm{NQC}_i = \begin{cases} \mathrm{IOH}_{i,T} \cdot c_i & \text{if } \sum_{k=1}^{26} \mathrm{F}_{i,T,k} = 0 \\ 0 & \text{if } \sum_{k=1}^{26} \mathrm{F}_{i,T,k} > 0 \end{cases}$$

Where the inventory on hand end is defined by the last period's leftover inventory at the condition that there is no forecast in the future horizon. This procedure follows the procedures given by Persona et al. (2005) and Battini et al. (2014).

6.2.4 | Supplier data

In addition to the cost data, the simulation approach also incorporates supplier-imposed data. It is reasonable to ascertain the minimum order quantities (MOQs) and the units stored on a pallet in order to determine the pallet costs and to identify whether an item is a vendor-managed inventory item or is using the purchase order methodology.

Minimum order quantities (MOQ)
Each item is associated with a minimum order quantity, which is taken into account in the model when determining whether to place an order. This decision is based on either the minimum order quantity or the difference between the order up to level and the inventory position at the start of the period. For each item included in the analysis, this minimum order quantity is used. However, for some items, the necessary data was not available. In these cases, the minimum order quantity of a similar item from a similar supplier has been assumed.

VMI item
Furthermore, data has been provided on whether items are delivered on a VMI or PO basis which has been incorporated in the code to segment based on those groups. As seen for several suppliers in Chapter 5, there could be a difference in VMI or PO items within sites, or across sites thus making it important to distinguish this difference accordingly.

Palletization coefficient (units per pallet) (δ)
Finally, for determining the holding costs it is important to ensure the number of pallets for each material as the holding costs are given for each pallet. Thus, these holding costs are calculated on the average number of pallets for an item which is rounded up as for items with 0.5 pallets in stock the full 1 pallet holding costs are incurred.

6.2.5 | Warm-up period

Since the inventory system manages phase-in and phase-out items, the forecast ensures a smooth phase-in process without impacting the fill rate constraint. However, for some items with a stable demand pattern prior to the studied period, an initial inventory must be established. This prevents incorrect stockouts during the lead time, as items ordered at the start of the period will only be delivered after the lead time, potentially leading to significant shortages. To address this, a warm-up period is introduced. The length of this warm-up period is determined as the studied period minus the duration of the demand input. This approach allows earlier periods to be simulated, enabling the system to build an initial inventory. However, performance metrics and results are only collected after the warm-up period, ensuring an accurate representation of system performance during the studied timeframe.

6.3 | Current situation benchmark

As mentioned in Chapter 5 on the supplier analysis, several policies have been either received by the supplier survey or have been proposed by Mars to establish optimal policies for the VMI suppliers. Therefore, these models will be tested using the simulation model and can be benchmarked against the optimization model provided in the subsequent section. This will provide insight into how the inventory optimization of the system as well as subsequent subgroups can improve target fill rate levels, and reduce inventory and total costs for both supply chain partners. Furthermore, it benchmarks the proposals set by Mars to test for feasibility as the proposed process for all suppliers will generally lead to stock increase and increased service level. However, possibly the warehouse capacity is insufficient to manage this process for all suppliers.

6.3.1 | Mars Proposal

The Mars proposal employs a service segmentation strategy exclusively for Flexible and Carton/Corrugate materials. Accordingly, the settings of these materials will be utilized. The min and max are set at 2 to 10 weeks plus the fixed lead time for flexible materials and 2 to 7 weeks plus the fixed lead time for carton and corrugated materials tested in the Veghel site (NL01). In general, this proposal could be best translated to the ROL, OUTL policy for flexibles as 8-16 weeks and for cartons as 6-11 weeks.

6.3.2 | Benchmark Supplier Survey

As a result of the supplier survey, the reorder level and order up to level in weeks have been found for almost every supplier. For the scope of this benchmark, the suppliers of Veghel have been used and nearly every supplier delivering VMI to Veghel has responded. For a few items, the respective supplier has not responded to the survey. For these items, the policy from a similarly sized supplier that delivers similar materials has been used. In Chapter 5.4, a boxplot is given on the respective ROL and OUTL used by suppliers for their respective items. For confidentiality, the supplier and its respective policy could not be named in the thesis.

6.4 | Optimization model

In the optimization model, all assumptions derived from the simulation model are employed. In contrast to the previous model, the parameters ROL and OUTL are now treated as decision variables. Based on these variables, the optimal solution can be determined. Furthermore, the efficient frontiers for the system can be defined, and the improvement of the optimization model in comparison to the current Mars and supplier model can be visualized on the efficient frontier. The following subsections describe the decision variables that are now used for the optimization, the objective function and associated constraints are given, and finally, the pseudo-code is displayed in Appendix F.3.

6.4.1 | Constraints

Fill rate target
The fill rate target has been set to 0.95% to ensure pack availability in most situations for all items. In the sensitivity analysis, this constraint has been relaxed to see the impact on the system when increasing or decreasing this target.
Warehouse capacity
As earlier described in the problem context (Chapter 2), the warehouse capacity of Mars at the Veghel (NL01) site is 18275 in total where 4800 is reserved for conditioned materials and 13475 for ambient items. However, this space is not all free to be used as a lot of obsolete items are required to be scrapped use capacity and Mars wants to reserve 10% of space for increased movability within the warehouse. Therefore, some assumptions have been made on the total capacity. Furthermore, not all active items are in scope or are VMI items that need to be required to be tested. Around 400 pallets are used for obsoletes in the conditioned warehouse and 2500 are estimated to be used for the ambient warehouse. Furthermore, as 75% of items of both categories have been placed in scope Table 6.2 shows the estimated warehouse capacity for the studied group.

Warehouse type	Pallet Places
Ambient	8231
Conditioned	3300
Total	11531

Table 6.2: Warehouse capacity model

6.4.2 | Objective function

The objective is to minimize the total cost, which is the sum of holding costs, ordering costs, and obsolescence costs, subject to a fill rate and warehouse capacity constraint.

$$\text{Minimize} \quad TC = \sum_{k\in K} y_k \cdot \left(\sum_{i\in N} \text{Holding Cost}_{i,k} + \sum_{i\in N} \text{Setup Cost}_{i,k} + \sum_{i\in N} \text{Obsolescence Cost}_{i,k} \right)$$

$$\text{Minimize} \quad \sum_{k\in K} y_k \cdot \left(\sum_{i\in N} \left(h_i \cdot \left\lceil \frac{\text{IOH}^{avg}_{i,k}}{\delta_i} \right\rceil + A_i \cdot nO_{i,k} + \text{NQC}_{i,k} \right) \right)$$

s.t.

$$\frac{1}{|N|}\sum_{i\in N} y_k \cdot P_{2,i,k} \geq P_{2,\text{target}}, \quad \forall k \in K$$

$$\sum_{i\in N} y_k \cdot \left\lceil \frac{\text{IOH}_{i,k}^{avg}}{\delta_i} \right\rceil \leq C_{\max}, \quad \forall k \in K$$

$$y_k \cdot \text{ROL}_{w,k} \leq \text{OUTL}_{w,k}, \quad \forall k \in K$$

$$y_k \cdot Q_{i,k} \geq y_k \cdot \text{MOQ}_i, \quad \forall i \in N,\ k \in K$$

$$\sum_{k\in K} y_k = 1$$

$$y_k \in \{0,1\}, \quad \forall k \in K$$

Note: Each policy k is characterized by a specific combination of $\text{ROL}_{w,k}$ (Reorder Level) and $\text{OUTL}_{w,k}$ (Order-Up-To Level). The decision variable y_k determines which combination is active. Additionally, this formulation is flexible and can be applied to any subset of items $S \subseteq N$. For any subset S, the same decision structure applies, with policies y_k activating combinations of ROL and OUTL specifically for the subset S. However, only the C_{max} should be adjusted accordingly to match the subset of items in scope to the relative reserved warehouse space of this subset.

6.4.3 | Procedure

We iterate over possible values of ROL and OUTL within specified ranges:

$$1 \leq \text{ROL}_w \leq 24, \quad \text{ROL}_w + 1 \leq \text{OUTL}_w \leq 25$$

For each combination of ROL and OUTL:

- Simulate the inventory system
- Extract total costs, fill rate and inventory in pallets
- Find a valid solution and choose the cost-optimal one

Deviations:

- **ROL and OUTL input bounds:** The input bounds for ROL_w and $OUTL_w$ can deviate based on the approach used to calculate these levels. Specifically: A predefined ROL_w and $OUTL_w$ may be used, based on external calculations or empirical data. This is used for the supplier benchmark and Mars policy. Therefore these procedures do not use the optimization procedure but simply provide the metrics for a given input. This deviation allows for a system-defined Min-Max approach, resulting in different ROL_w and $OUTL_w$ values for each item.

  This approach is given with policy type: **OPT (ROL, OUTL)** as used in results.

- **Min and Max input Bounds:** The bounds for Min_w and Max_w are given as:

  $$-1 \leq Min_w \leq 9, \quad Min_w + 1 \leq Max_w \leq 20,$$

  Ensuring valid and practical ranges for these parameters in the inventory system. Alternatively, ROL and OUTL can be derived dynamically as:

  $$\text{ROL}_w = \text{Min}_w + L_i, \quad \text{OUTL}_w = \text{Max}_w + L_i,$$

  Where Min and Max represent the system's minimum and maximum inventory levels for each item. In this case, the Min_w and Max_w are iterated and based on the respective Min_w and Max_w the given making the Min_w and Max_w the decision variables in the optimization problem where the calculated.

  This approach is given with policy type **OPT (Min, Max)** as used in the results.

- **Iteration for one item:** In this formulation, the decision variable for the policy y_k can be looped over each item individually. As a result, the minimization will output a solution for each item separately, allowing for item-specific policies.

  This approach is given with policy type: **OPT per item (theoretical)** as used in results.

6.5 | Validation of the models

In this section, the validation of the scientific model is given. It contains three sections:

- Validation and verification
- Comparison of stationary and non-stationary demand to established models (e.g DoBr tool)
- The investigation of whether this model is relevant and thus generalizable and scalable to other Mars factories

The following three sections will assess the functionality of the model, the robustness of the code, the relationship between established formulas and the model output, and finally, the generalizability of the model for other applications.

6.5.1 | Validation and verification

The framework of Sargent (2010) is employed for the verification and validation of simulation models. This approach ensures that the simulation model is thoroughly tested across the problem entity, the computerized model, and the conceptual model. Such testing is essential to establish the validity and reliability of the simulation model. Therefore, in the following section, a comparison is made using other models, in this case, the DoBr tool. This tool is an implementation of the R,s,nQ replenishment policy and can find optimal reorder levels and extract results for critical KPIs such as P_2, IOH, B for these replenishment systems also introduced in van Donselaar & Broekmeulen (2021). For a normally distributed demand instance, the optimal reorder level is tested for a fill rate constraint and plotted against the simulation of this item using the proposed model. The model has been validated by setting the input parameters of the simulation to match those used in the DoBr dashboard. The results were then compared to ensure consistency with the outputs based on the parameters provided in Appendix C. Furthermore, the use of extreme conditions tests has tested the validity of the model. In the later-mentioned sensitivity analysis, some extreme values will be used to test the performance of the system. During these tests, no out-of-the-ordinary results have been observed. Additionally, the validity of the events has been tested manually to ensure the robustness of the system. These results were also compared to actual delivery sizes obtained from the current approach, as outlined in the supplier survey. Finally, based on the aggregated results, the face validity has been interpreted by Mars experts explaining the nature of all relationships and whether the logic also shows expected behavior experienced by material planners in the actual system. Sadly, no real-life verification could be performed based on historical data as the historical data on the availability of packs with the respective policies appear clouded. If there was a shortage, actual consumption would just be postponed and 100% availability would be registered for this packaging material. Thus, the 8 steps for model validation have been followed but the system behavior could not be tested due to the lack of logging out of stock situations and the incorrect monitoring of these processes. At last, the list of obsolete items incorporated into the simulation has been evaluated for actual obsolescence. The number of stock-keeping units (SKUs) identified as obsolete and corresponding to similar stock levels, as determined by the minimum-maximum (min-max) procedure inherent to the simulation, has also been established.

6.5.2 | DoBr tool

A validation procedure has been performed comparing the results of the model to established formulas defined by van Donselaar & Broekmeulen (2021). In Appendix C, the output of the validation is given based on the given parameters inputted in both the tool and the simulation. Only minor differences are observed between both models proving the robustness of the simulation compared to mathematical formulas and showing that for sampled normally distributed stationary demand the results are as expected.

6.5.3 | Other Mars site

The simulation-optimization model has also been tested on another Mars site (in this case the PL01 site). This Mars site shows a similar behavior compared to the NL01 research site. Therefore, it is shown that the model can be generalized to other sites to find the optimal balance for vendor-managed inventory suppliers within the full scope of a Mars process. The same trade-offs are made and a similar pattern is followed using the same forecast and demand process. Therefore, based on this validation no out-of-the-ordinary results have been concluded and generalization across the regional planning scope of Mars can be performed using this model.

6.6 | Results

This section displays the results of the simulation optimization model. The section is divided into the following subsections: the benchmark of the optimization to the policy, and the efficient frontier as several options can still be preferred by Mars if increasing the fill rate is improved over the costs for example. Afterwards, the optimal solution for Mars is provided and a sensitivity analysis is provided in case further parameter optimization can be performed by integrating more extensive supplier synchronization to the problem.

6.6.1 | Comparison of policies

Table 6.3 shows the possible policies with their respective outcomes. These explored policies are the min-max for a one-size-fits-all Mars proposal and supplier simulating the given input for the decision variables ROL_w and $OUTL_w$. These are compared to several optimization solutions either segmenting or not segmenting the model. The table shows the optimal results for each policy and gives the key metrics used namely the fill rate, total required inventory in pallets, and the total costs for this solution. In section 6.4.3 the exact differences between each procedure are described in detail. For both the min, max, and ROL, OUTL optimization the segmentation approach splitting items classified as Carton and as Flexibles have been employed and the respective policies with this split show improved results to their respective non-segmented policies. In addition, it is good to compare the solutions to find the most optimal choice

Policy type	Bounds		Metrics			
	Lower	Upper	Fill rate	Inventory	Costs	Feasible
Mars (one size)	$ROL_w = 8$	$OUTL_w = 16$	0.9796	21559	4070984	No (Warehouse violation)
Supplier	Per supplier	Per supplier	0.9395	9971	2591967	No (Fill rate violation)
OPT (ROL, OUTL)	$ROL_w = 6$	$OUTL_w = 10$	0.9549	11381	2768512	Yes
OPT (ROL, OUTL) Flex/Carton split			0.9580	10232	2444293	Yes
OPT (Min,Max)	$Min_w = 0$	$Max_w = 7$	0.9509	10708	2398468	Yes
OPT (Min, Max) Flex/Carton split			0.9529	8113	2362295	Yes
—>Flex	$Min_w = 0$	$Max_w = 9$	0.9531	1328	883010	
—>Carton	$Min_w = 1$	$Max_w = 4$	0.9591	6785	1479285	
OPT per item (theoretical)	Per item	Per item	0.9757	6772	1225291	Yes

Table 6.3: Results absolute

for Mars. One optimal solution set is found in the feasible region which provides the best result for Mars if strictly adhered to the provided policy. Table 6.4 shows the reduction of required inventory and total costs for the respective policies. In addition, when comparing the policies to the supplier benchmark,

Policy type	Fill rate	Inventory	Costs	Feasible
Mars (one size)	0	0	0	No (Capacity)
Supplier Benchmark	-4.09%	-53.75%	-36.33%	No (low service)
OPT (ROL, OUTL)	-2.52%	-47.21%	-31.99%	Yes
OPT (ROL, OUTL), Flex/Carton split	-2.21%	-52.54%	-39.96%	Yes
OPT (Min,Max)	-2.93%	-50.33%	-41.08%	Yes
OPT (Min,Max), Flex/Carton split	-2.09%	-62.37%	-41.97%	Yes
OPT per item (theoretical)	-0.40%	-68.59%	-69.90%	Yes

Table 6.4: Results compared to Mars proposal

some cost reductions and fill rate improvements are still generated given in Table 6.5. However, it is especially important to also establish the room for improvement which will be done in the following sections. The optimal solution shows a cost decrease of 41.97% to the Mars proposal and 8.86% to the supplier benchmark. Moreover, it seems to be fitting in the appropriate capacity and fill rate bounds.

Policy type	Fill rate	Inventory	Costs	Feasible
Supplier Benchmark	0.00%	0.00%	0.00%	No (low service)
OPT (ROL, OUTL)	1.64%	14.14%	6.81%	Yes
OPT (ROL, OUTL), Flex/Carton split	1.97%	2.62%	-5.70%	Yes
OPT (Min,Max)	1.21%	7.39%	-7.47%	Yes
OPT (Min,Max), Flex/Carton split	2.09%	-18.63%	-8.86%	Yes
OPT per item (theoretical)	3.85%	-32.08%	-52.73%	Yes

Table 6.5: Results compared to supplier benchmark

However, it should also be tested for significance. Therefore, the Welch's t-test is used. The Welch t-test and underlying assumptions are given in Appendix D. Based on this test the cost difference is insignificant due to the high standard deviation for the supplier items. However, based on the Mars policy, there is a significant reduction with $p \leq 0.01$. Following the fact that all metrics that are used are outperforming the supplier benchmark as well, it can be concluded that synchronization is strictly preferred over the supplier solution.

6.6.2 | Relationship fill rate and capacity

Achieving a higher fill rate within the Mars supply chain requires either increasing warehouse capacity or raising the number of replenishment cycles—both of which come at a cost. Figure 6.3 illustrates the trade-offs between fill rate and warehouse capacity, showing the frontier of feasible solutions. Each dot represents a specific combination of reorder level (ROL) and order-up-to level (OUTL), along with the associated total cost.
The figure highlights that increasing the cycle length (OUTL - ROL) affects cost metrics, providing Mars with flexibility to select a preferred solution based on these trade-offs. For higher fill rates, additional capacity or increased operational costs may be required. These trade-offs and their implications are further explored in the sensitivity analysis in Section 6.6.4.

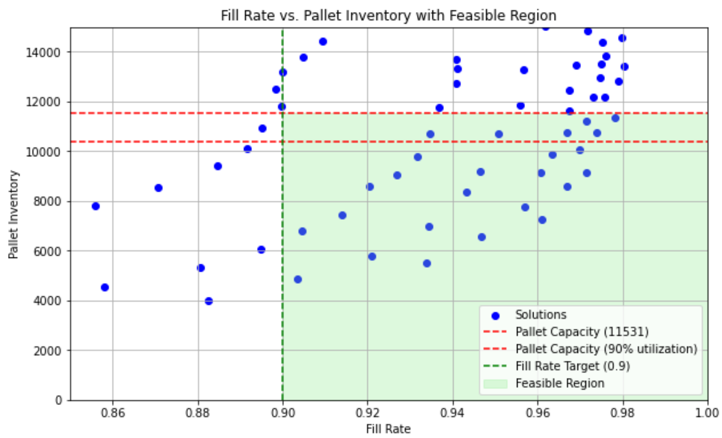


Figure 6.3: Fill rate vs. Capacity

6.6.3 | The value of the multi-echelon forecast

In this case study, the multi-echelon forecast was utilized as an input, and the resulting outcomes were compared with those derived from the MRP forecast. The multi-echelon forecast clearly shows potential to be shared with suppliers if there is more availability on the stocking position. The results in fill rate, total costs, and order patterns are all relatively similar which is as expected due to the same aggregated consumption over a full forecast period. However, the cycle lengths are relatively longer and the min is significantly increased to achieve the required fill rate due to the earlier mentioned production lead time. In addition, from a vendor-managed inventory perspective this type of information sharing provides an extended openness on the stock position of Mars showing potential for further integration and collaboration as demand drops and demand increases could be seen earlier by the supplier. Moreover, the supplier is better able to see the actual demand of the customer. Table 6.6 shows the different outcomes for the multi-echelon and MRP forecast as earlier defined in the product analysis (see chapter 4. The overview

Forecast type	Segment Type	Min	Max	Inventory in Pallets	Fill Rate	Total costs	Total orders
Single	One size	0	7	10708	0.9509	2398468	1669
	Split			8113	0.9562	2362296	2095
	Carton	1	4	6785	0.9591	1479286	1395
	Flex	0	9	1328	0.9531	883010	700
Multi	One size	6	18	11362	0.9519	2904300	2106
	Split			10838	0.9521	2868423	2254
	Carton	7	16	9795	0.9531	1979154	1272
	Flex	6	20	1043	0.9510	889269	982

Table 6.6: Multi-echelon or MRP forecast

highlights that the forecast types exhibit slight performance differences, with the multi-echelon forecast incurring slightly higher costs due to additional orders or increased storage expenses. This is because the short-term planning has not been allocated to the right moment causing the supplier to deliver too little more often when a large batch is pulled forward causing an increase in holding costs. However, this approach allows the supplier to manage market demand forecasts more effectively, as it directly reflects actual demand without relying on additional assumptions. This suggests it may be worthwhile to explore whether the multi-echelon approach could deliver more optimal stock levels in an increasingly integrated supply chain. By sharing detailed information on shortages closer to the customer, this method could positively impact the reduction of the bullwhip effect.

6.6.4 | Sensitivity Analysis

In addition to the simulation-optimization model, which focuses on rebuilding the supplier process and policy for managing inventory at Mars, it is paramount to perform additional analysis on the parameters used. For example, the agreed lead times might vary significantly from the actual lead times as also found in the Supplier Analysis (see Chapter 5). Therefore the core of this thesis is not only to set correct guidelines under assumptions of the supplier process but to display feasible improvement directions to further enhance collaborations with suppliers. Therefore this sensitivity analysis will provide output on the following parameters:

- Leadtime: varying from 1 week per item to 10 weeks per item
- MOQ: no MOQ requirements.
- Unlimited warehouse capacity
- Fill rate improvement
- The exclusion of obsolescence costs
- Cost sensitivity analysis

The identification of sensitivity analysis method from Frey & Patil (2002) has been used. For this sensitivity analysis, a nominal range has been used for the potential different parameter inputs. Therefore, the different factors provide different results, and following from this also different efficient frontiers. Additional results from the sensitivity analysis can be found in Appendix B. In this section, the focus is on the potential lead time reduction and its implications as Chapter 5 has shown the potential for this lead time reduction in both the planning of final production in the supplier survey, the supplier process description and the flexibility during the lead time extensively mentioned both in quantity as in delivery moment for almost all suppliers.

Leadtime reduction

When reducing lead time in the sensitivity analysis, it is best to compare the same min-max to see how the varying leadtime influences the performance metrics. When comparing these differences, using the MRP forecast where the min is defined as 2 weeks and the max defined as 6 weeks the potential inventory reduction, cost reduction and fill rate improvement is given in Table 6.7. It also clearly shows that the number of setups in this policy remains relatively stable due to the same difference between min and max and as expected having the same Q over time. However, the holding and obsolescence costs significantly reduce when having a reduced lead time. Furthermore, the total cost difference has been tested using Welch's t-test and found statistical differences between each lead time. However, comparing smaller lead time differences such as 1 and 2 provides lower significance as the difference is smaller in this situation when comparing 1 and 10 for example.

Lead Time	Min	Max	Inventory in Pallets	Fill Rate	Total Costs	Inventory Reduction	Fill rate Improvement	Cost reduction
1	2	6	7682	0.981127	2172384	-61.07%	5.97%	-50.41%
2	2	6	9045	0.981728	2344259	-54.17%	6.04%	-46.48%
3	2	6	10197	0.976847	2514409	-48.33%	5.51%	-42.60%
4	2	6	11303	0.972555	2767122	-42.72%	5.05%	-36.83%
5	2	6	12757	0.969845	2961354	-35.36%	4.75%	-32.40%
6	2	6	14333	0.965619	3172589	-27.37%	4.30%	-27.57%
7	2	6	15827	0.961457	3468272	-19.80%	3.85%	-20.82%
8	2	6	17174	0.9578	3808391	-12.97%	3.45%	-13.06%
9	2	6	18382	0.939063	4032171	-6.85%	1.43%	-7.95%
10	2	6	19734	0.925825	4380439	100%	100%	100%

Table 6.7: Leadtime improvements

Additionally, when selecting the optimal solution for each given lead time, no valid solutions are found for items with a lead time greater than 7 weeks. For longer lead times (e.g 5,6 and 7 weeks), the proposed policies implement progressively shorter cycles to meet the warehouse constraint, resulting in increased costs. In contrast, the aforementioned policy for each respective lead time clearly demonstrates the impact of lead time reduction.

Suboptimal MOQs

Following the simulation, an example is also given on the level of suboptimal MOQs in each respective policy. Especially when a VMI min-max is set it is impossible to adhere to the policy if the MOQ is higher than the respective order up to level. The results in Figure 6.4 indicate that a significant proportion of items (approximately 10%) have an MOQ that covers more than 10 weeks of stock. This shows that for these items the MOQ causes the system to order MOQ regularly. This causes these items to generally be in overstock much more frequently adding more risk of obsolescence and more holding costs compared to a more optimal situation. However, it can then be investigated if, for these types of items, a negotiation with the supplier can be performed to reduce the respective MOQ.

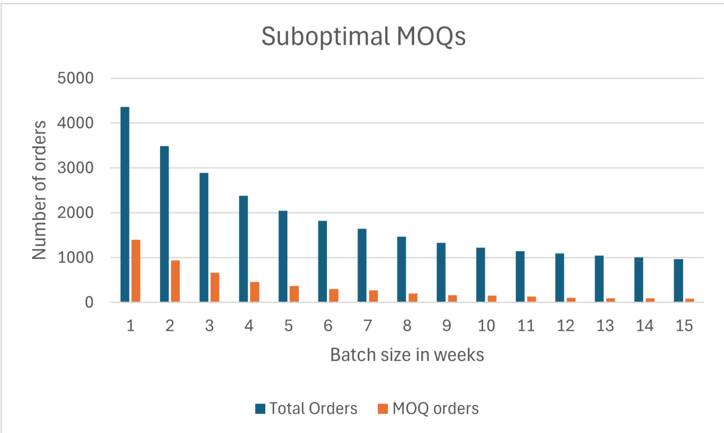


Figure 6.4: MOQ per batch size

Capacity relaxation
As the setup costs are relatively high compared to the holding costs, a more optimal solution might suggest longer cycles with larger batch sizes. In the sensitivity analysis on the capacity relaxation, it has been found that moving the ROL and OUTL from 6 and 10 to 3 and 18 weeks respectively reduces total inventory costs. However, this causes the pallet inventory to be 13384 pallets which exceeds the pallet capacity for the items in scope by 1853 pallets. Therefore, the setup cost sensitivity, given in B), as well as the capacity relaxation shows that the cost of setups is the key factor in determining the optimal number of cycles, and as a longer cycle per definition causes a higher fill rate a lower safety stock/safety time is required for Mars. Furthermore, a capacity increase can result in fill rate improvements. Table 6.8 shows the minimum capacity increase required to get an additional 1% fill rate. This procedure overlooks the most cost-effective solution, instead presenting the minimum required capacity solution that meets the fill rate target. As can be seen, this is similar behavior to the increased safety stocks metric described in the problem context (See Chapter 2).

Fill rate	Capacity
0.8	3859
0.9	4880
0.95	7245
0.96	7245
0.97	9162
0.98	13399

Table 6.8: Capacity relaxation

Fill rate improvement
As previously discussed, Table 6.8 demonstrates the potential improvements in fill rate; however, these improvements significantly increase the holding and obsolescence costs. Therefore, when aiming to improve the fill rate, it is crucial to consider the associated costs. For instance, achieving a fill rate of 0.8 at a minimum cost can potentially reduce the cost by 18.5% significantly increasing the cycle length by 4 weeks to reduce setups. However, the required capacity shifts from 3859 required pallets to 7138 required pallets which is an increase of 84.97%. This clearly illustrates the trade-off between the capacity constraint and total relevant costs.

No obsolescence
In case there is no obsolescence included for the items at hand and no costs are incurred, the setup costs and holding cost framework would look like the costs given in Appendix B. This implication would make a key difference in the required number of cycles. The best min-max policy for Carton results in a ROL of 4 and an OUTL of 11 weeks, extending the best cycle length from 3 to 7 weeks. For flexibles, the proposed cycle is even longer, with the ROL increasing to 6 and the OUTL to 18, thereby extending the best cycle length from 9 weeks to 12 weeks in the cost trade-off. Therefore, it is important to consider the impact of these obsolete items especially for the cost model with the supplier as more frequent setups lead to fewer obsolete items while maintaining the same service level.

Cost sensitivity
Finally, a brief section examines the sensitivity of cost parameters by adjusting holding costs for varying pallet-per-week rates. Additionally, setup costs are analyzed, with values ranging from €100 to €1,000 for all items. Appendix B provides an overview of these adjustments. Both models incorporate the EOQ framework, excluding the obsolescence parameter for holding costs. The results highlight the significant influence of cost parameters on optimal outputs, emphasizing the importance of integrated optimization with suppliers to determine optimal stock levels.

6.6.5 | Demand segmentation

Since item-based segmentation lacks sufficient statistical significance due to the short time series, low demand occurrences, and limited order cycles, a small section is dedicated to the approach of further segmenting different SKUs. This section shows the implementation of a material group with the same properties but different demand patterns in the simulation-optimization model. Based on this, the high and slow runners can be identified between groups and within groups having the same material properties. Within each material group, it can be seen that all the aforementioned parameters are the same. These are units per pallet, setup costs, holding cost per pallet, MOQ, lead time, review period, etc. However, the demand patterns within each material in the respective material group may vary. Therefore, this section shows the impact of further segmentation based on deviating demand patterns for two small subsets of the material groups of Mars. As such the material group can generally be considered the same product but used for a different market segment. The material group regarding the first wrap (Flexible) of Bounty is used containing 27 active items and the case (Carton) of Mars is used containing 30 items to compare. Both item categories are fully delivered VMI and both are delivered by the same respective Carton/Corrugate and flexible supplier. Both item categories show different outcomes based on the respective forecast error and demand pattern. However, due to the short time series of independent items, it cannot be concluded that within-group segmentation significantly adds value to the segmentation approach. However, this provides a key next step for further research and better data collection.
Furthermore, segmentation can be performed based on the classification of Boylan et al. (2008) where the items are classified based on the average demand interval (ADI) and Squared coefficient of variation (CV^2). In Figure 6.5, it is shortly demonstrated that the demand pattern classification provides different fill rates when adhering to the same min-max policy. Thus, it is valuable to segment the approach further based on these given policies as for a specific demand pattern different fill rates are achieved causing some items to require a higher min level or increased cycle length to cover for the additional variability and intermittence of demand. However, due to the relatively small number of SKUs per respective group, the

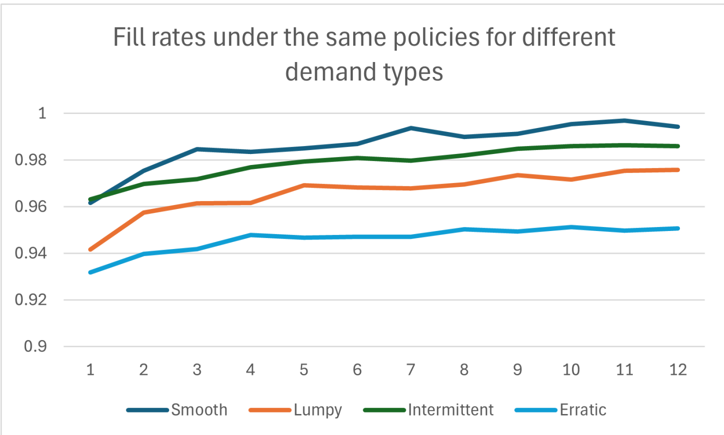


Figure 6.5: Classification of items

policies are rather sensitive to changes, which makes it challenging to determine the optimal levels based on the cost structures of items given in the flexible and carton segmentation approach. This, in turn, makes it difficult to provide an exact optimal solution for each category. Nevertheless, it offers insights that a distinct demand pattern necessitates a distinct Min-Max combination, where increased volatility within an item group results in a higher requisite min-max, as anticipated and outlined in Chapter 2 in paragraph 2.2.2. It has been demonstrated that the application of identical policies for the selection of a Min and Max, coupled with varying fill rates, a differing number of required pallets, and cost data, results in the generation of suboptimal outcomes. Nevertheless, further segmentation based on demand data is unfeasible due to the insufficient length of time-series of packaging materials, which makes the item approach to the optimization problem untenable and lacks value to the business. One of the most significant recommendations to Mars is that sufficient time-series data should be established to better interpret both the demand pattern and the associated forecast error for specific items and item categories. Therefore it is recommended to follow a stocking procedure based on the availability requirements of the finished goods materials. Proposals for this approach have already been given in Chapter 4 on product segmentation.

7 | VMI Process redesign

This section primarily focuses on the possible improvements made based on different information-sharing approaches, data-sharing, supplier portals, and closed feedback loops. Therefore, this section will discuss insights derived for improvement from the supplier survey and supplier discussions. Based on the results of the simulation-optimization model and the inventory item classification model, the proposed method of setting min-max levels for suppliers is given. Following this, the fully redesigned process will be elaborated in combination with potential room for improvements regarding lead-time and/or MOQ reductions to give a possible research direction to improving the parameters used for the optimization approach. Therefore, based on the findings in Chapter 2, the problem context within Mars, and the general VMI process, a framework for VMI optimization is developed for a fast-moving consumer goods company. This chapter describes the key requirements based on earlier proposed VMI models and gives concrete examples of the implementation and relevance of this newly developed VMI management approach.

7.1 | Method

The methods used for this section arise from the VMI framework described by Marques et al. (2010) and Achabal et al. (2000) and provide insights into preferred choices within fast-moving consumer goods companies in an MRP situation. Furthermore, there is an in-depth exploration of supplier collaboration and the potential implications of not just sharing information, setting min-max levels, and wishing the supplier good luck. It extends to offering additional opportunities for collaboration, aiming to better integrate both parties' processes. This collaboration can help align their operations more effectively, ultimately minimizing stock levels and achieving optimal cost efficiency for both supply chain partners. By improving the joint economic lot size problem, both from an optimality and process perspective, this approach enhances the overall performance of the supply chain. Therefore, the following sections are built to provide the framework for measuring performance and providing a closed-feedback loop for all suppliers, sharing the optimal min-max levels for the different item categories, the opportunities for further collaboration moving towards decision synchronization and incentive alignment found in the research of Simatupang & Sridharan (2008) and further deep-dive on improved information sharing across the chain as proposed by Soosay & Hyland (2015). The key principles of the VMI process thus entail:

- Information sharing quality
- Optimal agreements along the joint economic lot size problem
- A closed feedback loop with suppliers assessing the performance and establishing root cause analyses
- Analysis on the feasibility of parameter redesign (e.g. lead time) within both supply chain partners

Following this the supply chain maturity model of Ho et al. (2020), given in Figure 7.1, has been used to identify the current maturity within Mars at the start of the research and shows the practical contribution this research has delivered to the improved maturity of the processes. Consequently, this section outlines research directions for further enhancing the maturity level of supplier collaboration. It combines product, supplier, and simulation analyses to highlight opportunities for deeper collaboration. Additionally, based on the sensitivity analysis in Chapter 6, it provides a foundation for potential cost reductions through greater integration of processes between supplier and buyer. This approach explores these opportunities in a real-life case study using empirical data.

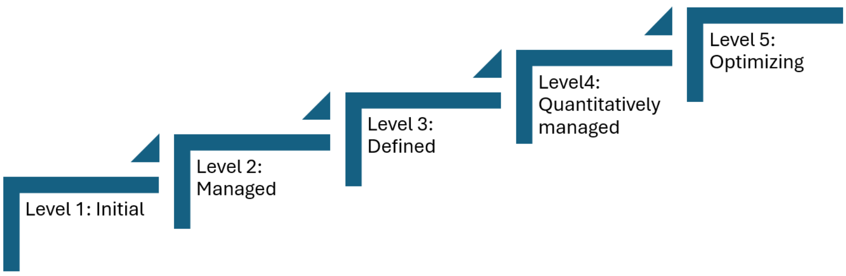


Figure 7.1: Capability Maturity Model Integration (Ho et al., 2020)

As defined in the introduction, the initial level of supplier collaboration before this research project was defined as level 2: managed. There were some agreements in place but the collaboration level was mostly reactive and relied on basic activities where material planners tried their best to manage the process but there was no established guideline. Furthermore, the management of the data has been established in an error-prone and manual manner, which lacks transparency and restricts the capacity for accurate planning and forward-thinking. In the definition of the process the supplier pilot has shown a standardized process leads to improved processes and structure. Moreover, the quantitative measurements lead to a closed feedback cycle. Finally, the simulation optimization model provides for continuous improvement utilizing a simplified version of the joint economic lot-size model and provides general guidelines with suppliers to maximize the system's effectiveness. However, these optimizations still rely on major assumptions that limit the applicability of the model and provide further possibilities. In addition, to optimize the partnership, further steps can be taken to not only manage the process quantitatively but also enhance forecast stability, optimize production cycles, improve data availability, and implement a multi-item inventory control approach. This approach would account for the numerous interdependencies within the Mars production process, as well as the key interdependencies within the supplier's process, such as second setups of machines. By focusing on optimizing the production process through an integrated approach with Mars' suppliers, the overall efficiency and effectiveness of the supply chain can be significantly improved. The subsequent sections deep dive into these respective improvement directions and provide guidelines for enhancing the framework as described by Achabal et al. (2000) and Marques et al. (2010) as implemented in this research.

7.2 | Process redesign

In addition to implementing key inventory control methods, such as identifying KPIs and optimizing the inventory control process based on total supply chain costs, it is crucial to recognize the importance of a practical framework. Achieving a mathematical optimum is essential, but integrating a feasible framework within the supply chain is what ultimately leads to improved performance. Therefore, for the renewed process it is not only important to describe the optimal mathematical value but also within what process this logistical agreement can be managed best. Therefore the following section presents the process of information sharing with the respective VMI supplier as well as the content of information sharing. The section will outline the as-is situation shortly again to establish the room for improvements within the scope of these and the potential next steps in line with the Capability Maturity Model Integration presented by Ho et al. (2020).

7.2.1 | Information Sharing Process

Regarding the information-sharing process, the current approach relies on the manual sharing of the supplier connectivity report with suppliers. This information flow has been given in Chapter 5. Therefore, in Figure 7.2, the proposed VMI process is given to be used as a process manual for VMI suppliers. This process will eliminate the additional work of managing the supplier and provide real-time feedback on proposed actions instead of managing it outside the scope of information systems.

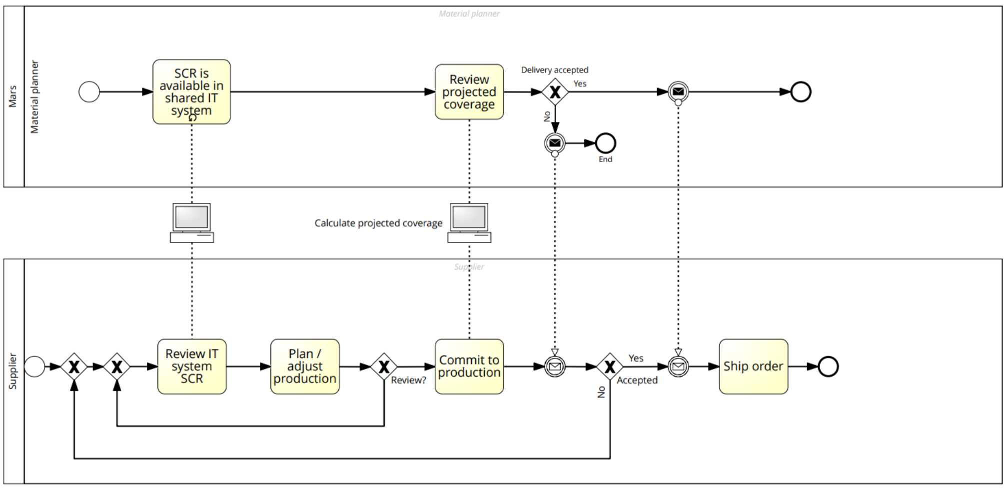


Figure 7.2: Proposed VMI process

7.2.2 | Information Sharing Content

The current information-sharing process is primarily based on the model proposed by Marques et al. (2010), as discussed earlier. This model identifies the current situation in combination with the missing content from the model concerning the context of Mars. Furthermore, this thesis provides insights into best practices related to the model and a case study to demonstrate its application. Figure 7.3 shows the proposed system for Mars to be implemented. The key aspect of the system integration between Mars and the supplier is of paramount importance for being able to manage the process maturely. The key aspect this model extends is that, at the start of the project, only the inventory forecast and stock positions are shared with the supplier. The key extensions thus entail integrated capacity management, inventory optimization, closed-feedback loop, supplier performance measurement, and a clear vision on continuous improvement among the supply chain partners. This new integrated design will lead the Mars supply chain to be effectively managed instead of having a reactionary methodology. Furthermore, this extends the visibility for the vendor-managed inventory supplier to effectively plan their processes much more in advance. This shifts the process from reacting to weekly updated forecasts to more effective supply chain planning by incorporating end-consumer demand to better forecast potential needs, without relying on batching procedures. As a result, the supplier can manage the process more effectively, align with customer demand, and reduce the bullwhip effect, as demonstrated in Disney & Towill (2003a). The

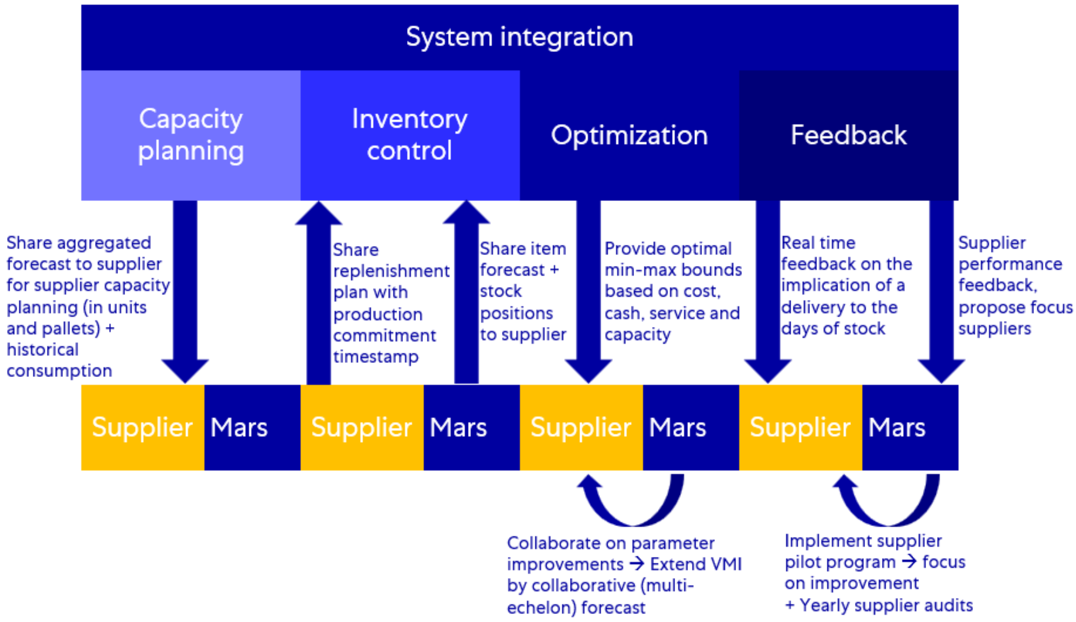


Figure 7.3: System Integration

framework of required data for all suppliers and all items is demonstrated in the following list:

1. Min-Max range for each type of supplier (i.e. Flexible and Carton / Corrugate). The tighter this min-max setting the less trust is provided to the supplier Claassen et al. (2008). This range is therefore not only important from a financial perspective but especially also implies a behavior change for the respective suppliers.

2. Commitment of the supplier for stock planning: One point of truth in forecast, clear-cut supplier measurement based on this production plan, otherwise the supplier will / can hide behind the forecast). Integrate the advanced shipment notice better in the system to be able to steer if necessary.

3. Item forecast for short-term inventory planning by suppliers.

4. Historical consumption data per item including quality and aggregated supplier forecast volume for capacity planning.

5. Logging of MOQ deliveries per item to determine follow-up bottom-up to Mars business on the value of this tail as well as the potential for optimizing parameters (MOQ reduction).

6. Logging of item changeovers to enhance demand analysis together with suppliers.

7. Stock position of finished goods codes to extend the VMI approach.

8. Supplier feedback metrics to be shared with all suppliers periodically.

By managing the aforementioned content, the procedure of information sharing content is implemented based on the decision framework proposed by Marques et al. (2010). This approach facilitates the primary objective of supplier synchronization within Mars and provides clear guidance on managing the supplier process. By offering suppliers more information, particularly regarding the required capacity over time, their decision-making can be enhanced. This enables suppliers to reserve capacity for Mars and accommodate last-minute changes within the allocated capacity.

7.2.3 | Roll-out scalable process

To effectively manage the process while minimizing the additional workload it is important when implementing the aforementioned framework to incorporate the scalability of the design. Especially as one of the key benefits of vendor-managed inventory is the reduced workload of inventory and material planning. Thus this section will further outline the rollout framework to incorporate a feasible process for all suppliers and all Mars manufacturing sites.
The following enumeration will provide the focus areas of each respective site and supplier combination.

- Overstocking suppliers to reduce warehouse utilization
- Understocking suppliers to improve service level
- Large suppliers which account for multiple items and a large part of the stocks

As the supplier pilot process is rather time-consuming the supplier performance measurement should be continued and the focus on either overstocked or understocked suppliers should be used when the supplier performance reaches a certain threshold for a consecutive period. For understock, the items at risk should not be made up of more than 5% of the total stock whereas for overstock the group should not exceed 40% posing that the majority of items should be set within the proposed stock limits. Otherwise, an escalation must be initiated to intensify the supplier monitoring process. Based on these limits it can be decided to increase the minimum or decrease the maximum stock level for a supplier to stimulate more effective inventory management for Mars.

7.3 | Parameter redesign

Building on the supplier process descriptions, the supplier survey, and the sensitivity analysis, Mars can achieve significant improvements by redesigning parameters such as lead time and minimum order quantity. Based on the process descriptions and the final production plan from the supplier survey, a reduction of the lead time to 3 weeks was tested, as this adjustment is deemed feasible according to the supplier responses. Although this change is expected to increase setup costs, the sensitivity analysis suggests potential benefits in such cases. The following subsections outline the additional value and costs associated with these tests.

7.3.1 | Leadtime

The lead time can be significantly reduced if the gross requirements are available for planning purposes. Subsequently, the exact requirement should be configured in the final few weeks before delivery. The simulation has demonstrated the effectiveness of reducing the lead time in reducing the average inventory, and average costs and improving the fill rate. Suppliers have already demonstrated that under the vendor-managed inventory contract, shorter lead times are used and there is significant flexibility, as stated in chapter 5. It seems reasonable to hypothesize that committing to and agreeing on a reduced lead time will result in greater capacity in the warehouse, thereby enabling improved fill rates and cost reduction for both supply chain partners. However, it is important to consider the additional cost to suppliers in terms of their flexibility to cut the lead time. Further research would be beneficial to gain a better understanding of the trade-off between increased cost for reduced lead time and whether this outweighs the cost increase.

7.3.2 | Minimum Order Quantity

A reduction in the minimum order quantity could facilitate greater flexibility within the supply chain, enabling the delivery of smaller batches in the event of a heightened risk of obsolescence. Furthermore, the minimum order quantities established for the Mars purchase order process are not aligned with those of suppliers, as multiple material group items can utilize the same minimum order quantity, resulting in a significantly reduced minimum order quantity per pack code through resource sharing. Furthermore, the sensitivity analysis has demonstrated that the average pallet inventory can be reduced by 1.8 % if the minimum order quantities are reduced to 0. Consequently, it would be advantageous to establish closer collaborations with suppliers to reduce the double minimum order quantity in the economic order interval and economic order quantity simultaneously and align these quantities on the agreed cycles on a commercial basis. However, based on the current analysis, the MOQs generally do not pose the biggest improvement to the replenishment system as the MOQ is usually not more than several pallets and thus does not provide the largest gain. In this case, the MOQ orders presented in the results reveal that items with an MOQ covering more than 15 weeks, which account for 9% of the full portfolio, should be considered as tail items. This raises the question of whether these items are worth maintaining, as they represent slow-moving stock with a high risk of obsolescence.

7.3.3 | Multi-item optimization

An additional improvement direction with suppliers is including the interdependencies between items and their respective setup times and costs to improve efficiencies throughout the chain by reducing setup costs and aligning productions. However, this improvement procedure is out of the scope of the current thesis but provides great potential for Mars and further research in establishing the value of multi-item inventory optimization including production efficiencies for similar materials of both supplier and Mars.

7.4 | The value of supplier synchronization

Finally, to delineate the the aforementioned categories for demonstration of the renewed framework it is important to understand the value of supplier synchronization from process, data, and system integration perspectives. As seen in the problem context and supplier and product analysis, several challenges arise from the asynchronous behavior of all suppliers. For Mars, it is incredibly hard to manage this process in a structured way. Therefore, the framework provides a guideline that should lead to a managed and structured process which could be further improved by parameter tuning with the respective suppliers. Furthermore, it has provided a generalized model for testing implications of the capacity and service constraints imposed by Mars and what steps can potentially be taken to improve performance across the supply chain. Additionally, providing a more proper information flow to suppliers and structuring the process and data will enable the suppliers to perform better to the needs of Mars. Therefore, the key improvements the framework delivers are improved data-sharing and establishing a common goal for both supplier and Mars to create a mature supply chain model that is quantitatively managed and has room for continuous improvement as proposed by Ho et al. (2020).

7.5 | Summary

Chapter 7 incorporates a mathematical model with all required processes for managing a VMI supplier successfully from a buyer perspective. The combination of the mathematical model and a practical framework incorporates the product analysis of all Mars items, the identification of supplier differences, and a methodology for finding optimal inventory levels. It also provides room for further improvements to this framework. The section has discussed the necessity of closing the feedback loop, establishing optimal levels, and constructing a foundation for the VMI process, data, and parameter improvement. It is paramount that parameters can be redesigned to improve the performance of the system as also shown in the optimization procedure. Furthermore, especially the process provides a clear framework for managing the VMI supply chain from a buyer perspective. Consequently, this concludes the analysis of the VMI process. The subsequent chapter will respond to the research questions, recommendations, an examination of the limitations of this research, and directions for further research.

8 | Conclusion and Recommendations

This final chapter of the thesis presents the conclusions and recommendations. First, the research questions presented in Chapter 1, are answered in section 8.1. The recommendations for Mars are presented in section 8.2. Afterward, the theoretical contribution and the practical relevance are discussed in sections 8.3 and 8.4 respectively. Finally, the limitations and further research are addressed in section 8.5 and 8.6.

8.1 | Conclusion

This subsection answers the main and sub-research questions to draw a conclusion based on the presented findings in this thesis.

8.1.1 | Sub-questions

What are optimal methods for evaluating the performance of suppliers?
When evaluating suppliers, it is crucial to determine the appropriate metrics for assessment. In this research, a method has been developed for measuring suppliers using a dynamic inventory control system, which involves determining the expected min-max levels and scoring suppliers in each category. The methodology assesses supplier performance based on both volume and item-based metrics. Additionally, supplier flexibility during lead times has been evaluated through a survey. The flexibility metric can be incorporated into supplier performance measurement by tracking the number of shortages resolved during the agreed leadtime.

How can the demand forecast be interpreted more accurately based on the production planning? What segmentation approaches can be employed to enhance the interpretation of demand forecasts for various demand profiles?
In an MRP system, determining the relationship between forecasted and dependent production demand can be challenging. To address this, this research has analyzed the demand profiles of the items to be estimated using a time-varying dynamic inventory policy. This policy adjusts in accordance with the forecasted demand patterns, and in cases where the forecast is biased, the optimization model recommends a negative or positive safety time to ensure the availability of the respective products. The research has found that segmentation based on product type, in this case, flexible or carton material, has been found to be most valuable. Furthermore, the model of Boylan et al. (2008) has been used for further segmentation proving potential for further segmentation as well as significant performance reduction for fully segmented policies per individual item.

How can near-optimal replenishment policies be found accounting for fast-moving consumer goods items upstream the supply chain? And how can these near-optimal replenishment policies be implemented under warehouse capacity constraints?
Using simulation-optimization, near-optimal replenishment policies can be found for all suppliers. Due to high item changeovers, it is best to follow the demand pattern in combination with the forecast over a longer period of time to provide a given SLA criteria bound to provide optimal replenishment policies. In this research, this approach has been found to cope with the relevant costs, capacity, and fill rate requirements given in Chapter 6. The warehouse capacity constraint forces shorter cycles at higher setup costs to ensure availability. To manage this, the inventory model suggests either relaxing the fill rate constraint for certain items or requiring suppliers to run shorter cycles. Capacity needs are heavily influenced by product density, as some materials, like cartons, use more pallets than others, such as flexible materials. High-density items are proposed to follow just in time, while lower-density items have longer cycles. In the case study of Mars, cartons operate with a min-max policy of 1 and 4 weeks, using safety time due to high holding cost pressure. Flexible materials, with a min-max of 0 to 9 weeks, the safety relies more on longer cycles without safety time but can incorporate safety time (1–6 weeks) to improve fill rates cost-effectively, balancing holding and obsolescence costs.

What are the best management strategies for this replenishment process under a vendor-managed inventory contract?
This research has provided a process redesign for optimally managing the suppliers. Under vendor-managed inventory, the role of the buyer is to provide the supplier with the right intel so that the supplier can make the best decisions. Therefore, the best management policy is to manage and measure the performance

of the suppliers, define healthy and unhealthy stock positions, and optimize based on the costs of both supply chain partners to have a mature supply chain process model. This research has shown how to manage this process in full by synchronizing the expectations of suppliers to establish a manageable and measurable process.

8.1.2 | Main research question

How can a near-optimal replenishment policy within a fast-moving consumer goods company be determined under high demand uncertainty within a vendor-managed inventory structure?
A step-by-step plan has been developed to determine an optimal inventory structure based on a demand forecast within a vendor-managed inventory (VMI) framework. This structure ensures that overall stock levels remain dynamic, adjusting according to the demand forecast, with increases made to meet a specific service level target by using the earlier mentioned simulation-optimization model from Chapter 6. Additionally, the plan has been fully scoped within the context of a relevant case study, providing near-optimal stock levels while accounting for costs and capacity. Finally, it provided a manageable framework for Mars and its respective suppliers.

8.2 | Recommendations

The main recommendations for designing an inventory control system under vendor-managed inventory are given as follows:

1. Close the feedback loop: Implement a weekly feedback cycle with all suppliers, scoring them on delivery performance and measuring overstocking and understocking.
2. Set Min-Max Policies: Use the model to establish cost-effective min-max inventory policies for each supplier type (i.e., flexibles and cartons). This provides a guideline for what is healthy stock for Mars based on cost, service, and capacity.
3. Extended information sharing: Transition from manual Excel-based processes to an integrated system. This increases the visibility of commitments of a supplier to better measure the reason for being in given stock regions to provide an accountable system.
4. Focus on long-term capacity planning: As presented in Chapter 7, it is important to inform suppliers about their respective capacity planning. In this way, the supplier is generally available for Mars to deliver also when having short-term changes in what to produce.

Finally, A shortened overview based on the given research design is shown in Figure 8.1. The key advice provided for Mars is also based on the CMMI model to keep taking steps for further improvement.

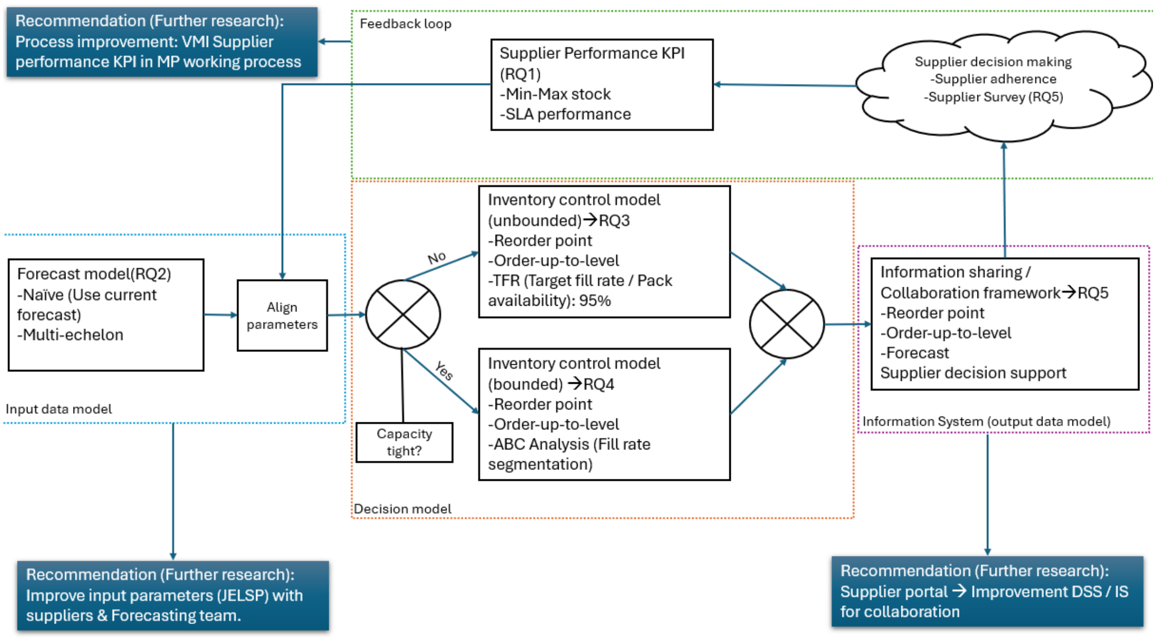


Figure 8.1: Recommendations

Therefore for further improvement of the accuracy and value of the model, Mars can extend on the following principles. By extending the service segmentation the research has shown a potential of an increase of 3.85% fill rate and a reduction of 32.08% inventory and 52.73% costs. In addition, reduction of leadtime has proven to add significant value. Finally, the model is highly reliant on the forecast input, thus additional accuracy leads to improved results.

8.3 | Theoretical contribution

In this thesis, a full VMI framework has been developed following the CMMI model. In this way, a proof of concept has been built on how to move a large-scale VMI organization to a higher level in this model. Regarding the theoretical contribution, several methods have been tested in the supply chain regarding cost, cash, and service and a heuristic using safety time has been implemented for inventory control optimization. The main limitation of this concept is that it only approximates optimality. However, it offers a flexible and dynamic method for inventory control with vendor-managed inventory suppliers, minimizing the need for frequent updates while supporting information sharing. The model directly integrates the forecast into the reorder and order up to levels and provides a basis for an extended joint economic lot sizing problem enhancing supplier collaboration. This research's practical applicability is enhanced by item segmentation in a materials requirements planning environment, demonstrating cost reductions achieved by segmenting optimal reorder levels and order-up-to levels in weeks. Therefore, the model combines the theoretical framework of integrating VMI and further supply chain collaboration in a fast-moving consumer goods organization by providing a proof of concept of all related inventory problems providing a full scoped guideline for further VMI research. This research has extended this methodology by testing the flexibilities in the parameters utilizing an extensive sensitivity analysis as well as measuring actual performance and linking this to proposed policies. As shown in Chapter 5, the variables for determining the reorder and order up to levels in weeks do not always provide the expected performance thus proving the value of further research bridging the gap between actual performance and simulated performance. Therefore, a blueprint for vendor-managed inventory has been established in a fast-moving consumer goods company with non-stationary demand patterns and a dynamic min-max policy which, as a combination of factors have not been found in literature. Referring to the established research gap in chapter 3, the twofold gap of managing an inventory control solution under high demand variability which is manageable and visible for the VMI supplier has been found in this research.

8.4 | Practical relevance

This research offers significant practical relevance for Mars by establishing a blueprint for implementing a vendor-managed inventory (VMI) structure with suppliers of raw materials and packaging. This research has provided a manageable inventory control structure implementing all relevant costs within Mars to find optimal min-max levels for different supplier types. This model outperforms the performance of suppliers found in the supplier survey and outperforms the proposed SLA agreement from Mars. Therefore, this research has provided insights into how to manage and measure a supplier in a vendor-managed inventory collaboration, how to set optimal stock levels, and what information to share with suppliers to improve supply chain performance. Furthermore, this research has provided a plethora of further directions to improve parameters in a joint economic lot size model and has shown which parameters significantly influence performance and especially to what extent. Thus, this model can be further generalized to other applications where an MRP system is used in a fast-moving consumer goods company to provide an agile approach to inventory control following the forecast for phase-in and phase-out items.

8.5 | Limitations

The most important limitation of the research is the use of changeover codes within Mars causing a relatively short time-series to be implemented in the model. Therefore, it is difficult to consider a stable item set representing the model under warehouse capacity constraints. However, this has been resolved by taking the full system scope of VMI items and not segmenting the items to find the best relative policy for each item as this loses statistical significance. For further research, these extended time-series provide enhanced insights into the behavior of certain items providing better estimations on the best possible min-max levels for these different item categories. In addition, the policy optimization has a relatively small state space as it is currently linked to the forecasted demand in weeks. This significantly reduces the state space and possible options which also simplifies the SLA sharing with suppliers. Although the solver is quite quick, increasing the number of SKUs, the simulation length, or the leadtime, leads to a larger required forecast horizon and many other indicators of a more data-intensive optimization approach. Therefore, for example, Vandeput (2020) has shown search algorithms that could even decrease the runtime further by providing initial guesses in the optimization search and/or adding a stopping criterion if the incremental improvement is relatively small. Furthermore, the weekly aggregation of data is a limitation as the supplier survey shows that a lot of different timeslots are used for sending the SCRs, and consequently each different forecast moment highly impacts the delivery decision. In addition, the leadtimes are now fully deterministic leaving no room for variability. In the real-world application, this is not the case. However, due to the nature of the vendor-managed inventory process, the deviations in leadtime could not be established in the supplier process as this decision moment has not been exchanged between supplier and buyer. Although the simulation model mimics the choices of the suppliers, it is not as accurate as logging the actual decision moment at the supplier and the associated leadtime. Finally, only the repeat setups have been accounted for in both situations as this was expected to mimic reality best due to the large volumes used by Mars generally requiring a consistent delivery from the suppliers. However, in extraordinary cases, this might be managed differently.

8.5.1 | Master Data Accuracy

Master Data accuracy is also a key factor in the reliability of the model. For example, the units per pallet drive the holding costs to a large extent. The trade-off between holding costs and setup costs determines the final order quantity decision and the attached number of cycles being off by a factor 10 totally changes the model and thus also leads to significantly reduced accuracy. Moreover, in the forecast data, a large subset of weeks was missing which has been thoroughly cleaned by filling the gaps with the shifted forecast of the previous week to assume that if there is a missing week of information sharing the previous data will be used. All these outputs will lead to a different performance of the system and should thus be carefully handled to propose min-max levels.

8.6 | Further Research

For further research, several research directions have been established. As this research has been highly exploratory, it has highlighted key differences in information-sharing approaches and demonstrated the impact of various parameters within the system. However, some assumptions still warrant further investigation to gain a deeper understanding. One of the key avenues for further research could be testing the assumptions of suppliers in a more integrated approach and relaxing the assumption of fixed leadtimes by incorporating flexibility in the leadtime and their respective implications. Moreover, the following outlines potential areas for enhancing the optimization model for vendor-managed inventory (VMI) within a fast-moving consumer goods (FMCG) company.

1. Multi-Item Replenishment: Coordinate replenishments for items within the same material group to reduce setup costs. Implement decision rules to align replenishments for interrelated items.

2. Multi-Echelon Inventory Control: Extend VMI with shared stock position visibility for packaging and packaged materials, reducing shortages based on actual demand and eliminating the bullwhip effect caused by order batching.

3. Integrated Supply Chain Batching: Align batching principles for suppliers and buyers by matching setups to packaging group efficiencies, reducing total supply chain costs.

4. Supplier Portal Implementation: Enhance information sharing through a portal that logs supplier decisions, establishes commitment zones for deliveries, and measures performance.

5. Joint Economic Lot Size Extensions: Incorporate transportation, order, system, multi-item, emission, obsolescence, and ownership-shift costs into the model, alongside interest rates on cash.

6. Forecasting Model Evaluation: Test various forecasting models to determine the most effective for dependent demand processes and analyze their impact on inventory control and forecast accuracy.

By refining these components, the model can optimize order quantities, improve input parameter precision, and create a synchronized supply chain. Additionally, integrating lead time reductions and flexibility in production planning will enhance VMI's agility and profitability for both supply chain partners.

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Appendix

A | Supplier Survey

The following section describe the supplier survey questions. The survey has been send to 38 VMI suppliers of which 25 responded.

A.1 | Factory-specific questions

Do you deliver to VMI factory X?

- Yes
- No

How often do you generally deliver to VMI factory X?

- Daily
- Twice a week
- Weekly
- Twice a month
- Monthly

What is your target for weeks coverage for VMI factory X? (i.e. if you plan a delivery, how many weeks do you plan to deliver in general)?

- Bulleted from 1-12 weeks and an open-ended other option

What is the trigger to plan a production? How many weeks of projected stock cover should only be left in the SCR to trigger production for VMI factory X? (eg. 3 weeks stock cover remaining will trigger new production at the supplier means fill in 3 weeks in the survey)

- Bulleted from 1-3 days, 4-6 days and then 1-10 weeks with an open-ended other option

Are you holding safety stock for finished good items delivered to VMI factory X at the Mars site?
What is the key metric to calculate the safety stock?

- Yes
- No

Could you please elaborate on the scale of the number of weeks, quantity chosen or percentages additional cover (e.g 1 or 2 weeks, 1 or 10 pallets, or 20%/30% extra)
Answer: ____________________

A.2 | General questions

Do you have different inventory targets for different items?

- Yes
- No

On what characteristics do you differentiate these inventory targets (weeks cover)?

- Weeks additional cover
- Deliver more pieces than the forecast (fixed quantity)
- Deliver more pieces than the forecast (percentage)
- Historical demand data
- Mars predefined quantity
- Other

Do you want to elaborate how you have different inventory targets for different items by providing an example?
Answer: ____
Which process do you prefer, VMI or PO? (1 means strongest preference for VMI, 7 means strongest preference for PO, 4 means no preference)
Likert scale from 1 to 7 as described above
How satisfied are you with the VMI process at Mars?

- Very satisfied
- Satisfied
- Neutral
- Dissatisfied
- Very dissatisfied

What is your experience with the supplier connectivity report?

- Very positive
- Positive
- Neutral
- Negative
- Very negative

Do you have an automatic process for handling the SCR information?

- Yes
- No

If yes, please elaborate on the process?
Answer: ____
If no, in what way do you process the information to make a delivery decision?
Answer: ____

On which days do you currently receive the SCR report?

- Monday
- Tuesday
- Wednesday
- Thursday
- Friday
- Saturday
- Sunday

What action (if any) do you take from the report on those specific days (Please state the day of the week and the action)?
Answer: ______________________________
How often do you review the SCR report to make your production plan?

- Daily
- Twice a week
- Weekly
- Twice a month
- Monthly

At what day do you plan your production?

- Monday
- Tuesday
- Wednesday
- Thursday
- Friday
- Saturday
- Sunday

How many weeks in advance do you make your final production plan?
-1 to 8 weeks and an other option
Do you keep finished goods inventory for Mars at your own warehouse?

- Yes
- No

How much warehouse capacity do you generally reserve for Mars (in pallets)?
Do you keep Work-in-Progress (WIP) or raw materials as a safety stock measure at your site?

- Yes
- No

What type of base materials do you generally keep additional / safety stock for?
Do you make adjustments to your production schedule during the lead time?

- Yes
- No

What adjustments do you generally make?
Answer: ______________________________
Do you make adjustments to the delivery schedule / moment during the lead time?

- Yes
- No

What adjustments do you generally make?
Answer: ______________________________
Do you make adjustments to the delivery quantity during the lead time?

- Yes
- No

What adjustments do you generally make?
Answer: ______________________________
Do you use historical data to make decisions?

- Yes
- No

For what decisions do you use historical data?
Answer: ______________________________
Do you have any best practices in your VMI process (Possibly with other customers?)
Answer: ______________________________
Do you have general improvements for the current VMI process within Mars?
Answer: ______________________________
Would you be open to an interview discussing the possibilities for Mars improvement?

- Yes
- No

General remarks or additions to any closed-ended questions (Please indicate the question number and title)
Answer: ______________________________

B | Sensitivity Analysis Results

This section extends the sensitivity analysis shown in chapter 6. It considers the changing of key variables for the determination of the reorder and order up to level. As such the MOQ reduction to zero has been displayed in Table B.1. The table clearly shows a larger average reduction when the cycle length becomes smaller as expected.

Cycle weeks	Inventory reduction
1	-4.37%
2	-2.99%
3	-1.98%
4	-1.41%
5	-1.01%
6	-0.77%
7	-0.68%
8	-0.53%
9	-0.54%
10	-0.38%

Table B.1: MOQ reduction

Furthermore, a figure is given for the alteration of the respective holding and ordering costs. Figure B.1 shows the relation of the holding costs to the objective function and demonstrates the optimal cycle length in weeks for a given reorder level. For the setup costs the same relationship holds in reverse where increasing the setup costs increases the optimal cycle weeks and the increasing the holding costs decreases the respective length of the number of cycle weeks, in this case the difference between OUTL and ROL.

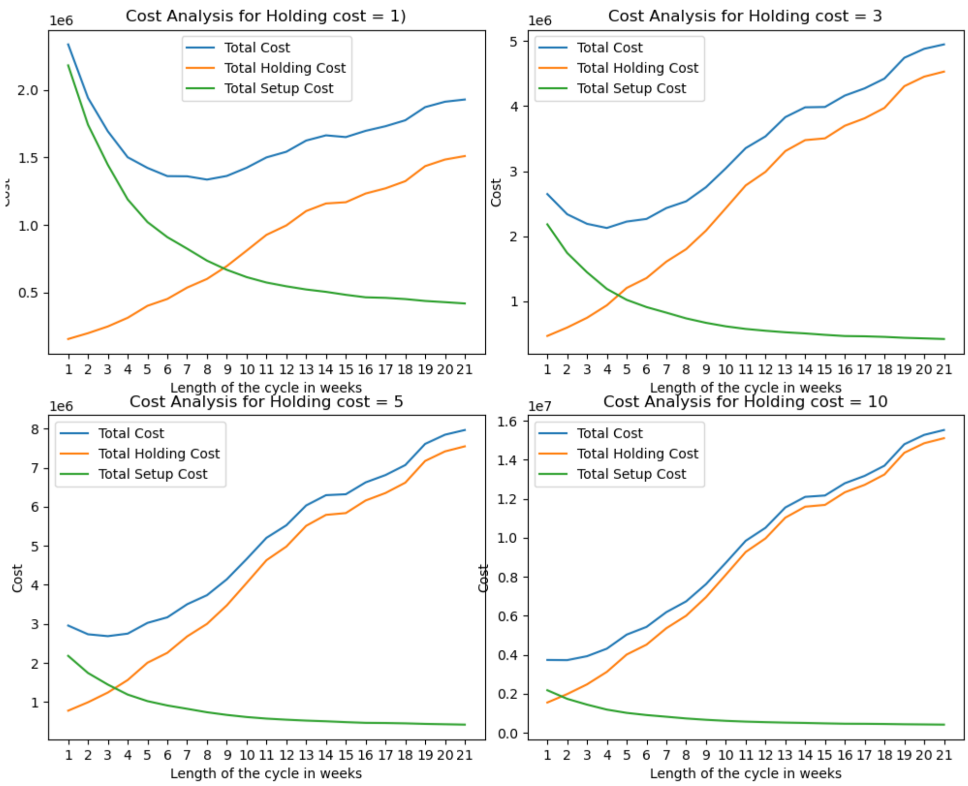

Figure B.1: Holding Sensitivity

For adjusting the setup costs a similar pattern is observed where the proposed cycle length increase with an increased setup cost. Figure B.2 clearly shows a cycle reduction to 1 week cycles with 100 euros costs to 6 weeks cycles with 1000 euros costs.

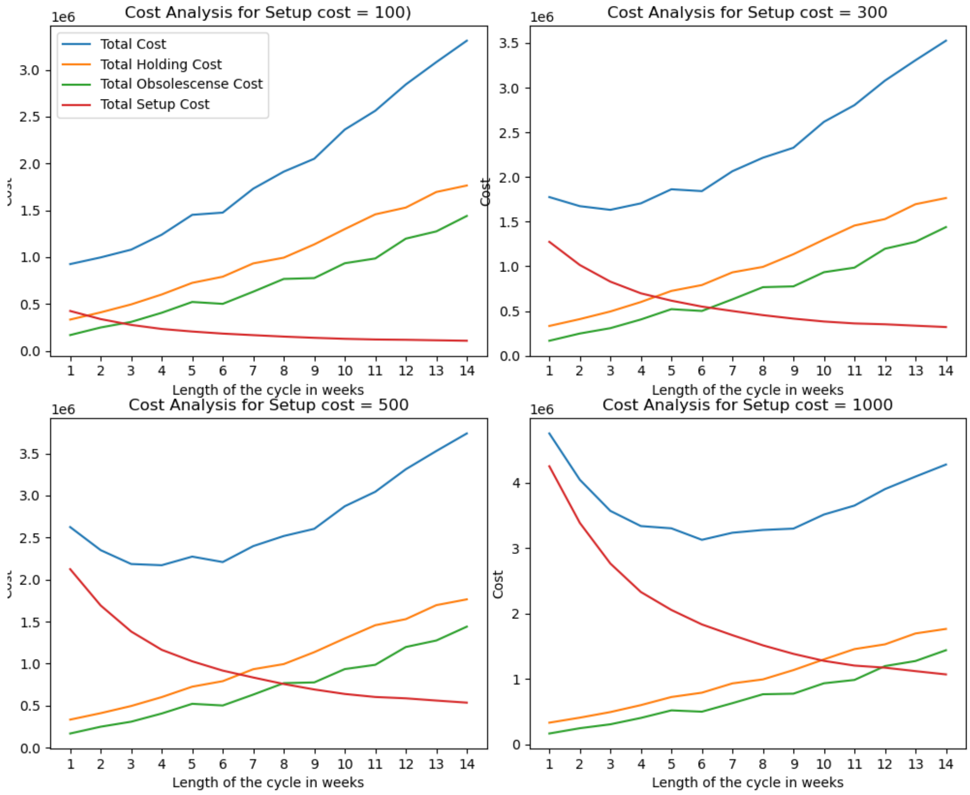

Figure B.2: Setup Sensitivity

C | DoBr tool validation

In this section validation of the tool and its respective output has been tested against the DoBr tool. Three different SKUs have been tested to verify the calculation of the simulation when the reorder levels and order up to levels have been strictly set. Table C.1 shows the input parameters of the three SKUs which have been used. Table C.2, C.3 and C.4 show the respective results and differences between the DoBr tool and the simulation used.

Input parameters	SKU 1	SKU 2	SKU 3
Distribution	Normal	Normal	Normal
Lead-time	2	4	6
stdev leadtime	0	0	0
review period	1	1	1
Mean period demand	100	200	500
stdev period demand	50	20	100
IOQ	800	400	1000
Reorder level	400	700	2500

Table C.1: Input parameters 3 example SKUs DoBr tool

SKU 1			
KPIs	DoBr result	SimResult	Difference
P2	0.998	0.9975	-0.05%
EBO_avg	0.125	0.1261	0.88%
EIOH_avg	550.125	550.51	0.07%

Table C.2: SKU 1 DoBr results

SKU 2			
	DoBr result	SimResult	Difference
P2	0.498	0.4952	-0.56%
EBO_avg	64.7455	65.1249	0.59%
EIOH_avg	64.7455	64.1899	-0.86%

Table C.3: SKU 2 DoBr results

SKU 3			
	DoBr result	SimResult	Difference
P2	0.274	0.27399	0.00%
EBO_avg	336.097	337.3577	0.38%
EIOH_avg	86.097	85.9976	-0.12%

Table C.4: SKU 3 DoBr results

D | Welch's t-test

The following section describes the procedure for the Welch's t-test (Delacre et al., 2017).

$$t = \frac{\bar{X}_1 - \bar{X}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}$$

$$\begin{aligned}
&\bar{X}_1 \text{ and } \bar{X}_2 \text{ are the sample means of the two groups,}\\
&s_1^2 \text{ and } s_2^2 \text{ are the sample variances of the two groups,}\\
&n_1 \text{ and } n_2 \text{ are the sample sizes of the two groups.}
\end{aligned}$$

$$df = \frac{\left(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}\right)^2}{\frac{\left(\frac{s_1^2}{n_1}\right)^2}{n_1 - 1} + \frac{\left(\frac{s_2^2}{n_2}\right)^2}{n_2 - 1}}$$

For a two-tailed test:

$$\begin{aligned}
H_0 &: \mu_1 = \mu_2\\
H_1 &: \mu_1 \neq \mu_2
\end{aligned}$$

For a one-tailed test:

$$\begin{aligned}
H_0 &: \mu_1 \leq \mu_2 \text{ or } \mu_1 \geq \mu_2\\
H_1 &: \mu_1 > \mu_2 \text{ or } \mu_1 < \mu_2
\end{aligned}$$

To determine statistical significance, compare the calculated t-statistic with the critical value from the t-distribution based on df, or calculate the p-value for the t-statistic given the degrees of freedom.

E | Data sources

Required dataset	Tool	Worksheet	Variables
Actual demand data	SAP (Databricks)	goods_movement_factory_consumption & goods_movement_factory_return	Actual_demand
Forecast demand data	SAP (Databricks)	MRP Table	Actual_forecast
Multi-echelon forecast	Kinaxis	Consensus Forecast + Bill of Materials for translation	Multi_echelon forecast
Supplier and MOQ table	Kinaxis	Current stock coverage report	Supplier ID, Supplier Name, MOQ, Units per pallet
Leadtime table	Kinaxis	Part Properties table - Sourcing - Lead Time Details	Leadtime
Product families and subfamily	Kinaxis	Part Properties table - General	DescriptionFam, DescriptionSubFam
Setup costs	Commercial Operations		Setup_costs
Holding costs	n.a.	Pallet costs = 1.50 per week: Logistics team	Holding_costs_per_pallet
Benchmark Mars	SLA agreement document	SLA	ROL and OUTL
Benchmark Survey	Survey forms	ROL and OUTL question per site	ROL and OUTL

F | Pseudo codes algorithms

This section provides background on the algorithms used and their respective logic.

F.1 | Supplier performance

This section describes Algorithm 1 which is used for measuring the supplier performance integrated in the supplier pilot.

Algorithm 1 Supplier Performance Measurement

```
Require: Supplier_Connectivity, VMI_Supplier_File, Pallet_File
Load data from input files
for each item in VMI_Supplier_File do
    Calculate Total_Stock_Position
    Retrieve Demand_Forecast
    Cumulative_Demand ← 0
    for each forecast_period do
        Update Cumulative_Demand
        if Cumulative_Demand > Total_Stock_Position then
            Set First_Stockout_Date
            break
        end if
    end for
    Determine Stock region based on First_Stockout_Period
end for
for each Supplier do
    Count item categories from Stock region
    Calculate pallet counts for each category
    Calculate percentages for each category
    Log Supplier_Performance
end for
for each Site do
    Output Items_by_Stock region to Excel
    Output Supplier_Performance to Excel
end for
return Excel files detailing Items_by_Stock region and Supplier_Performance
```

F.2 | Simulation model

Algorithm 2 presents the implementation of the simulation model.

Algorithm 2 Simulation model

Require: `Actual_Demand_Data`, `Forecast_Data` (26-week horizon), `Parameters` (Units per Pallet, Setup Costs, Holding Costs, Cost per item, Supplier Details, Lead Time, MOQ, Fill Rate Target)

Initialize `InventoryItem` object for each material (`mat_num`)
Initialize `InventoryItem` values: `IOH`, `IP`, order quantities, `ROL`, `OUTL`, and forecast-based `ROL` and `OUTL` values
Initialize `Future Event Set (FES)` and `Simulation Results (SimResults)`
Calculate Reorder Points (ROL) and Order-Up-To Levels (OUTL):
Define `calculate_reorder_point_and_order_up_to()`:
for each week **do**
  Calculate ROL_i and $OUTL_i$ based on cumulative forecast from 1 week to ROL_w and $OUTL_w$ weeks
end for
Weekly Simulation Loop:
for each week **do**
  Update Inventory Levels:
  Set `IOH` and `IP` to initial values or previous week's end values
  Place Orders (if needed):
  if `IP_start` < `ROL` **then**
    Calculate `order_quantity` to reach `OUTL`, ensuring it meets `MOQ`
    Record `order_quantity` and schedule a receipt event in `FES` for lead time + review period
  end if
  Receive Orders:
  for each event in `FES` **do**
    if event matches the current week **then**
      Receive the order by adding it to `IOH`
    end if
  end for
  Update Simulation Results:
  Count demands and unfulfilled demands
  Update `IOH` and `IP` end values based on actual demand
  Calculate and record `ROL` and `OUTL` in `SimResults`
end for
Calculate Metrics in SimulationResults:
Calculate `Fill Rate` `Fill Rate` $\leftarrow 1 - \frac{\texttt{unfulfilled demand}}{\texttt{total demand}}$
Calculate `Average Inventory Level` $\leftarrow$ Mean of `IOH_start` and `IOH_end` values
Calculate `Total Inventory Level` $\leftarrow$ Aggregate average levels across all items for system-wide analysis
Calculate `Total Relevant Costs` $\leftarrow$ Aggregate the costs for all items in the given policy
return Simulation Results

F.3 | Optimization model

Algorithm 3 presents the implementation of the optimization model.

Algorithm 3 Optimization model

```
Require: all_item_data, fill_rate_target, warehouse_constraint
Initialize valid_solutions to store solutions with P_2 ≥ P_{2,target} target and total_inventory_pallets ≤ C_max
for ROL_w in range 1 to 24 do
  for OUTL_w in range ROL + 1 to 25 do
    Initialize AFR, total_inventory, total_inventory_pallets, total_cost, and total_orders
    for item in all_item_data do
      Run InventorySimulation (See Algorithm 2)
      Retrieve avg_inventory, pallet_inventory, fill_rate, and number_of_orders from simulation results
      Accumulate total_inventory, total_inventory_pallets, total_fill_rate, and total_orders
      Calculate holding_cost and ordering_cost obsolescence_cost for InventoryItem and add to total_cost
    end for
    Calculate avg_fill_rate, avg_inventory, avg_inventory_pallets, and avg_total_cost across all items
    if avg_fill_rate ≥ fill_rate_target and avg_inventory_pallets ≤ warehouse_constraint then
      Append (ROL_w, OUTL_w, avg_inventory, avg_inventory_pallets, avg_fill_rate, avg_total_cost, total_orders) to valid_solutions
    end if
  end for
end for
if valid_solutions is not empty then
  optimal_solution ← solution from valid_solutions with minimal total_cost
else
  optimal_solution ← None {No valid solutions found}
end if
return optimal_solution, all_solutions
```

As for the optimization model two different types of decision variables have been used, Algorithm 4 gives the pseudo-code for the Min-Max procedure.

Algorithm 4 Optimization model extension Min Max

```
Require: all_item_data, fill_rate_target, warehouse_constraint
Initialize valid_solutions to store solutions with P_2 ≥ P_{2,target} target and total_inventory_pallets ≤ C_max
for Min_w in range 1 to 9 do
  for Max_w in range Min_w + 1 to 20 do
    Initialize AFR, total_inventory, total_inventory_pallets, total_cost, and total_orders
    for item in all_item_data do
      Run InventorySimulation (See Algorithm 2 with ROL_w = Min_w + Leadtime and OUTL_w = Max_w + Leadtime)
      Retrieve avg_inventory, pallet_inventory, fill_rate, and number_of_orders from simulation results
      Accumulate total_inventory, total_inventory_pallets, total_fill_rate, and total_orders
      Calculate holding_cost and ordering_cost obsolescence_cost for InventoryItem and add to total_cost
    end for
    Calculate avg_fill_rate, avg_inventory, avg_inventory_pallets, and avg_total_cost across all items
    if avg_fill_rate ≥ fill_rate_target and avg_inventory_pallets ≤ warehouse_constraint then
      Append (Min, Max, avg_inventory, avg_inventory_pallets, avg_fill_rate, avg_total_cost, total_orders) to valid_solutions
    end if
  end for
end for
if valid_solutions is not empty then
  optimal_solution ← solution from valid_solutions with minimal total_cost
else
  optimal_solution ← None {No valid solutions found}
end if
return optimal_solution, all_solutions
```