UNIVERSITY OF TWENTE.

Master Thesis

A Mathematical Model for a Single-Retailer, Single-Vendor, Multi-Item Vendor Management Inventory for the Export Business of Jacobs Douwe Egberts

by

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Preface

Dear reader,

This master's thesis means the end of my studies in Industrial Engineering and Management at the University of Twente, but the start of my professional career. Over the past few months, I have dedicated myself to this project, and I am happy to present my research. I would like to thank the whole GBD team, and especially Sander Dekhuijzen and Arjan Sintemaartensdijk, for their support, guidance, enthusiasm, and faith throughout the internship and the project. They warmly welcomed me into the team and offered assistance whenever needed. Their contributions were important not only in successfully conducting this research but also in developing my personal and professional growth. Thank you for all the opportunities and responsibilities you gave me within the team.
I am thankful to both of my supervisors at the University of Twente. Firstly, I would like to extend my appreciation to Breno Alves Beirigo, my primary supervisor, for his invaluable feedback sessions aimed at refining the academic quality of my Master's Thesis. I also value his structured approach to our collaboration. Secondly, I want to express my gratitude to Dennis Prak, my secondary supervisor, for his constructive feedback, which contributed to elevating and enhancing the outcomes to a higher level.
Last but not least, I would like to thank my friends and family for their support throughout the completion of this report. I extend my thanks to Floor Veuger for the biweekly buddy meetings, where we discussed our progress in detail and provided mutual encouragement. Additionally, I am thankful to my boyfriend, Ralph Spijkman, for his constant encouragement, never-ending support, and enthusiasm in celebrating every success along the way. His motivation has been instrumental in keeping me focused on my thesis, especially during moments of reluctance.

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Utrecht
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Abstract

The export operations of Jacobs Douwe Egberts (JDE) faced inefficiencies in partner order profiles characterized by high order frequency but relatively low volumes, resulting in non-full pallet orders, underutilized transport, and elevated warehouse and distribution costs. This study seeks to optimize these costs by improving partner order frequency and volume through the design of an effective order strategy. Employing a single vendor, single retailer, multi item VMI model, this research aims to minimize total warehouse and distribution expenses while accounting for stochastic demand using chance constraint programming. The model offers insight into optimal order frequency, volume for each item, and transportation modes. Results indicate that implementing VMI can indeed reduce overall costs; however, success heavily relies on effective information sharing between the vendor and the retailer.

Management Summary

This management summary provides an overview of the MSc thesis, which addresses Vendor Management Inventory specific to the supply chain of the export department of Jacobs Douwe Egberts. The research question is formulated as: "How can GBD optimize the order profile of the partners to minimize the total distribution and warehouse costs while maintaining service levels?".

Objective

The main goal of this study is to develop an effective inventory management strategy aimed at minimizing the warehouse and distribution costs of GBD. This is achieved by refining the order profiles of its partners, focusing on order frequency and volume optimization. The aim is to streamline transport utilization by consolidating shipments into fewer, yet larger deliveries.

Problem Statement

1. **Order Volume:** Partners frequently place orders for individual items or boxes, resulting in additional warehousing expenses due to the need for repackaging goods. Additionally, the order volumes often do not match full transport quantities.

2. **Order Frequency:** Numerous orders are placed within short timeframes, without consolidation.

3. **Transport Utilization:** The combination of frequent order placement and low order volume leads to an average transport utilization of 53%.

4. **Total Costs:** These factors collectively contribute to high overall warehouse and distribution costs, impacting the profitability and competitiveness of the business. By addressing these inefficiencies, organizations can enhance cost effectiveness, streamline operations, and improve overall financial performance.

Proposed Solution

We propose the implementation of a VMI strategy with a single retailer and vendor, managing multiple items while considering static lead time and uncertain demand. To address this, we develop a MILP model aimed at minimizing the total costs incurred in warehousing and distribution for both the retailer and the vendor. Uncertain demand is managed through a chance constraint, ensuring a maximum 5% probability of stock-out occurrences. The model incorporates forecast errors by modeling actual demand as a normal distribution. At each period, decisions are made regarding whether to place orders, the volume of each item, and the corresponding transportation mode. The suggested strategy involves consolidating orders leading to fewer but larger orders to enhance transport utilization efficiency and reduce overall warehouse and distribution expenses. We validate the model using data from a specific partner, referred to as Partner X.

Results

The results of the experiments are evaluated on four metrics: objective function, transport utilization, run time, and optimality gap.

- **Cost Reduction:** The model significantly cuts down on total costs related to warehousing and distribution by consolidating orders, leading to fewer but larger shipments and increased transport utilization. Adaption of the VMI model to 2023 data shows potential expense reduction by up to 16.5%.
- **Transport Utilization:** Transport utilization increases to approximately 98%, a significant improvement compared to the current average utilization rate of only 53%.
- **40-foot Container Preferred:** Opting for 40-foot containers proves to be more cost-effective than 20-foot containers in the majority of cases.
- **Storage Capacity:** The agreed storage capacity with Partner X was already sufficient; increasing it does not impact the model's performance.
- **Forecast Accuracy:** Improving forecast accuracy could enhance the model's performance and reduce warehouse and distribution expenses by up to 4.3%, from €33,255 with a medium forecast accuracy to €31,826 with a perfect forecast.
- **Lead Time.** Reducing the lead time does not immediately impact total costs, as the same orders are simply placed later in the new model.
- **JIT vs. VMI:** The VMI model outperforms the JIT model, with reductions of 4.5%, 4.1%, and 3.0% observed in medium, low, and perfect forecast accuracy scenarios, respectively.

Conclusion & Recommendation

- **Partial VMI:** Implement partial VMI for all partners, ensuring mutual agreement on comprehensive information sharing between both parties.
- **Forecast Accuracy:** Enhance the forecasting capabilities of partners to improve the model's performance.
- **Make-to-order:** Upon successful implementation of VMI, prioritize reducing lead times by transitioning from a make-to-order to a make-to-stock paradigm.

Contents

Acronyms

CCP Chance Constraint Programming. 25, 35

DRP Distribution requirements planning. 18, 19

EOQ Economic Order Quantity. 21, 23, 25, 27

FCA Free Carrier. 9, 12, 16

FTL Full Truck Load. 13–16

GA Genetic Algorithm. 24, 25, 30

GBD Global Business Development. i, v, vii, 1–5, 7–10, 12–16, 18, 25, 29, 31–37, 39, 41, 42, 49, 53, 55–57

ICA Imperialist Competitive Algorithm. 24, 30

JDE Jacobs Douwe Egberts. iii, v, vii, 1, 2, 5, 7–10, 15, 53

JIT Just-in-time. vi, viii, x, 23, 50–52, 54, 55

KPIs Key Performance Indicators. vii, 1, 2, 5, 19

LSP logistic service provider. 9

LTL Less Than Truckload. 2, 13, 14

MAPE Mean Absolute Percentage Error. 34

MILP Mixed Integer Linear Program. v, ix, 23, 24, 27–30, 39

MIP Mixed Integer Program. 24

PSO Particle Swarm Optimization. 24, 30

SCOS Supply Chain Operating System. 1

SKU Stock Keeping Unit. ix, x, 7, 9, 10, 13, 15, 16, 31, 34, 45, 64

ss Safety Stock. 21

VMI Vendor Management Inventory. iii, v, vi, viii–x, 17–20, 22–24, 28–31, 38, 39, 41, 48–57

Glossary

checkup the frequency of evaluating whether to place an order. viii, x, 41, 45–48, 50–52, 54

CSL The probability of having enough stock to meet demand. 12, 18

GBD CSL The goal of GBD to deliver a minimum of 95% of orders within the specified lead time.. 10

incoterm clarifies the rules and terms that buyers and sellers use in international and domestic trade contracts Troy Segal (40). vii, 9, 10, 12, 16, 36

make-to-order a production strategy in which items are only produced after receiving customer orders. vi, 8, 10, 13, 15, 42, 56, 57

make-to-stock a production strategy that is used to match inventory with demand forecast of the customers. vi, 8, 56, 57

partner regional distributors with who GBD collaborate closely to ensure the supply of relevant brands on each specific market. v, vii, viii, 2–4, 7–10, 12–19, 31, 32, 34–36, 42, 49, 50, 53, 55–57

Partner X the partner for who we test the VMI model. ii, vi, x, 31–35, 41, 42, 48–50, 52, 54, 64

PAX the main Logistic Service Provider for GBD, located in The Netherlands.. 8–10, 12, 15, 33

professional sales to entities such as hotels, hospitals and corporations. vii, 8, 10, 12

retail sales to wholesalers and supermarket chains. vii, 8–10, 12

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Chapter 1

Introduction

1.1 Company Description and Context

Jacobs Douwe Egberts (JDE) is the world's leading coffee and tea company, headquartered in The Netherlands, with a portfolio of over fifty brands including L'Or, Jacobs, Senseo, Douwe Egberts, and Pickwick. For more than 265 years, JDE has been inspired by the belief that it is amazing what can happen over a cup of coffee (17). This project is conducted within the Global Business Development (GBD) supply chain team. This team is responsible for overseeing the domain of Export business and the order-to-cash process with customers in North and South America, Europe, Africa, and Asia.

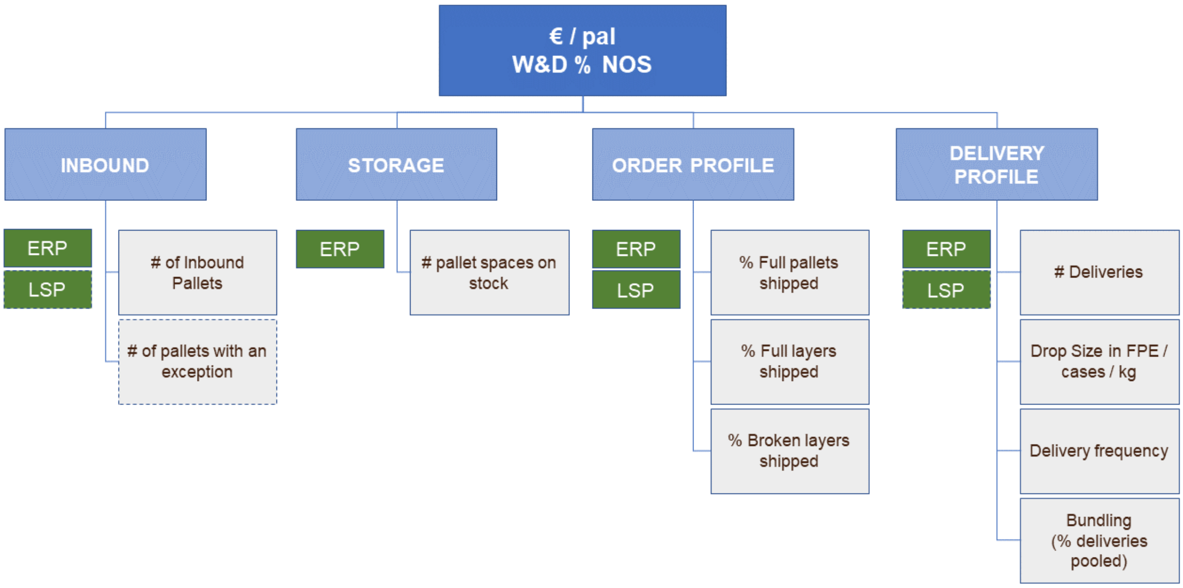
1.2 Research Motivation

A new initiative, denoted as the Supply Chain Operating System (SCOS), has been implemented on a comprehensive scale throughout JDE. The fundamental aim of SCOS is multifaceted; to rediscover growth, attain and sustain a leadership position in costs & cash, and create a culture of pride and performance. Among other things, for GBD the introduction of SCOS entails that they need to obtain, monitor, evaluate, and improve significant Key Performance Indicators (KPIs) about its warehousing and distribution costs. Specifically, the SCOS program prescribes to focus on two high level KPIs, namely:

- *EUR/Pal*: Warehousing and distribution costs in respect of full pallet equivalents delivered to the customer.
- *W&D % NOS*: Warehousing and distribution costs expressed as a percentage of the net outside sales.

Figure 1.1 visualizes the factors that have an immediate impact on the performance of the EUR/pal and W&D % NOS, namely: inbound, storage, order profile, and delivery profile. In the current situation, the order and delivery profile are important factors where GBD underperforms. Customers frequently place orders that do not consist of full pallets, but of a pallet layer, or even a small amount of items. In addition, customers frequently do not order for a full container or truckload, resulting in higher relative distribution costs of an order. Acquiring an order and delivery strategy is of great importance to GBD, as it serves as a foundational step towards recognizing potential improvements for distribution cost optimization.

Figure 1.1: The KPI tree of the GBD export department of JDE, with the EUR/pal and W&D % NOS as the high level KPIs. The factors inbound, storage, order profile, and delivery profile have an important influence on the performance of these high-level KPIs. For each factor, several low-level KPIs are determined.



1.3 Problem Statement

1.3.1 Problem Identification

The primary objective of this research is to design an efficient solution to reduce the distribution expenses of GBD by optimizing the order of the partners. The main problem that this study addresses is as follows:
In the present situation, the order and delivery profile of the customers is an important shortcoming. Customers frequently order partial pallets and Less Than Truckload (LTL) quantities. The distribution expenditures associated with export are documentation, labeling, transportation, and administrative tasks. Importantly, it is worth noting that a portion of these distribution costs assumes a fixed nature, meaning that they do not fluctuate in proportion to the order size. Consequently, when partners do not place orders constituting full pallets or complete truck or container loads, the relative cost per unit of goods transported increases. This phenomenon hurts the performance of the high level KPIs: EUR/pal and W&D % NOS.

1.3.2 Significance of the Study

This study can have a significant impact on the operation of GBD by reducing distribution costs and exploring the possibilities of order and delivery profile optimization. Additionally, this research contributes to the broader field of optimization methods in order and delivery profiles by addressing a real-world problem with practical implications.

1.3.3 Research Objectives

In the ideal situation, customers order less frequently but always order full pallets and full transportation utilization quantities. Acquiring such an order and delivery profiles is of great importance to GBD, as it serves as a foundational step towards the reduction of the warehouse and distribution costs.
The research objectives of this thesis are as follows:

1. To conduct comprehensive literature research on existing optimization methods and inventory management strategies, with a focus on improving customers' order and delivery profiles.

2. To analyze and model the current order and delivery profile of GBD customers, taking into account the capacity constraints and the forecast.

3. To develop a model that optimizes the order and delivery profile, aiming to reduce warehouse and distribution costs.

4. To test and evaluate the performance of the proposed solution, using historical data of one partner.

5. To provide practical recommendations and insights to GBD based on the results obtained, to minimize the warehouse and distribution expenses by improving the order and delivery profiles.

1.4 Research Questions

To guide this research, the following research questions are formulated:

1.4.1 Main Research Question

RQ1: How can GBD optimize the order profile of the partners to minimize the total warehouse and distribution costs while maintaining service levels?

1.4.2 Sub-Research Questions

Each chapter of this thesis corresponds to a sub-research question addressing specific aspects of the main research question. These sub-research questions are as follows:

1. **Chapter 2: Problem Context**

    - *RQ2:* What are the key components and steps in the current order-to-cash process of GBD as part of its supply chain operations?

2. **Chapter 3: Literature Review**

    - *RQ3:* What inventory management strategies can address cost minimization challenges associated with improving the order profile via order consolidation, resulting in fewer but larger shipments?

3. **Chapter 4: Solution Methodology**

- *RQ4:* How can we apply the modeling techniques outlined in the previous chapter to the specific GBD case and modify them to enhance its operational performance?

4. **Chapter 5: Experimental Evaluation**

   - *RQ5:* How does the new proposed solution perform, reviewed on total costs and transport utilization, compared to the current approach of GBD?

5. **Chapter 6: Discussion and Recommendations**

   - *RQ6:* What are the practical implications of the results obtained, and what other recommendations can be made to GBD for optimizing the order and delivery profiles?

1.5 Scope and Limitations

GBD engages with a diverse range of partners, but this study specifically concentrates on those aligned with a particular distribution channel, excluding partners using an alternative warehouse flow. Given that the majority of products are distributed through this warehouse, the focus is on optimizing improvements in that specific area. Additionally, the sale of spare parts and pre-used machines is outside the scope of this study. In this study, the emphasis is on inventory management strategies applicable to the partner, rather than focusing solely on our internal inventory management practices.

1.6 Problem Solving Approach

This thesis is structured as follows:

- **Chapter 2: Problem Context** - In this chapter, we elaborate on the supply chain of GBD and the shortcomings in the order and delivery profile.
- **Chapter 3: Literature Review** - This chapter provides a review of the existing literature related to inventory management strategies.
- **Chapter 4: Solution Methodology** - This chapter presents the algorithm or methodology developed to address the problem, including a mathematical model and implementation details.
- **Chapter 5: Experimental Evaluation** - Here, we discuss the data collection, the experimental setup, and the results obtained from testing the model on historical data of one partner of GBD.
- **Chapter 6: Conclusion & Recommendations** - This chapter summarizes the key findings, discusses the implications, and provides practical recommendations to the GBD team and future research topics.

1.7 Summary

This research is conducted within the export department of JDE. The primary objective is to optimize the order and delivery profile of the GBD's partners, focusing on aspects such as order frequency and quantity, to minimize the warehouse and distribution costs. Currently, GBD is facing challenges with underperformance in these KPIs, leading to elevated warehouse and distribution expenses. The research question of this study is then formulated as; "What inventory management strategies can be employed to address cost minimization challenges associated with enhancing the order profile?". The next chapter elaborates on the relevant operation characteristics of GBD and its supply chain.

Chapter 2

Problem Context

This chapter focuses on describing the relevant operation characteristics of GBD to answer the first research question "What are the key components and steps in the current order-to-cash process of GBD as part of its supply chain operations?". In Section 2.1, we elaborate on the whole supply chain and separate into four main stages: raw materials & factory, warehouse, transportation, and partners & end consumers. We then dive deeper into the order-to-cash process in Section 2.2. In Section 2.3 we elaborate on the current order and delivery profile of the partners, explained by a simplified visualization. We finish by outlining the key characteristics that must be considered in an optimization model in Section 2.4.

2.1 The Supply Chain

JDE maintains a portfolio comprising over fifty coffee and tea brands including L'Or, Jacobs, Senseo, Douwe Egberts, and Pickwick, yielding a total of approximately four hundred distinct Stock Keeping Unit (SKU). Additionally, the department engages in the trade of pre-owned machines and spare parts, but this is not considered in this research. Many products JDE sells have an expiry date to consider. Partners prefer products that are 'fresh' and have a shelf life extending into the distant future. This is especially crucial for customers with longer shipping times.
Figure 2.1 shows how the GBD products move through the supply chain. This section elaborates on each distinct step in the supply chain.

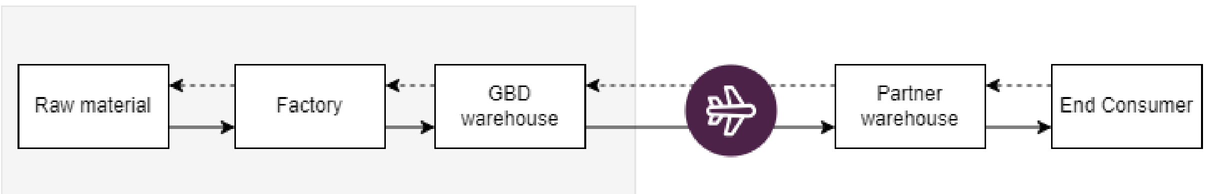


Figure 2.1: A schematic representation showing how GBD products move through the entire supply chain. It starts with raw materials from plantations and goes through factories and the GBD warehouse. From there, the goods are transported to the warehouses, and finally, end consumers receive the products. The steps delineated in grey within the supply chain lie under JDE responsibility.

2.1.1 Raw Material & Factory

The tea leaves and coffee beans originate from South America and Asia. Factories are situated across the globe, with a significant portion located in Europe. Each factory specializes in producing its range of products. Subsequently, the products are distributed from the factories to the warehouses of all JDE teams. Figure 2.2 provides an overview of the factory and warehouse locations, with factories represented in red.

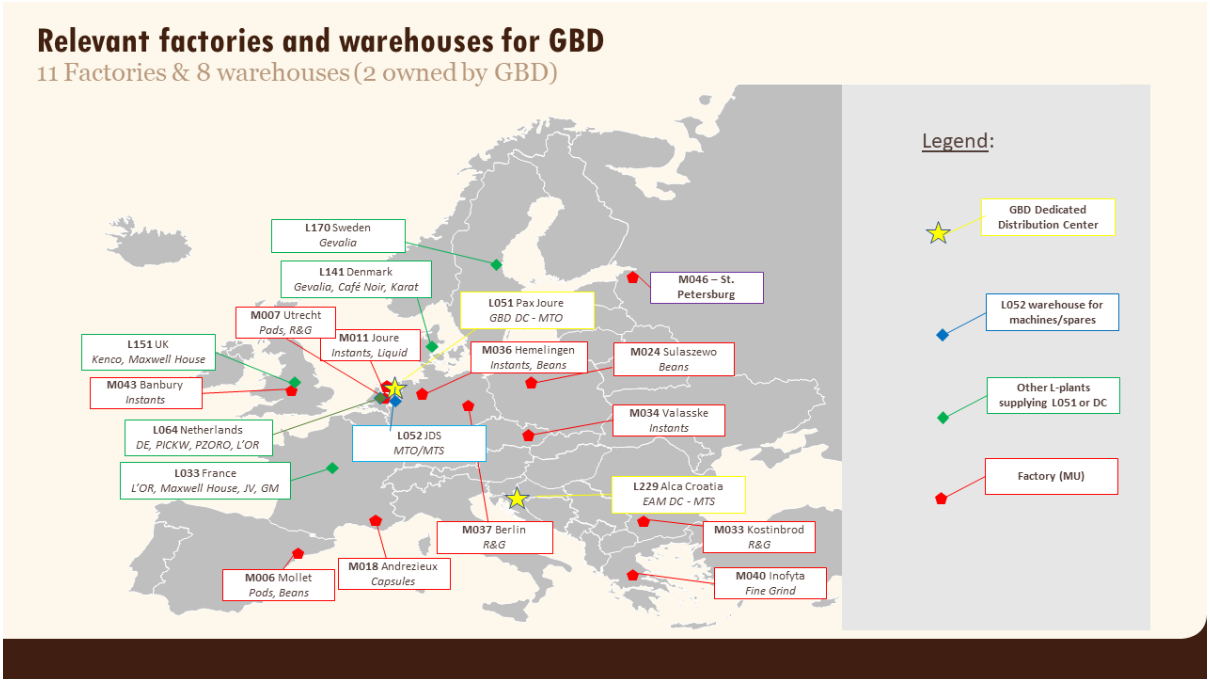


Figure 2.2: An overview of the locations of the two owned GBD warehouses PAX and ALCA (depicted in yellow), other JDE warehouses that supply the GBD partners (depicted in green) and the supplying factories (depicted in red).

2.1.2 GBD Warehouse

The stock gets collected from all production sites in Europe and is consolidated to the designated GBD warehouse. GBD assumes ownership of two warehouses, PAX (located in Joure, The Netherlands) and Alca (located in Croatia), from which 100% of the professional and 55% of the retail volume is distributed. The other 45% of retail volume is distributed from different JDE warehouses. GBD assumes three warehousing flows:

1. **PAX Flow**: the first flow considers a make-to-order paradigm and goes through the GBD warehouse PAX, located in The Netherlands, with a corresponding lead time of approximately six weeks. Currently, 100% of the professional volume and 15% of the retail volume follow this flow. The PAX warehouse is depicted in yellow in Figure 2.2.

2. **ALCA Flow**: the second flow considers a make-to-stock production strategy. The goods are stored in the GBD warehouse ALCA, located in Croatia, and are distributed to the partner in the Eastern Adriatic Markets. It corresponds with a

lead time of one week and approximately 40% of the retail volume follows this flow. The ALCA warehouse is also depicted in yellow in Figure 2.2.

3. **Sharing stock Flow**: the last flow considers sharing stock of other JDE warehouses, which are depicted in green in Figure 2.2. The lead time of this flow equals four weeks and currently, approximately 45% of the retail volume follows this flow.

The GBD warehouses are of type manufacturer storage with direct shipping and in-transit merge, which means that they combine pieces of the order coming from different locations so that the customer gets a single delivery (7). The following costs are associated with the warehousing and are invoiced either directly or indirectly to GBD:

- An indirect flat fee per pallet is charged for warehouse services, encompassing general inbound handling and storage costs. Annually, the specific flat fee for each warehouse is determined, taking into account the performance of the preceding year.

- The specific order-related costs to warehousing and distribution are billed directly to GBD. These actual distribution costs cover various aspects such as export documentation, labeling, order processing, and equipment required for transportation.

Due to the high volume and the great improvement possibilities, this research zooms in on the partners that follow the flow through PAX. The close collaboration between GBD and the logistic service provider (LSP) PAX makes it manageable to retrieve insight into the operations and costs of warehouse and distribution, giving a solid foundation for the analysis.

2.1.3 Transportation

The goods are transported by either land, sea, or air shipment. Each customer operates with a specific incoterm, which clarifies the rules and terms for international trade. The determination of the invoice date depends on the specific incoterm agreed between GBD and the partner. Figure 2.3 provides an overview of the existing incoterms. 75% of the partners adopted the incoterm Free Carrier (FCA), meaning that the responsibility of goods transportation lies by the partner. Following this incoterm, GBD is responsible for delivering the goods to the GBD warehouse, and from that point the responsibility shifts to the partner. The partner arranges the transportation of the goods or outsources the task to a third party.
The transportation of the goods involves either twenty or forty-foot containers or trucks. Loading of these containers or trucks is executed using either euro or block pallets, contingent upon the SKU specifications. Additionally, certain SKUs have the characteristic of being stackable, allowing the accommodation of two pallets within a singular pallet space. The capacity of both containers and trucks is shown in Figure 2.4, demonstrating its dependency on the attributes of the specific SKU. Economical efficiency is attained through the delivery of full pallets and the optimization of container and truck capacities.

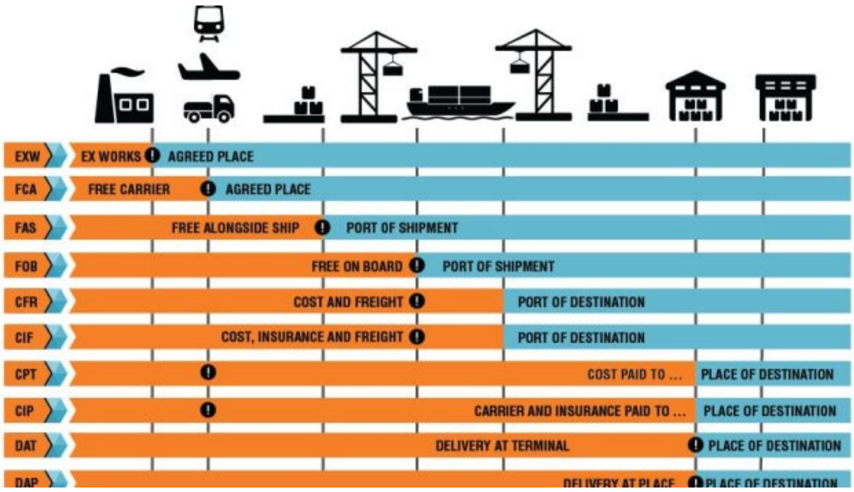


Figure 2.3: An overview of existing incoterm introduced by the International Chamber of Commerce, where each incoterm specifies different points at which responsibility and risk transfer from the seller to the buyer. In this overview, the color orange signifies that the responsibility lies with GBD, while blue indicates responsibility held by the partner. The exclamation mark '!' signifies the point in transportation where responsibility shifts from GBD to the partner. Notably, the incoterm "Free Carrier" is contracted by 75% of the partners (SFAA).

2.1.4 Partners & End Consumer

The partners are located in North and South America, Europe, Africa, and Asia. JDE makes a distinction between retail and professional partners, where retail focuses on the sales to wholesalers and supermarket chains, while the professional domain caters to entities such as hotels, hospitals, and corporations. Presently, GBD serves over fifty customers supplying a comprehensive range of products under fourteen distinct brands. The GBD team collaborates closely with regional distributors, called partner, ensuring the supply of relevant brands on each specific market. Each partner owns a warehouse in their corresponding area and introduces the JDE products in the market of that country. The partner is responsible for the distribution of the goods to the end consumer. In collaboration with the account manager from GBD, the partner makes decisions regarding the SKUs within their portfolio.

2.2 Order-to-cash process

This research is conducted within the supply chain department of GBD. As explained in Section 2.1.2, GBD operates via three distinct warehouses. The majority of the partner of GBD operates through the GBD owned warehouse PAX. This particular flow adheres to a make-to-order model, resulting in an average lead time of six weeks. GBD adopts a distinctive definition for the customer service level. Typically it denotes the probability of having enough stock to meet demand. GBD upholds a customer service level of 95%, which indicates their goal to deliver a minimum of 95% of orders within the specified lead time. For clarity, in this report, we refer to this as GBD CSL. The timeline of the order-to-cash process is illustrated in Figure 2.6 and encompasses the following stages:

Full 20ft container	
Block pallet places	Euro pallet places
10	0
9	1
8	2
7	3
6	4
5	5
4	6
3	8
2	9
1	10
0	11

(a) Capacity of a 20 feet container

Full 40ft container	
Block pallet places	Euro pallet places
0	25
1	24
2	23
3	22
4	21
5	20
6	19
7	18
8	17
9	16
10	15
11	13
12	12
13	11
14	10
15	8
16	7
17	6
18	5
19	3
20	2
21	1
22	0

(b) Capacity of a 40 feet container

Full truck		
Block pallets single stack	26	pallets
Block pallets double stacked	52	pallets
Euro pallets single stack	33	pallets
Euro pallets double stacked	66	pallets

(c) Capacity of a truck

Figure 2.4: The capacities of the various shipping methods, are defined by the type of pallet and stackability of the items. A euro pallet measures 80 x 120 cm, while a block pallet measures 100 x 120 cm. The table illustrates the capacity of Euro pallets and block pallets in various transportation modes, including 20-feet containers, 40-feet containers, and trucks.

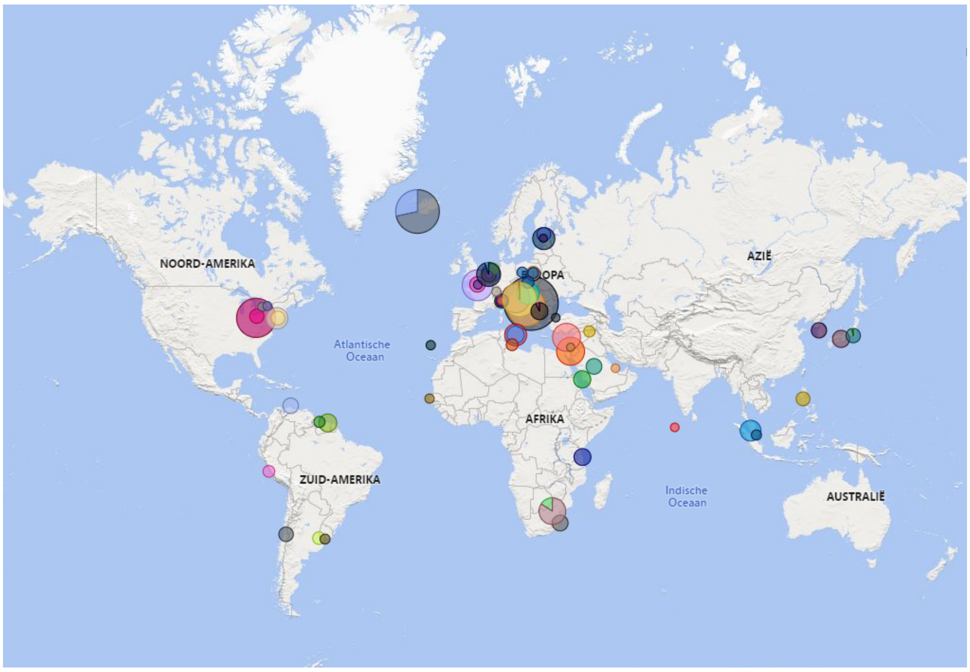


Figure 2.5: An overview of the sales volume of GBD partners in the year 2023. The size of each pie chart corresponds to the sales volume, with larger charts indicating higher volumes. For partners categorized as both retail and professional, the pie chart is divided into two colors, representing the respective shares of volume for retail and professional segments.

- Week 0: The partner places an order based on their forecast and current stock level.
- Week 5: The order should be in stock at the warehouse PAX.
- Week 6: Orders with incoterm FCA and without extra export labeling should be ready for pickup.
- Week 7-8-9: For orders where the transportation is arranged by GBD some export time is included. The exact time depends on the partner requirements and location. It includes arranging export documentation, special export labeling, and transportation.

The partner assumes responsibility for introducing and distributing items throughout the country's market. Partners typically operate under a 95% CSL, striving to maintain sufficient stock to fulfill demand in 95% of cases.

2.3 Order and Delivery Profile

As explained in Section 1.2, the order and delivery profile are interesting factors, where GBD underperforms. In the current situation often partners order pallet layers or small quantities of items, instead of ordering full pallet quantities. The goods are delivered to the warehouse in full pallets, ordering smaller quantities leads to additional warehousing costs since the pallets need to be repacked. The probability of obsolescence also increases by ordering smaller quantities. Additionally, partners frequently order

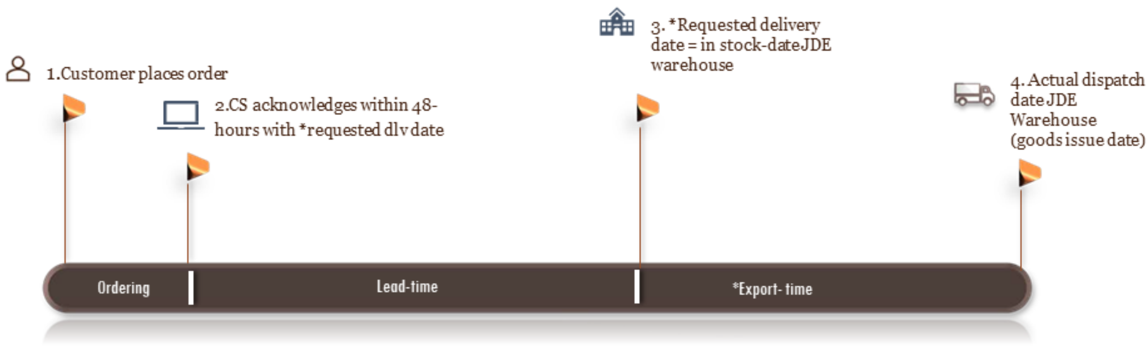


Figure 2.6: The general order-to-cash-process of GBD.

less than full truck or container quantities. Approximately, only 25% of the orders in the year 2023 correspond to a full truck or container load.

2.3.1 Demand Forecast

A challenge confronting the export department lies in the fluctuations in the partner demand, which has prompted the company to operate within the framework of make-to-order paradigm. Under such a strategy, the production is initiated exclusively upon placement of a customer order, resulting in a relatively high lead time for the delivery of the products. The transition from this make-to-order paradigm to a make-to-stock strategy depends significantly upon the establishment of a precise and accurate volume forecast. Currently, a significant majority of the GBD partners submit a monthly demand forecast of the upcoming month at SKU level. However, GBD lacks assurance regarding the accuracy and reliability of this forecast.

2.3.2 Full Truck Load

Full Truck Load (FTL) represents a type of shipping mode whereby a truck carries one dedicated shipment (10), whereas Less Than Truckload (LTL) is a transport method whereby a truck is available to carry more than one shipment (11). Typically, FTL is usually employed in cases where the shipment is large enough to fill an entire truck or container load, while LTL is suitable for smaller quantities. FTL offers numerous advantages, including cost efficiency, faster transit times, enhanced security, and improved inventory management.
GBD currently adopts the principle of LTL instead of the alternative FTL approach. The LTL principle is incompatible with the operations of GBD, particularly in the context of an export business where order consolidation poses challenges. Firstly, transportation responsibility lies with 75% of the partners, who either manage it internally or outsource it to third parties. Secondly, the transportation of food commodities involves export documentation and compliance with customs regulations. Introducing order consolidation across partners in different countries would complicate documentation processes. Lastly, the diverse geographic locations of partners would result in

longer shipment duration, which, when added to the already six-week lead time for products, is undesirable. Therefore, in this research, the focus is on the FTL principle and improving transport utilization.

2.3.3 Example Order Profile

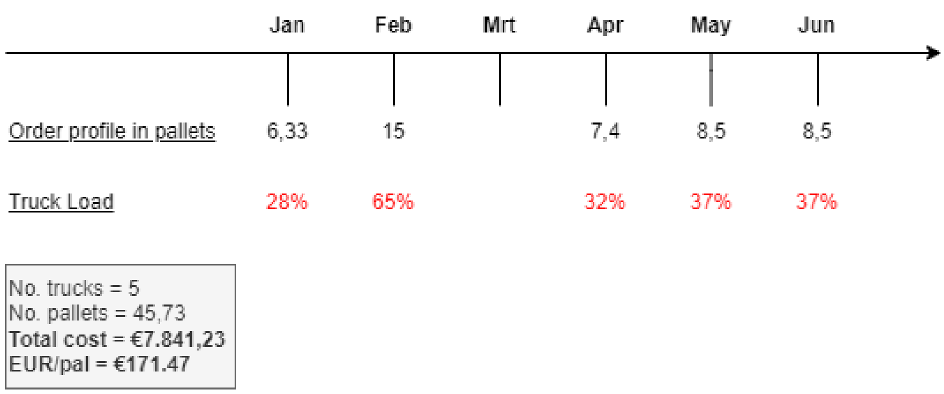
Figure 2.7 presents a simplified visualization of the current order profile observed among partners and an example of an improved order profile, yielding a reduction in total warehouse and distribution costs. It is important to recognize that certain simplifications employed in this illustrative model may not adequately reflect real-world situations but are used for simplification. The model relies on the following assumptions and simplifications

- The partner orders only one item, which has a corresponding shelf life of 365 days
- The net price of one pallet equals €1,000
- We consider only one pallet type, euro pallet, and the item is not stackable
- The partner uses a truck for transport; the truck has a capacity of 25 pallets
- The truck transportation cost equals €1,000
- The fixed order cost equals €150
- The variable costs equal €13.36 per pallet

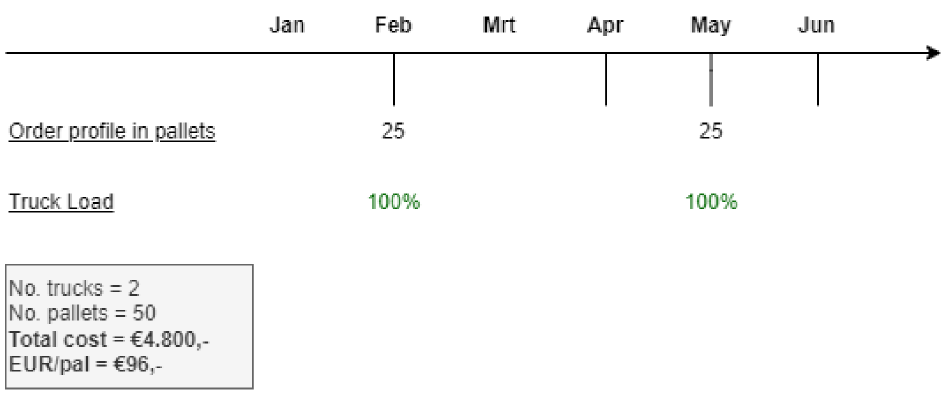
In the current situation, as shown in Figure 2.7a, a partner places approximately once per month an order, which corresponds to LTL. Due to the fixed order and distribution costs, the total costs of such an order profile equals approximately €7,900, resulting in a euro per pallet (EUR/pal) of €171.47. In an improved situation, as illustrated in Figure 2.7b, the partner adopts a less frequent ordering strategy, consolidating multiple orders into Full Truck Load (FTL) quantities. Given the product's one-year shelf life, it is feasible to bundle the orders, that are placed in the current situation in January, February, and March, into a single order placed in February. This transition results in a shift from the previous operation, where five trucks were dispatched to deliver 45 pallets, to a new and more efficient approach where only two trucks suffice to transport 50 pallets. In this improved situation, the total warehouse and distribution costs equal €4800, resulting in a cost per pallet of €96. This reduction in costs signifies a noteworthy 39% decrease in warehouse and distribution expenses and a 44% reduction in the EUR/pal KPI.

2.4 Summary

This chapter focuses on the features of GBD business's supply chain. In the current scenario, partners commonly place orders for pallet layers or smaller quantities of items, deviating from ordering full pallet and truck/container quantities. To explore optimization models in the literature, the following key characteristics must be considered:



(a) An example of how partners currently place orders, exemplified by one partner ordering one particular item. The figure shows that the partner orders five times in six months. They order non-full pallet quantities and the transport utilization is between 28% and 65%. Such an order pattern results in total warehouse and distribution costs of approximately €8, 000 and a EUR/pal of €171.



(b) An example of an order pattern a partner can implement, which reduces the total warehouse and distribution costs. In this situation, the partner orders twice a FTL in six months a total of 50 pallets, resulting in a total cost of approximately €5, 000 and a EUR/pal of €96.

Figure 2.7: A simplified example of the current order pattern and an improved order pattern, which results in a reduction of total warehouse and distribution costs and the KPI EUR/pal. The example is based on the assumptions made in Section 2.3.3.

- GBD is the export department of JDE and collaborates closely with geographically dispersed partners.
- The research focal point is the flow through PAX, Section 2.1.2, characterized by a corresponding lead time of six weeks.
- Production through PAX adheres to a make-to-order paradigm, eliminating the necessity for inventory holding. Fixed lead times are presumed for each distinct item category, without accounting for stochastic variability.
- The focus is on finished SKU's, encompassing coffee, tea, and various other commodities. Production and the warehousing facility operates under the condition of unlimited capacity.

- Each partner is associated with a predetermined transportation method; either via land, sea, or air shipment.
- Each partner operates under a predetermined incoterm, with Free Carrier (FCA) adopted by 75% of them.
- The distribution costs are billed directly to GBD and highly depend on the incoterm and export prerequisites of the partner. Each partner has a predetermined fixed transportation tariff that remains unaffected by price fluctuations.
- Warehousing costs associated with inbound handling and storage are billed indirectly to GBD and therefore a warehouse tariff per pallet is predetermined each year, Section 2.1.2.
- Shipping mode Full Truck Load (FTL) is considered, without consolidation of partners orders, Section 2.3.2.
- Each partner provides a monthly demand forecast on SKU level and it is essential to consider the accuracy of these forecasts.

The next chapter focuses on exploring inventory management models and methods, presented in literature, that minimize the overall warehouse and distribution costs.

Chapter 3

Literature Study

In this chapter, we explore research that employs optimization models with a primary emphasis on enhancing the partner's order profile to answer the second research question "What inventory management strategies can address cost minimization challenges associated with improving the order profile via order consolidation, resulting in fewer but larger shipments?". The objective is to boost transport utilization, ultimately leading to a reduction in overall warehouse and distribution costs. Focusing on inventory policies can be crucial when aiming to increase transport utilization and reduce overall warehouse and distribution costs. By adopting an efficient inventory policy, businesses can consolidate orders more effectively, enhance load planning, and minimize stockouts and overstock, which ultimately leads to a reduction in warehouse and distribution costs. This is why our literature study centers on the examination of inventory policies. As the vehicle routing is presumed to be optimal and production is assumed to be unlimited, we will omit these aspects from our study.
Section 3.1 provides an in-depth analysis of inventory strategies proposed in the literature. Subsequently, Section 3.2 explores the characteristics of VMI. In Section 3.3 we present potential solution methodologies for the identified optimization problems, featuring two mathematical models presented in the literature with similar features as our model requirements.

3.1 Inventory Management Strategy

Effective inventory management is critical to any business, influencing its overall operational performance. Inventory management strategies aim to enhance productivity, reduce costs, and improve customer satisfaction by minimizing stockouts and preventing overstock. The selected inventory management must satisfy the following criteria:

- *Demand of Finished Products*: The main emphasis is on optimizing finished product distribution to partners rather than production concerns, which entail planning and inventory management of semi-finished products. Furthermore, the SKUs sold to customers are neither substitutes nor complements. The primary criterion for the inventory management policy is its capacity to handle independent demand, particularly focusing on finished product inventory rather than the dependent demand associated with semi-finished products.

- *Push approach*: As explained in Section 2.2, partners uphold inventory levels for all items to mitigate stockout risks and ensure timely fulfillment of end consumer demand. Typically, partners maintain a CSL of no less than 95%. A push inventory approach allows companies to have more control over the distribution process, as it involves delivering goods from pre-existing inventory. The chosen inventory policy should align with this objective and assist GBD in attaining the specified target.

- *Single facility approach*: As outlined in Section 2.3.2, it is not compelling for GBD to consider the consolidation of orders from various partners. The focus is specifically on one partner intending to minimize the warehouse and distribution costs for that partner. This criterion ensures that the inventory management policy exclusively centers on a single facility, rather than considering multi-facility approaches.
- *Stochastic demand*: As explained in Section 2.3.1, every partner submits a monthly forecast for the upcoming year. It is essential to note that this forecast is an estimate and may not accurately reflect the actual demand, as sales can deviate from the forecast due to its inherent inaccuracies. The challenge lies in managing inventory when the actual demand is uncertain and the forecast, provided by the partner, still has room for improvement in terms of accuracy. The inventory management policy should effectively handle stochastic demand and support to mitigate the risk of stockouts while concurrently minimizing overall warehouse and distribution expenses.
- *Transport utilization*: An important aim of this study is to enhance transportation utilization, as explained in Section 1.3. The selected policy should optimize truck or container utilization through proactive planning and the consolidation of orders from a partner.

Mentzer et al. (26) describe two interesting inventory management policies that center around enhancing distribution, namely Distribution requirements planning (DRP) and Vendor Management Inventory (VMI). These policies are elaborated upon and assessed based on the aforementioned criteria.

Distribution Requirements Planning. DRP is an inventory management approach focusing on optimizing the distribution and allocation of finished goods to meet customer demand efficiently while minimizing overstocking. Ho (15) argue that the most successful implementation of DRP occurs in a multi-facility supply chain, leveraging trans-shipment possibilities. Additionally, DRP tackles uncertainty in demand by relying on demand forecasts and maintaining appropriate safety stock levels to anticipate and buffer against fluctuations. Notably, DRP enhances transportation efficiency by optimizing the distribution network and planning efficient transportation routes, emphasizing improvements in logistics rather than focusing solely on order quantity and frequency enhancements.

Vendor Management Inventory. VMI is a collaborative inventory strategy where the supplier is responsible for monitoring and replenishing the customer's inventory to minimize costs and optimize stock levels. VMI is particularly effective in managing the demand for finished goods that are uncertain and influenced by various factors. The continuous communication and information sharing between the supplier and the buyer enable a more responsive approach to changes in market conditions or unexpected demand variations. Besides, VMI contributes to enhancing transport utilization by allowing the supplier to optimize shipment quantities and frequencies based on the actual demand and inventory levels (31).

While DRP primarily emphasizes optimizing the distribution network and efficient transportation routes, VMI centers on customer inventory management. For this study, VMI meets all the criteria. It allows for a push approach and can be tailored for a single facility approach. VMI effectively handles both independent and stochastic demand while also improving transport utilization. Consequently, we delve into a detailed exploration of the VMI approach in the Section 3.2.

3.2 Vendor Management Inventory

Vendor Management Inventory (VMI) is a supply chain management strategy, where the supplier or vendor takes responsibility for managing the inventory levels of their products at their customer in the next echelon of the supply. In a traditional inventory management system, the customer is responsible for ordering and maintaining the inventory levels. However, in a VMI system, the vendor monitors the customer's inventory and replenishes it as needed. Various companies already adopted either a full-fledged implementation or a partial VMI implementation, which differs in terms of ICT support and agreed functions of the vendor. Vigtil and Dreyer (43) identified current inventory level and sales forecasts as the most valuable information for suppliers to improve their planning of replenishment processes in situations where VMI is considered. Figure 3.1 visualizes the information and material flow in a two-stage VMI supply chain.

Van der Plas (41) presents a case study where an improved VMI framework is implemented inside the Dutch supply chain of Heineken. This study carries out a simulation study that models the VMI process and evaluates the performance of the VMI based on three KPIs: transport utilization, stocks levels, and out-of-stock performance. This study concluded that there is a substantial increase in transport utilization and a decrease in out-of-stock levels obtained through VMI collaboration. Borade and Sweeney (5) presents another successful example of the implementation of VMI in a bread-manufacturing company, where the retailers are geographically dispersed and have different demands each day. This study considers the distribution of one single product to multiple retailers, where vehicles are assumed identical and unsatisfied demand is assumed a stock out. The results show that the VMI decisions help to improve profit, vehicle utilization, and service levels. Table 3.1 explains the potential strengths and weaknesses of VMI implementation.

The objective of this research is to reduce the total warehouse and distribution costs of a partner by modifying its order profile, such that the transport utilization is optimized. Implementing a full or partial VMI collaboration sounds promising to achieve this goal.

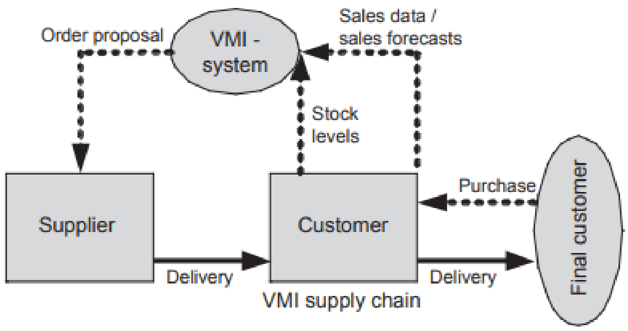


Figure 3.1: Information and material flow in a two-stage VMI supply chain presented by Gronalt and Rauch (13)

Table 3.1: Strengths and weaknesses of Vendor Management Inventory-collaboration

Strength	Weakness
• Prevents 'bull-whip' effect (22) • Unite vendor and retail as a team for logistical planning (5) • Establish trust among supply chain partners (21) • Increased flexibility in the manufacturer's operations (34) • Reduce demand variations (21)	• Forecasting ability of the retailers (31) • Insufficient visibility of the whole supply chain (41) • ERP-applications necessary for data sharing (31)

3.2.1 Inventory Policy Components

Various inventory policies exist that are distinct in terms of periodic versus continuous review and fixed versus variable lot size. Typically, continuous review systems require less safety stock, whereas periodic review systems facilitate coordination across multiple items. Weißhuhn and Hoberg (44) proposes a reorder corridor policy, where besides an order quantity a maximum order level is introduced. This corridor policy provides the opportunity to enhance transport utilization.

Safety Stock (ss)

According to Axsater (2), inventory control is among other things performed by the calculation of the safety stock, which maintains the availability of the goods. Safety stock refers to the additional quantity of a product or inventory that a company holds to mitigate the risk of stockouts or shortages caused by uncertainties in demand, supply chain delays, or other unexpected factors. In essence, safety stock acts as a buffer to ensure that there is sufficient inventory available to meet customer demand even when there are fluctuations or uncertainties in the supply and demand patterns. One of the rules for calculating safety stock which is frequently referred to as the standard formula, makes the common assumption that the demand per cycle is normally distributed (35). The formula for calculating the safety stock is as follows:

$$ss = z \times \sigma_d \times \sqrt{L} \tag{3.1}$$

where σ_d is the standard deviation of the demand during the lead time and z is the safety factor which depends on the target customer service level, such that

$$P[\text{demand during lead time} \leq z] = \text{target customer service level} \tag{3.2}$$

The target customer service level is often set by business policy, for example, 95%.

Reorder Point, r

The reorder point is another factor that needs to be determined for inventory control. A reorder point is the inventory level at which a new order should be placed to replenish stock before running out. It can be determined by the following formula (24):

$$r_i(t) = \sum_{t}^{t+L} F_i(t) + ss \tag{3.3}$$

where $r_i(t)$ stands for the dynamic reorder point of item i. The reorder point is the sum of the safety stock plus the expected demand during the lead time. The lead time is considered static. When the stock level drops below the value of the reorder point, a new order is placed that will be delivered after the given lead time.

Initial Order Quantity, q

Under normal circumstances, the initial order quantity for an item is based on the Economic Order Quantity (EOQ), assuming that the demand for the product is constant over time (1).

$$q = \sqrt{\frac{2Dc}{h}} \tag{3.4}$$

where D is the expected demand during the lead time and equals $\sum_t^{t+L} F_i(t)$. h and c represent the inventory holding costs per unit and the ordering cost of the buyer, respectively. Yao et al. (45) assumes that the buyer's order quantity (Q) and the supplier's order quantity (q) are chosen under VMI such that $k = Q/q$ equals a natural number. This means there are k replenishments of quantity q during each supplier's inventory cycle. This leads to the following buyer's order quantity:

$$q = \sqrt{\frac{2cD}{H+h}} \tag{3.5}$$

where H represents the inventory holding cost of the supplier. In his study, Van der Plas (41) proposes a method where the order quantity is based on the demand forecast of the next period.

Upper Stock Level, USL

Another important choice concerns the maximum stock level, which must be determined to prevent overstocking, avoid obsolescence, and control holding costs. Van der Plas (41) suggests that a range between the safety inventory level and the maximum stock level provides the opportunity to enhance transport utilization. The literature describes two situations: the target is expressed in pieces or days of stock (25). Van der Plas (41) proposes the following formula to calculate the maximum stock level in pieces:

$$USL_i = \sum_t^{t+L+x} F_i(t) \tag{3.6}$$

where USL_i stands for the maximum stock level of item i and x is a predetermined factor agreed between the vendor and retailer to determine the maximum stock level. In general, the literature assumes the upper limit of stock has already been decided based on negotiations between the vendor and the buyer, considering the demand for the item and the warehouse capacity of the buyer (14). Chakraborty et al. (6) imposes a penalty cost for overloading the buyer with inventory, which is charged for every unit that exceeds the upper limit. This technique is different from setting the maximum storage limit since it now allows the inventory level to be higher than the upper stock level.

3.2.2 Replenishment Strategies

The integration of VMI systems facilitates the vendor's capacity to refine the ordering profile of the retailer. When the inventory of a specific item falls below a predefined reorder point, an automated purchase order is promptly initiated. However, to derive an optimal order, a systematic method for order optimization must be considered. Van der Plas (41) elaborates on the VMI design implemented in the Dutch supply chain of Heineken. This study introduced three different replenishment methods for optimizing transport utilization, they are as follows:

- In the first method, the decision is not to fill up the initial partly loaded truck.
- The second method adds not more than one pallet extra of a product. The pallets are selected based on the demand forecast of the item in descending order.

- The third fill-up method selects the product with the highest demand and adds the maximum allowed pallets from an item. Van der Plas (41) states that this method is preferred less when the turnover of inventory is relatively slow since it can lead to overstocking.

Weißhuhn and Hoberg (44) suggests a comparable replenishment approach for situations where the order does not utilize the full capacity. In such instances, the reorder points for items are incrementally raised by one unit of inventory. This process ensures the generation of a new order that fully utilizes the available capacity.
There are two other inventory policies that can be adopted within the VMI, namely Just-in-time (JIT) and Economic Order Quantity (EOQ).

Just-In-Time. JIT is an inventory management approach aiming to minimize overstocking by receiving goods and producing items only when they are needed in the production process. JIT can be applied to handle independent demand, but it may require more sophisticated forecasting compared to situations with more predictable demand patterns. It is considered a pull approach, which means that the amount and time of material flow are determined by the rate and time of the actual stock consumption (27). According to Bon and Garai (4), implementing JIT involves the direct delivery of finished goods to buyers, leading to numerous small deliveries that do not align with our criteria for optimizing full truck loads. Additionally, they emphasize that JIT advocates for maintaining small inventories and minimizing buffer stock. The performance of JIT approach relies heavily on the higher echelons, and any delays or disruptions in production or supply chain can result in stock outs. Consequently, this strategy does not contribute to maintaining the cycle service level in the presence of stochastic demand.

Economic Order Quantity. EOQ is an inventory management approach that calculates the optimal order quantity of independent demand to minimize total inventory holding and ordering costs, balancing the probability of understocking and overstocking. It is generally considered a push approach and it can be applied to both centralized and decentralized inventory management. EOQ is more suitable in situations with stable demand, since it assumes a constant demand rate and known order and holding cost (19).

3.3 Solution Methods for Mathematical Models

Knowing that we will be introducing a VMI-collaboration, we can now explore the methods presented in the literature for solving the optimization problem. Broadly speaking, the literature suggests two options for tackling the issue: either solving the mathematical model to achieve optimality or employing meta-heuristics to find a near-optimal solution.
A mathematical programming approach provides advantages in optimization problems due to its ability to handle both continuous and discrete variables, allowing for more optimal solutions. It also allows the expression of many types of constraints. However, solving optimally risks high runtime, even in linear systems with few constraints but large solution spaces. The prediction of the runtime of a MILP model is

difficult and can vary wildly with different inputs (16). The greatest challenge of using a MIP model with a large scale is dealing with long runtime and sometimes even the inability to find a feasible solution (18).

Meta heuristics are widely applied to address NP-hard problems, offering approaches to tackle computational challenges. According to Glover and Kochenberger (12), meta-heuristics are a type of algorithm that is used to find approximate solutions to solve mathematical models. They are often used when the exact solution is too computationally expensive to find. Meta heuristics function by iterative improving on a solution until it reaches a point where the solution is considered good enough as a final solution. Balancing exploration and exploitation is crucial in heuristics, as it enables the algorithm to effectively search for promising solutions while also refining its focus on areas likely to yield optimal results. Exploration diversifies the search space, uncovering new potential solutions, while exploitation intensifies efforts in promising regions, refining and maximizing the chances of finding the global optimum in optimization problems (32). The ability of meta-heuristics to provide near-optimal solutions, within a reasonable time frame, makes them suitable for a wide range of applications. However, the reliance on heuristics may result in solutions that are not guaranteed to be globally optimal.

In their study, Borade and Sweeney (5) examine a multi-retailer, single-vendor, single-item VMI model that optimizes the inventory levels of the retailer, vehicle routes, and vehicle utilization to maximize profits for both the retailer and the vendor. The objective is to determine, for each discrete period, the quantity to be shipped to each retailer and the vehicle route. The first part of the problem is formulated as a MILP model and solved to optimally, while a GA meta heuristic is employed for vehicle routing. This study highlights the suitability of the GA-approach in addressing maximization problems. Kaasgari et al. (20) formulate the VMI model as a nonlinear program, where they consider a two-level multi-retailer, single vendor, single-item supply chain with perishable products. An GA and Particle Swarm Optimization (PSO) algorithm were developed for solving it appropriately. It was presented that the PSO algorithm has better performance for solving the problem in this paper than the GA. Najafnejhad et al. (28) propose a study where a multi-retailer, single-vendor, single-item VMI is modeled through a nonlinear programming model, and is solved by the meta-heuristic Imperialist Competitive Algorithm (ICA). They employed this new algorithm since it shows an accurate and fast solution compared with PSO and GA.

In the subsequent two sections, we provide detailed elaboration on two VMI models outlined in the literature and discuss their respective solution methods. These models offer intriguing features that complement our research.

3.3.1 Single-retailer, Single-vendor, Multi-item Model

Pasandideh et al. (30) presents a nonlinear programming model, as shown in Table 3.2, designed specifically for a system that partly resembles our research focus: a single-vendor, single-retailer, multi-item scenario. The primary goal of this model is to minimize overall distribution and inventory costs, with the research taking into account the following assumptions:

1. Single-vendor, single-retailer supply chain
2. There are n products

3. The planning horizon is infinite
4. For each product shortage is allowed and back-ordered ($\phi \neq 0$ and $\pi = 0$)
5. The order deliveries are assumed instantaneous, so the lead time is zero
6. The prices for all products are fixed in the planning period
7. The production rate for all products is infinite (EOQ model)
8. The customer's demand rate for all products is deterministic
9. The vendor's storage capacity for all products is limited
10. The total number of orders for all products is limited

This model diverges from our research in several aspects: it assumes zero lead time, lacks consideration of transportation modes, and assumes a deterministic demand. Because of its nonlinear nature, the authors propose solving the model using metaheuristics, particularly the GA approach (29; 9; 33; 30). Cárdenas-Barrón et al. (9) stated in their study that in some cases, the GA can be computationally expensive, and therefore proposed a new algorithm, called the golden algorithm. This algorithm does not require tedious computational effort and obtains the solution in a very short time.

3.3.2 Stochastic Demand Model

In many real-world situations, the values of some parameters might be uncertain, whereas, in traditional optimization models, the objective is to find an optimal solution assuming the exact values of all input parameters. Verderame et al. (42) presents an overview of methods that have been applied in the literature to address uncertainty in input parameters. They identify robust programming, chance constraint programming, and fuzzy programming as promising approaches.
Robust programming is an optimization approach that seeks to find a solution that performs well under the worst-case scenario within the predefined value range of the parameter. The goal is to ensure that the solution remains acceptable across all possible values. A benefit of robust programming is that it does not require any distribution for the uncertain parameter. A drawback, however, is that it uses the worst-case scenario, which means that the output of the model can deviate significantly from the optimal solution (38).
Chance Constraint Programming (CCP) provides a framework for handling uncertainties by incorporating probabilistic constraints into the optimization model (23). An assumption made in the CCP model is that the distribution of the uncertain parameter demand is known. Zhang et al. (46) shows how the original soft constraint 3.7 is then formulated as a chance constraint 3.8 by including the distribution function with mean μ and standard deviation σ and the predefined probability K_α. This method is particularly applicable in scenarios like the cycle service level, where GBD aims to meet all demand in at least 95% of the cases.

$$\sum_{j=1}^{n} a_j x_j \geq b \tag{3.7}$$

Table 3.2: A nonlinear programming model for a system involving a single vendor, single retailer, and multiple items, taking deterministic demand into account, was initially introduced by Pasandideh et al. (29) and subsequently applied in the studies of both Cárdenas-Barrón et al. (9) and Sadeghi et al. (33)

Parameters
A_j^S The vendor's fixed ordering costs per order of the j^{th} product A_j^R The retailer's fixed ordering cost per order of the j^{th} product D_j The buyer's demand rate of product j in a period P_j The production rate of product j in each period π The fixed backorder cost per unit (not depending on the time) ϕ The fixed backorder cost per unit per time unit h_{jR} The holding cost of product j per unit held in the retailer's store in a period ($h_{bj} = iC_j$) f_j Space occupied by each unit of product j F The vendor's available storage capacity for all products ρ_J Level of inventory depletion relative to the quantity ordered ($\rho_j = 1 - \frac{D_j}{Q_j}$) M The total number of orders for all products in each cycle n The number of products
Decision Variables
Q_j The order quantity of product j in a cycle b_j The maximum backorder level of product j in a cycle
Objective Function
$\min TC = \sum_{j=1}^{n}(\frac{D_j}{Q_j}(A_j^S + A_j^R) + \frac{h_{Bj}}{2Q_j}(Q_j - b_j)^2 + \frac{\phi b_j^2}{2Q_j} + \frac{\pi b_j D_j}{Q_j}$
Constraints
$\sum_{j=1}^{n} \rho_j f_j Q_j \leq F$ $\sum_{j=1}^{n} \frac{D_j}{Q_j} \leq M$ $Q_j, b_j \geq 0; j = 1, \ldots, n$

$$\sum_{j=1}^{n} a_j x_j \geq \mu + K_\alpha \sigma \tag{3.8}$$

In many cases, however, it may be difficult to determine the probability distribution of the underlying random parameter, in most cases the demand, due to insufficient data. Fuzzy programming is another method alternative to using probability functions. In fuzzy programming, constraints and objectives can be expressed in fuzzy terms allowing for partial membership within fuzzy sets. Instead of using Boolean variables, the binary variables are turned into continuous variables (3).

Choudhary (8) present a single-retailer, single-vendor, single-item system where stochastic demand is incorporated using a chance constraint. The model is presented in Table 3.3 and makes the following assumptions:

1. Two-echelon serial supply chain considering single-retailer, single-vendor
2. The planning horizon is fixed. Each discrete time period $t = 1, \ldots, T$ is of same duration
3. The customer's demand rate for the product is stochastic, incorporating the static-dynamic uncertainty strategy. The demand in each period is normally distributed with a known probability density function.
4. Different periods have mutually independent demands, which vary over time
5. For each product shortage is allowed and backordered. The maximum amount of backorders is restricted by a cycle service-level requirement.
6. The production rate for all products is infinite (EOQ model)
7. Lead time is not incorporated
8. The retailer's storage capacity is unlimited

This MILP model is optimally solved within a reasonable time frame. To streamline the model and prevent lengthy computation times, the authors limit it to twelve time periods, each corresponding to one month. They defend this simplification by pointing out that the orders are typically received on a weekly or monthly basis, rather than daily.

Table 3.3: A Mixed Integer Linear Program (MILP) model of a single-vendor, single-buyer, single-item system considering stochastic demand presented by Choudhary (8)

Parameters
d_t the demand in period t (a normally distributed random variable) o_t fixed cost incurred by the retailer per order issued in period t h_t^r Inventory carrying cost per item per period at the retailer in period t α_c Target cycle service-level requirement at the retailer S_t Fixed cost incurred by the supplier per setup in period t h_t^s Inventory carrying cost per item per period at the supplier in period t β Supplier's efficiency factor in issuing an order on behalf of the retailer under VMI $(1-\beta)o_t$ Supplier's cost of issuing an order on behalf of the retailer in period t under VMI M A large number I_t^r Inventory level of the retailer at the end of period t I_t^s Inventory level of the supplier at the end of period t I_0^r The stock on hand of the retailer at the beginning of period 1
Decision Variables
X_{tr} Replenishment quantity at the retailer from the supplier in period t X_{ts} Quantity that the supplier produces at the end-of-period t z_t^r Binary variable indicating whether the replenishment order is placed and delivered or not in period t z_t^s Binary variable indicating whether the supplier produces or not in period t
Objective Function
$\min TC = \sum_{t=1}^{T}(S_t Z_t^s + (1-\beta)o_t z_t^r + h_t^s I_t^s) + \sum_{t=1}^{T} h_t^r E[I_t^r]$
Constraints
$I_{t-1}^s + x_t^s - x_t^r = I_t^s$ $x_t^s \leq (\sum_{k=t}^{T} d_k) z_t^s$ $E[I_{t-1}^r] + x_t^r - d_t = E[I_t^r]$ $P(E[I_t^r] \geq 0) \geq \alpha_c$ $x_t^r \leq M z_t^r$ $x_t^s, x_t^r, I_t^s \geq 0$ $z_t^s, z_t^r \epsilon \{0,1\}$

3.4 Summary

Overall, our study presents optimization models focusing specifically on order quantity and frequency. Our main aim is to minimize overall warehouse and distribution expenses by adjusting the order quantity and frequency for each partner, thereby improving transport utilization. Extensive literature illustrates successful VMI implementations, making the adoption of a partial VMI approach in the context of GBD's business deemed adequate. This research explores a VMI collaboration within a single vendor, single supplier, multi-item supply chain, considering stochastic demand and a constant lead time. Table 3.4 summarizes noteworthy VMI models found in the literature. Our study addresses the gap in the literature by considering a single retailer, single vendor, multi-item supply chain with stochastic demand, constant lead time, and multiple transportation modes. While various characteristics have been individually introduced in prior literature, they have not been integrated into a single model. Given the linear nature of our model, we anticipate it can be solved within a reasonable time frame. Therefore, we plan to address the VMI collaboration by optimally solving the MILP. In Chapter 4, we propose and implement this model.

Table 3.4: Classification of VMI models based on supply chain system, objective function, decision variables, demand type, and solution approach. While each model shares similarities with our research, none encompasses all aspects. Consequently, our study integrates components from various sources. These papers are interesting as they each contribute aspects implemented in our research.

Literature	Supply Chain System	Objective Function	Decision Variables	Type of Demand	Solution Method
Borade and Sweeney (5)	MSS	MAX	OA, I, R	S	MILP, GA
Choudhary (8)	SSS	MIN	OA, PQ	S	MILP
Kaasgari et al. (20)	MSS	MIN	OA	S	GA, PSO
Najafnejhad et al. (28)	MSS	MIN	OA, I, RF	D	ICA
Pasandideh et al. (30)	SSM	MIN	OA, BO	D	GA
Cárdenas-Barrón et al. (9)	SSM	MIN	OA, BO	D	Golden Algorithm
Sadeghi et al. (33)	SSM	MIN	OA, BO	D	GA
Pasandideh et al. (29)	SSM	MIN	OA,BO	D	GA
This research	**SSM**	**MIN**	**OA, T**	**S**	**MILP**

Supply Chain:	**SSS** (Single-retailer, single-vendor, single item), **MSS** (multiple-retailer, single-vendor, single-item), **SSM** (Single-retailer, single-vendor, multi-item),
Objective:	**MIN** (Minimize total inventory and distribution costs), **MAX** (Maximise retailer and supplier profit),
Decision Variables:	**OA** (Order Quantity), **BO** (Max. Backorder level), **PQ** (Production Quantity), **RF** (Replenishment Frequency), **T** (Transport Type), **R** (Routing), **I** (Inventory Level)
Demand Type:	**S** (Stochastic), **D** (Deterministic)

Chapter 4

Model Design

The goal is to minimize the distribution and inventory expenses for each individual partner, all while respecting capacity, inventory, and demand limitations. This chapter formulates the model and we answer the third research question "How can we apply the modeling techniques outlined in the previous chapter to the specific GBD case and modify them to enhance its operational performance?". We assume that each partner agrees to share complete information regarding performance, including sales forecasts and inventory levels. In this section, we will elaborate on the model formulation of the VMI, discuss how we handle stochastic demand, and ultimately present the complete model. We will test the model using input values specific to one particular partner, hereafter referred to as Partner X.

4.1 Model Formulation

4.1.1 Sets & Indices

In this study, we examine a supply chain characterized by a single-vendor, single retailer, and multiple items. As detailed in Section 2.1.4, each partner possesses a distinctive portfolio of SKUs introduced to their market. The total number of SKUs is denoted by J. The schedule is established at the beginning and holds for one year. Adopting a finite horizon approach is well-suited for this problem, allowing us to examine each year separately, especially since GBD closes all orders at the end of the year. The planning horizon spans 365 days and is denoted by T.

- T = number of simulation days
- J = number of items
- Item $j \in \{1, 2, 3, \ldots, J\}$ = set of all items
- Day $t \in \{0, 1, 2, \ldots, T\}$ = set of all days

4.1.2 Parameters

In Section 2.3.1, we clarify that every partner associated with GBD submits a monthly forecast. It is crucial to acknowledge the uncertainty inherent in actual sales. To address this uncertainty, three variables are introduced. The first variable captures the forecast provided by the partner for item j on day t and is denoted by F_{jt}. FE_{jt} is a stochastic variable representing the forecast error. The derivation of the distribution for this error variable is explained in detail in Section 4.2. The actual demand rate for each item on each day is then determined by multiplying the forecast with the corresponding forecast error.

- F_{jt} = forecast of item j for day t
- FE_{jt} = forecast error for item j at day t, normally distributed
- d_{jt} = actual demand of item j on day t, equals $\frac{F_{jt}}{1+FE_{jt}}$

To address the inventory constraint, we incorporate certain parameters. The initial stock of item j at the start of the planning period must be sufficient to meet the anticipated demand during the lead time. Failure to meet this requirement would result in an immediate backorder. Additionally, GBD has reached an agreement with the partner regarding the maximum allowable inventory level for each product, which enables GBD to change the order quantity to enhance transport utilization. Moreover, GBD aims to deliver items to Partner X within an 8-week lead time. This lead time encompasses production time, warehouse picking at GBD, and transportation to the customer. Historical data provides a strong foundation for assuming a fixed lead time of 8 weeks for Partner X. The data indicates that in approximately 90% of cases, the lead time aligns with the 8-week estimate.

- I_{j0} = inventory level of item j at the beginning of day 1
- I_j^{MAX} = maximum inventory level for product j
- L = lead time of every item in days

To optimize the model, we must take into account the capacity of various transportation modes. Partner X utilizes both 20-foot and 40-foot containers for sea shipments, depending on the order quantity. As detailed in Section 2.1.3, items may also be double stackable. In such cases, the space occupied by the item is 1; otherwise, it is 2. GBD strives to ship containers with a minimum utilization of 90%. We understand that lowering costs will likely automatically lead to increased transport utilization, but for GBD, it is crucial that the 90% is met to prioritize cost efficiency and the C02 reduction. To achieve this, we introduce two variables specifying the minimum number of pallets required for a container load.

- K_{20}^{MAX} = total capacity of a single 20 feet container
- K_{40}^{MAX} = total capacity of a single 40 feet container
- k_j = space occupied by one unit of item j
- K_{20}^{MIN} = minimum number of pallets for a single 20 feet container load
- K_{40}^{MIN} = minimum amount of pallets for a single 40 feet container load

In Section 2.1.2, we elaborate on how warehouse and distribution costs are assessed. Firstly, there is a warehouse tariff applied per pallet, determined annually by Finance based on the preceding year's performance. For the year 2024, the warehouse tariff for PAX stands at 13.36 per pallet. Additionally, we take into account order placement costs, which are directly invoiced to GBD. Moreover, Partner X has predefined transportation costs for 20-foot and 40-foot containers, as outlined in Section 2.4.

- T_{20} = fixed transportation cost of a 20 feet container
- T_{40} = fixed transportation cost of a 40 feet container
- O = fixed order cost
- V = warehouse tariff charged per pallet shipped
- h = holding cost per item per day

4.1.3 Auxiliary Variables

Auxiliary variables refer to extra variables incorporated into a model to aid in the analysis or estimation of other variables. While these variables may not be the main focus, they serve a supportive role in the modeling process. To incorporate lead time into the model, we introduce a variable that tracks the number of items in transit each day. Furthermore, a dynamic variable is introduced to monitor the daily inventory levels of each item. The parameters for the forecast error are also modeled as auxiliary variables.

- y_{jt} = number of pallets of item j in transit at day t
- I_{jt} = inventory level of item j at the end of day t
- FE_{jt} = forecast error for item j at day t, normally distributed with mean μ and standard deviation σ

4.1.4 Decision Variables

The objective of this model is to establish the daily order quantity for each product. GBD strives to provide only full pallet equivalents; thus, treating a single item j as equivalent to one pallet of item j. In our model, we assume that ordering pallet layers, individual boxes, or pieces separately is not feasible, although it is currently possible. We assess the need to place an order daily. Furthermore, when choosing to proceed with an order, it is necessary to determine the number of transportation modes needed. Concerning Partner X, the option is available to select either a 20-foot or a 40-foot container. To accomplish this, we introduce four decision variables.

- Q_{jt} = order quantity of product j on day t
- z_t = binary variable indicating whether a replenishment order is placed on the day t
- N_t^{20} = number of 20 feet containers needed for the order on day t (integer)
- N_t^{40} = number of 40 feet containers needed for the order on the day t (integer)

4.2 Modeling Demand Uncertainty

A crucial element in the optimization process involves accounting for the uncertainty in the demand. To properly implement this in the model, it is necessary to mathematically define the demand and its associated uncertainty. GBD receives a forecast on monthly basis for each SKU of Partner X. In our model, we emphasize capturing the uncertainty between these forecasts and the actual sales. This section aims to identify a suitable probability distribution that aligns with the data and explains how the stochastic demand is incorporated into the model.

4.2.1 Demand Distribution

Every month, the partner provides a forecast for the demand of the upcoming month on SKU level. Given the dynamic nature of the demand, which is influenced significantly by market conditions, finding a probability distribution that accommodates all demands throughout the year is challenging. In our model, our focus lies in understanding the actual demand patterns relative to the respective monthly forecasts. GBD has archived the 2023 forecasts of Partner X, enabling us to assess forecast errors. If we successfully model a distribution for these forecast errors, it can serve as an input for the demand variable. This distribution essentially characterizes the forecasting accuracy of Partner X.
For the year 2023, Partner X provided forecasts for 20 SKUs, yielding a total of 240 forecast errors. We operate under the assumption that the forecasting proficiency of the partner remains consistent with that of 2023, and the market conditions exhibit comparable behavior. Therefore, we can use this data for our model. Shcherbakov et al. (37) examines various forecast error calculation methods and advocates for the adoption of the Mean Absolute Percentage Error (MAPE) in some situations. This recommendation is based on the method's attributes: it is a straightforward and easily interpretable measure, it is scale-independent, and it accounts for the absolute percentage difference for each observation. A notable shortcoming of this method is the appearance of division by zero when the actual sales equal zero. In our specific scenario, it becomes evident that when actual sales register as zero, the forecast also equals zero. Therefore, a potential solution is to manually adjust the forecast error for these data points to zero. The MAPE formula is as follows:

$$\text{Mean Absolute Percentage Error} = \frac{\text{Forecast} - \text{Actual Sales}}{\text{Actual Sales}} \tag{4.1}$$

We test whether these data points follow any distribution using hypothesis testing. Figure 4.1 shows a histogram of the forecast error for Partner X. Given the observable similarities between the plot and the normal distribution distribution, we start with assessing this distribution. Our null hypothesis is that the data fits a normal distribution, and we evaluate this using the Chi-Square Test. At a 95% significance level, we cannot reject the null hypothesis. Consequently, we assume a normal distribution with mean (μ) 0,094 and standard deviation (σ) 0,297. The forecast is on a monthly level, while our model is daily. Following the discussion with the partner on how demand is spread across the month, we can assume that sales are uniformly distributed over the entire month.

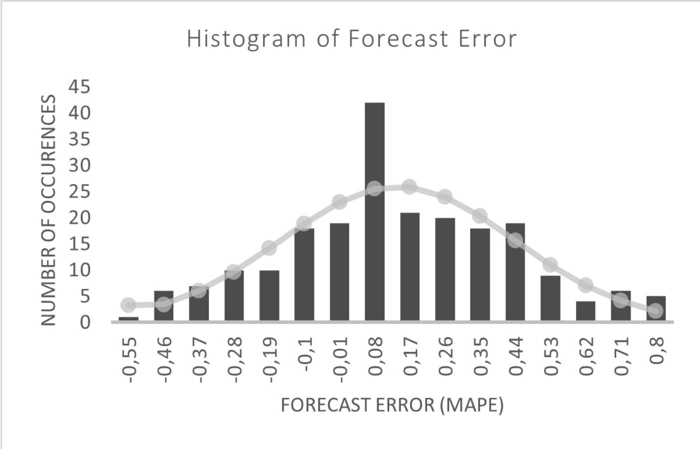


Figure 4.1: Histogram of the forecast error of 2023 of partner X.

4.2.2 Chance Constraint

Tarim and Kingsman (39) evaluate the static uncertainty model, which refers to a modeling approach in which uncertainty is considered constant over time. In the context of uncertainty modeling, a static model may be appropriate when the factors influencing the system are deemed to be stable or when the time dimension is not a significant consideration. In our model, we can assume that the forecasting capability of the partner remains constant over time, and the input parameters of the distribution remain consistent throughout the planning horizon. The model is designed for a relatively brief period, during which the partner has had limited opportunities to enhance their forecasting ability. We retain the following assumptions, as introduced by Tarim and Kingsman (39):

- At the beginning of the planning period, the exact demand is not known with certainty. The actual demand is uncertain and can be calculated by dividing the forecast of item j on day t F_{jt} by the stochastic forecast error parameter FE_t plus one, resulting in this formula: $\frac{F_{jt}}{1+FE_{jt}}$. The actual sales are represented by the stochastic parameter d_{jt}. In our research, the forecast error FE_t follows a normal distribution with a mean of 0,094 and a standard deviation of 0,297 as explained in previous section.

- In the event of a stockout, all demand is backordered and fulfilled as soon as the stock becomes available. A target service level of α has been established between GBD and Partner X. This signifies that the probability of a product's inventory level being non-negative is set to α. According to Tarim and Kingsman (39), we can assume that α incorporates the cost of backorders, thus allowing us to disregard shortage costs in the model.

As detailed in Section 3.3.2, employing the Chance Constraint Programming (CCP) is an effective approach for incorporating uncertainty into the model, especially when the probability distribution of the uncertain demand is known. This method is well-suited for scenarios involving cycle service levels. Our model satisfies both of these criteria. Consequently, we introduce a constraint that ensures the probability of experiencing stockouts does not exceed $1 - \alpha$. The general form of this equation is as follows:

$$P(I_{jt} > 0) \geq \alpha \qquad \forall j, t \tag{4.2}$$

The inventory level for day t is determined by adding the inventory from the previous day to the number of items received on that day and subtracting the demand for that day. In essence, the inventory on day t is the sum of the initial inventory on day 0 and the difference between the order quantity and the cumulative sales up to day t. When applied to the context of GBD, this formulation leads to the following constraint.

$$P(I_{j0} + \sum_{i=1}^{t-L} Q_{jt} > \sum_{i=1}^{t} D_{jt}) \geq \alpha \qquad \forall j, t \tag{4.3}$$

As we know that the forecast error is normally distributed, we can transform this chance constraint into its deterministic counterpart based on the probability density function in a similar fashion to Tarim and Kingsman (39). If you have a sum of normally distributed random variables, the sum follows a normal distribution as well. The mean of the sum is the sum of the means, and the variance of the sum is the sum of the variances, assuming independent demand. Therefore, we can replace constraint 4.3 with constraint 4.4:

$$\frac{I_{j,0} + \sum_{i=1}^{t-L} Q_{jt} - \sum_{i=1}^{t} \mu_{D_{jt}}}{\sqrt{\sum_{i=1}^{t} \sigma^2_{D_{jt}}}} \geq \phi^{-1}(1-\alpha) \qquad \forall j, t \tag{4.4}$$

, where

$$\sqrt{\sum_{i=1}^{t} \sigma^2_{D_{jt}}} = \sqrt{\sum_{i=1}^{t} F^2_{jt} * \sigma^2_{FE_{j,t}}} \tag{4.5}$$

$$\sum_{i=1}^{t} \mu_{D_{jt}} = \sum_{i=1}^{t} F_{j,t} * \mu_{FE_{j,t}} \tag{4.6}$$

4.3 Full Model

4.3.1 Objective Function

The primary aim of this research is to decrease warehouse and distribution costs. Consequently, the objective function in the model is a minimization function encompassing overall costs, which consist of transportation, order, variable warehouse, and inventory holding costs. The combined expenses for warehouse and distribution occur at two distinct locations, either under the responsibility of the partner or the GBD team. Inventory costs are managed by the partner, while the responsibility for transportation costs varies based on the agreed incoterm. However, distribution and warehouse costs fall under the purview of the GBD team.

- Transportation costs: $\sum_{t=1}^{T} z_t(N_t^{20}T_{20} + N_t^{40}T_{40})$
- Order costs: $\sum_{t=1}^{T} z_t O$
- Inbound warehouse costs: $\sum_{t=1}^{T} \sum_{j=1}^{J} z_t Q_{jt} V$

- Inventory costs: $\sum_{t=1}^{T}\sum_{j=1}^{J} hE[I_{jt}]$

The transportation costs are calculated by multiplying the quantity of each container type ordered by the predetermined tariff. Order costs comprise administration and documentation charges assessed per order. Inbound warehouse costs are determined by a flat fee per pallet, computed by multiplying the total number of ordered pallets with the specified fee. Finally, inventory costs are derived by multiplying the anticipated inventory level by the daily holding cost per item. Combining these expressions yields the following objective function:

$$\min TC = \sum_{t=1}^{T}(z_t(N_t^{20}T_{20} + N_t^{40}T_{40}) + z_tO + \sum_{j=1}^{J}(z_tQ_{jt}V + hE[I_{jt}])) \tag{4.7}$$

4.3.2 Constraints

Capacity Constraints
Constraint A.2 guarantees that an order must not surpass the maximum load of a container. Each container type is characterized by its specific maximum capacity, denoted as K_{20}^{MAX} and K_{40}^{MAX}. The aggregate order quantity for a particular order must align with the prescribed number of containers ordered.

$$\sum_{j=1}^{J} Q_{jt}k_j \leq N_t^{20}K_{20}^{\text{MAX}} + N_t^{40}K_{40}^{\text{MAX}} \qquad \forall t \tag{4.8}$$

Constraint A.3 guarantees that the containers meet a minimum load requirement, identified as K_{20}^{MIN} and K_{40}^{MIN}. GBD strives to fulfill orders with a minimum container utilization of 90%. The values of K_{20}^{MIN} and K_{40}^{MIN} are determined in accordance with this 90% utilization criterion.

$$\sum_{j=1}^{J} Q_{jt}k_j \geq N_t^{20}K_{20}^{\text{MIN}} + N_t^{40}K_{40}^{\text{MIN}} \qquad \forall t \tag{4.9}$$

Inventory Constraints
The inventory level on day t should be equivalent to the inventory level on the previous day, increased by the quantity of items received on that day and reduced by the demand on that day. Given the lead time, items ordered today will be received only L days later. Additionally, the demand at day t is treated as a stochastic variable. Constraint A.4 guarantees this principle.

$$I_{jt} = I_{jt-1} + Q_{j,t-L} - D_{jt} \qquad \forall j, t \tag{4.10}$$

GBD establishes an agreement with the customer specifying the maximum storage capacity for each product at the customer's warehouse, represented by I_j^{MAX}. The inventory level must consistently remain below the predetermined maximum stock level for each item, as ensured by constraint A.5.

$$I_{jt} \leq I_j^{\text{MAX}} \qquad \forall j, t \tag{4.11}$$

In Section 4.2, we already introduced a constraint that handles the uncertainty in the demand.

$$\frac{I_{j,0} + \sum_{i=1}^{t-L} Q_{jt} - \sum_{i=1}^{t} \mu_{D_{jt}}}{\sqrt{\sum_{i=1}^{t} \sigma_{D_{jt}}^2}} \geq \phi^{-1}(1-\alpha) \qquad \forall j, t \tag{4.12}$$

When determining the new order quantity, it is essential to consider the quantity of goods already in transit. The goods in transit on day t correspond to the item orders placed from L days ago up to day t. The order quantity should exceed the anticipated demand during the lead time, subtracting the current inventory level and the quantity of goods already in transit.

$$y_{jt} = \sum_{i=t-L}^{t} Q_{jt} \qquad \forall j, t \tag{4.13}$$

Additionally, it's necessary to incorporate a constraint that guarantees the binary variable $z[t]$ takes the value of one when an order is placed and zero otherwise. To achieve this, we introduce a variable M, representing a sufficiently large number.

$$\sum_{j=1}^{J} Q_{jt} \leq M * z_t \qquad \forall t \tag{4.14}$$

$$Q_{jt}, I_{jt}, y_{jt} \geq 0 \qquad \forall j, t \tag{4.15}$$

$$N_t^{20}, N_t^{40} \geq 0 \qquad \forall t \tag{4.16}$$

$$z_t \in \{0, 1\} \qquad \forall t \tag{4.17}$$

4.4 Summary

This chapter presents the formulation of the VMI model. We introduce a single-retailer, single-vendor, multi-item VMI model considering stochastic demand and static lead time. Our objective is to optimize overall warehouse and distribution costs by determining order volume and transportation mode at each time step. Stochastic demand is captured through a chance constraint ensuring that orders can be directly delivered from stock 95% of the time (referred to as cycle service level), with forecast error assumed to follow a normal distribution with mean μ and standard deviation σ. In Chapter 5, we delve into the experimental setup, model validation, and results.

Chapter 5

Validation and Performance

In the previous chapter, we formulated our VMI model. This chapter focuses on validating and evaluating the model's performance to answer the fourth research question "How does the new proposed solution perform, reviewed on total distribution costs and transport utilization, compared to the current approach of GBD?". Section 5.1 provides details on the experimental setup, including the performance metrics employed. Section 5.2 assesses the model's output to determine its alignment with real-world, while Section 5.3 presents the findings and outcomes of the conducted experiments.

5.1 Experimental Setup

Throughout this report, we use the following definitions:

- *Experiment*: A single set of input configurations.
- *Replication*: Repeating the experiment under the same input conditions, but with different random variables. The average of these replications represents the expected performance of the experiment.
- *Scenario*: Each outcome of a replication is referred to as a scenario. The total number of scenarios is determined by multiplying the number of experiments by the number of replications.

As explained in Section 3.4, we decided to solve the model optimally due to the linearity of the mathematical model. To find the optimal solution for this mathematical model, it must be translated into software equipped with an integrated solver capable of managing large-scale MILP models. Two primary options presented in the literature are Gurobi and CPLEX, which both are compatible with a variety of programming languages. Given our prior experience with employing Gurobi within Python, we decide to use this to solve our mathematical model. We use Gurobi to solve the model optimally on an HP ZBook Studio G5 with specifications Intel(R) Core(TM) i7-8750H CPU @ 2.20GHz 2.21 GHz.

5.1.1 Performance Metrics

We conduct various experiments to assess performance under different conditions. Our focus lies on four performance metrics:

- **Objective Value:** The optimal value for warehouse and distribution costs under the constraints and decision values defined in the model.

- **Transport Utilization:** Measures how effectively transportation resources are employed to transport goods. This metric is determined by dividing the total space occupied by an order by the capacity of the truck or container used for transportation.

$$\begin{aligned}\text{Transport Utilization} &= \frac{\text{Total Space Occupied}}{\text{Total Capacity}} \\ &= \frac{\sum_{j=1}^{J} Q_{jt} k_j}{N_t^{20} K_{20}^{\text{MAX}} + N_t^{40} K_{40}^{\text{MAX}}} \times 100\% \quad \forall t\end{aligned}$$

- **Run Time:** Refers to the time needed for the solver to find a solution, limited to 10 minutes per model.

- **Optimality Gap:** Indicates the solver's proximity to an optimal solution, offering valuable insights into model performance when computational times become excessive.

Objective value and transport utilization are crucial as they reflect solution quality; in our context, lower objective values indicate higher quality solutions, while also greater transport utilization signifies better solutions. The runtime is influenced by various external factors, meaning that running identical models with the same input values and a deterministic solving approach can yield different computational times. This variability complicates the comparison of this metric using actual runtime. To address this challenge, Gurobi introduces a measure called "work," which is deterministic and produces consistent results when running the same model multiple times. Therefore, we utilize "work" as an indicator of the model's runtime. Figure 5.1 shows how the computational time differs when solving the identical model, with a mean of 123.33 seconds and a standard deviation of 20.73. The number of work equals 228,839 and remains constant for each replication. The peak in runtime observed at replication 26 could potentially be attributed to variances in concurrent background processes or differences in memory allocation during that specific run.

5.1.2 Replications where no solution is found

In certain scenarios, our model encounters instances where it cannot find a feasible solution within the allocated time frame of ten minutes. In such cases, we categorize these runs as 'Time Limit Exceeded'. This categorization enables us to differentiate between situations where the model is genuinely infeasible and cases where it simply exceeds the specified work time. Particularly in models with more frequent checkups, the occurrence of 'Time Limit Exceeded' instances tends to rise. Consequently, we introduce a new metric to quantify the number of replications unable to produce a feasible solution. It is imperative to take this metric into account when analyzing the results of the experiments.

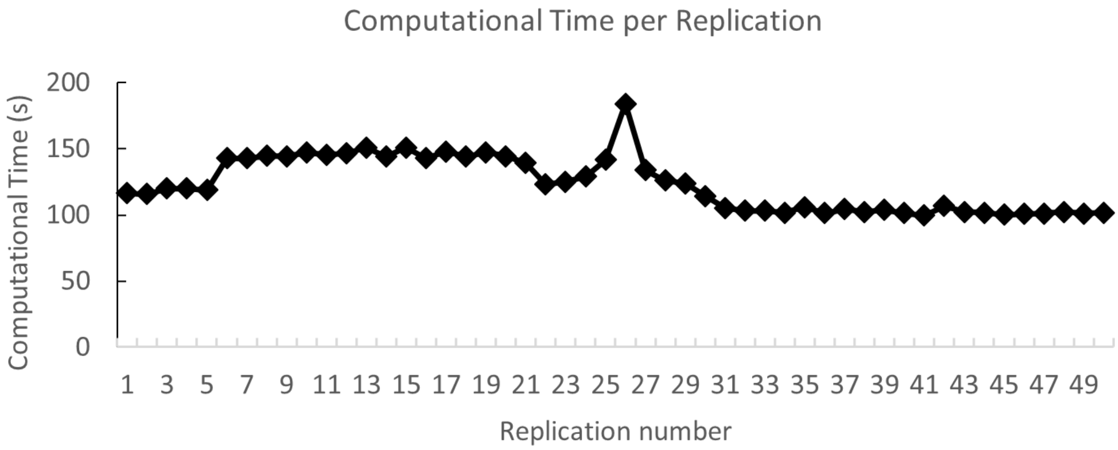


Figure 5.1: Computational time when running the identical model 50 times. The runtime has a mean of 123.33 (seconds) and a standard deviation of 20.73.

5.1.3 Experiments

To avoid immediate backorders, we established the initial stock level at Partner X's warehouse to ensure the inventory can meet demand during the lead time. Since orders are only placed on day one and then take the lead time to arrive, it is crucial to maintain adequate stock levels. These stock level ranges are determined through initial experiments; straying outside them would result in Gurobi flagging the model as infeasible as it is a requirement that at least 95% of orders must be fulfilled directly from the stock. Additionally, the transportation costs for both 20-foot and 40-foot containers are derived from 2023 data supplied by the logistic service provider. These parameters remain static and unchanged throughout the experiments.
The variables under experimentation will be the number of time steps (T), the maximum storage capacity of each item in the warehouse of the partner(I_j^{MAX}), and the forecast error denoted as FE_{jt}.

Time Steps. In Section 4.1, our initial design of the VMI model focused on daily inventory level checks. However, due to the relatively low daily demand from Partner X, we intend to conduct experiments to determine the optimal time intervals for balancing performance metrics. We plan to assess inventory levels on a daily, weekly, bimonthly, and monthly basis. Henceforth, we will denote this as checkup. The hypothesis is that transitioning to less frequent checks will better suit the relatively low daily demand and align with the lead time associated with GBD. Given this lead time, daily fluctuations in inventory levels are unlikely to significantly impact our ordering strategy. By adjusting the evaluation frequency, we anticipate maintaining sufficient oversight while accommodating longer lead times. Furthermore, reducing the evaluation frequency from daily to less frequent intervals will minimize administrative burdens.

Maximum Storage Capacity. In alignment with our Partner X, we adhere to a maximum storage capacity per item. Nonetheless, it is valuable to test the model's performance under varying capacities per item. Hence, we introduce two scenarios: medium, and high capacity. The medium capacity aligns with discussions with Partner X, while the high scenario represents a capacity 20% more. Using the results, we can provide recommendations to the partner to possibly increase their warehouse capacity.

1. *Medium Storage Capacity:* Corresponding to the storage capacity standards of Partner X.

2. *High Storage Capacity:* Providing a 20% increase in capacity for each item.

Forecast Error. Furthermore, we explore the impact of forecast error. Forecast error captures the variability in actual demand. To provide insight into the importance of an accurate forecast, we conduct experiments with the following forecast accuracy's:

- *Medium Forecast Error:* This error follows a normal distribution with a mean (μ) of 0.094 and a standard deviation (σ) of 0.297.

- *Low Forecast Error:* This error is normally distributed with a mean (μ) of 0.094 and a standard deviation (σ) of 0.149.

- *Perfect Forecast:* This represents a completely accurate forecast, where the forecasted value matches the actual demand precisely.

To determine the expected values while preventing excessive runtimes, each simulation model is replicated 50 times. Each replication is capped at a time limit of ten minutes. Table 5.1 summarizes the experimental settings.

Lead Time. Currently, GBD operates on a make-to-order paradigm where lead times typically span around two months, varying based on the partner involved. Many partners have expressed interest in shortening these lead times. Hence, we are conducting experiments with two lead time settings: two months and one month.

5.2 Output Validation

It is important to validate the output of the simulation to ensure that the model accurately represents the real-world system, so it can be used as a predictive tool for in our case the ordering schedule. Our validation process involves closely examining the detailed order schedule and metrics of specific models. To simplify illustration, we concentrate on validating a monthly-based model. Collaborating with a supply chain specialist from the GBD team, we analyze the model's results under various conditions to determine their realism. We assess the performance by analyzing three categories of input values: extreme initial stock levels, extreme holding cost, and the standard settings, as summarized in Table 5.1.

Table 5.1: Experimental settings summary: A total of 14 experiments were conducted, each comprising 50 replications, resulting in a total of 700 scenarios. For detailed definitions, refer to Section 5.1.

Parameter	**Value**
Supply Chain System	
Items (J)	20
Lead Time (L)	2 months 1 month
CSL (α)	0.95
Costs	
Transport Cost 20ft container (T_{20})	€1,435, –
Transport Cost 40ft container T_{40}	€2,175, –
Holding Cost (h)	€1.40 per item per half a month
Warehouse Tariff (V)	€13.36 per unit
Order Cost (O)	€100, – per order
Forecast Error	
Forecast Error (FE_{jt})	Perfect: $\mu = 0.094$, $\sigma = 0$ Low: $\mu = 0.094$, $\sigma = 0.149$ Medium: $\mu = 0.094$, $\sigma = 0.297$
Forecast (F_{jt})	see Chapter B
Capacity	
Max. 20ft-container load (K_{20}^{MAX})	22 pallet places
Max. 40ft-container load (K_{40}^{MAX})	50 pallet places
Min. 20ft-container load (K_{20}^{MIN})	20 pallet places
Min. 40ft-container load (K_{40}^{MIN})	45 pallet places
Space occupied (k_j)	1 or 2 (depending on item characteristic)
Max. Inventory Level (I_j^{MAX})	Medium High (+20%)
Simulation	
Simulation horizon	12 months
Time step interval	Monthly Bimonthly Weekly Daily

Extreme Initial Stock Level. To evaluate the model's performance, we focused on a scenario where the initial stock level was exceptionally high, enabling it to meet demand directly from stock with a high probability. We anticipated that under such conditions, the total costs would primarily comprise holding costs, with negligible transportation and ordering expenses due to the lack of necessity for placing orders. The initial stock for each item was set at 400 pallets, while the maximum storage capacity was elevated to 500 pallets. The model indicated a total cost of €261,392 , with the entirety of this cost attributed to holding costs. Notably, no orders were initiated as the initial inventory proved sufficient to satisfy demand without replenishment.

Table 5.2: Example of an order schedule accompanied by the performance metrics of a scenario considering monthly checkups, with moderate forecast error and storage capacity (scenario = 1). The total cost equal €35, 176, transport utilization 99.08%, number of work 32, 582 and optimality gap $3.1 * 10^{-5}$.

		Month												
		1	2	3	4	5	6	7	8	9	10	11	12	Total
Ordering Schedule	Order placed z_t	0	1	1	1	0	1	1	1	0	0	0	0	**6**
	No. 20-foot Container N_t^{20}	0	0	0	0	0	0	0	0	0	0	0	0	**0**
	No. 40-foot Container N_t^{40}	0	1	2	3	0	2	2	3	0	0	0	0	**13**

Extreme Holding Cost. Exploring the model's behavior under significantly high holding costs provides valuable insights for the validation process. When holding costs surpass transportation costs, we anticipate an increase in order placements to meet demand promptly. Adhering to the just-in-time principle, orders are triggered only when needed, as holding excessive inventory incurs substantial expenses. To examine this, we set the holding cost for each item at €500 per month. As anticipated, the model results indicate an increase in the order frequency. Each month, an order is generated to fulfill demand during the lead time with additional pallets included as necessary, adhering to the minimum 95% transport utilization rule. Additionally, in this model, the 20-foot containers are utilized more, as the cost of ordering such containers is lower than holding the excess inventory.

Standard Settings. We also assess the model's order schedule using standard input settings. Upon examining the forecast, we observe a rise in expected total demand from April to October, with approximately 50 pallets required each month. Consequently, given the two-month lead time, we anticipate a higher order frequency in February to June. We also project that no orders will be initiated in November and December, as they would only arrive after our planning period due to the two-month lead time. Table 5.2 illustrates an example order schedule for this model, along with its performance metrics. This schedule confirms our hypothesis, where many containers were shipped in February till August, and no orders were placed in the last four months. We can verify that we maintain a 95% cycle service level by observing in Table 5.3 that the inventory level for all items consistently remains above zero.
Based on these experiments, we confirm the model's performance and believe it accurately reflects real-world scenarios. The following section expands on the model's performance under various realistic situations.

5.3 Results

This section delves into the findings of the experiments. Initially, experiments were conducted to determine the optimal checkup frequency: daily, weekly, bimonthly, monthly. Subsequently, we performed additional experiments to evaluate the effects of varying storage capacities and forecast accuracy on the overall performance of the model.

Table 5.3: Illustration of the inventory levels, expressed in pallets, for the coffee and tea SKU's, corresponding to the model outlined in Table 5.2. The data indicates consistent inventory levels above zero for all items, thereby ensuring a 95% cycle service level. A scenario considering monthly checkups, with moderate forecast error and storage capacity (scenario = 1).

	Coffee & Tea SKU																			
Month	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	17.1	3.7	6.8	14.5	5.0	1.8	0.9	1.9	13.8	4.9	1.8	1.0	2.6	2.7	2.7	2.6	2.3	2.5	2.7	2.6
2	11.7	3.4	5.8	9.1	4.2	1.6	0.8	1.8	11.3	4.7	1.7	0.9	2.2	2.4	2.4	2.2	1.7	1.9	2.4	2.2
3	5.4	2.8	4.5	3.6	2.4	1.1	0.6	1.6	3.5	4.2	1.4	0.8	1.9	2.2	2.1	1.8	1.0	1.4	2.2	1.8
4	0.8	2.4	2.3	0.6	0.4	0.4	0.5	1.3	0.7	2.3	1.1	0.7	1.8	3.1	1.9	1.5	0.5	1.0	2.0	1.4
5	7.3	1.8	0.3	0.2	0.0	0.8	0.3	1.1	0.2	1.2	0.8	0.5	1.7	2.7	1.8	1.5	0.3	1.6	1.9	1.2
6	11.5	1.2	2.5	10.2	3.0	1.4	0.2	0.6	18.5	1.4	1.3	0.4	1.4	2.2	1.4	0.7	1.1	1.0	1.5	0.8
7	0.8	0.6	0.7	0.2	0.5	0.8	0.0	0.3	0.6	0.8	0.9	0.3	0.3	0.8	1.0	0.0	0.1	0.5	1.2	0.4
8	3.6	0.8	0.1	0.2	0.8	0.0	0.8	0.0	0.9	1.0	0.6	0.1	0.2	0.5	0.8	0.5	1.2	0.1	0.9	0.2
9	0.5	0.0	4.0	0.6	0.2	0.4	0.7	0.8	5.1	0.2	0.4	0.9	0.2	0.4	0.6	0.1	1.6	0.7	0.7	0.0
10	13.6	1.3	3.2	8.9	2.1	0.7	0.5	0.5	12.1	1.3	1.1	0.8	1.4	1.5	0.4	0.8	1.7	1.4	0.5	1.0
11	6.0	0.9	1.7	4.8	0.9	0.4	0.5	0.4	5.4	0.8	0.9	0.8	0.8	0.7	0.4	0.7	0.9	1.2	0.4	0.9
12	0.3	0.6	0.3	0.3	0.4	0.2	0.4	0.4	0.2	0.3	0.7	0.7	0.2	0.1	0.4	0.6	0.3	1.0	0.4	0.9

Table 5.4: The table presents the outcomes of four experiments with various time steps - monthly, bimonthly, weekly, and daily - intervals, with medium forecast error and medium storage capacity. Notably, due to significant runtime constraints, data for the daily checkup are unavailable. Based on medium forecast accuracy and medium storage capacity, 4 experiments and 50 replications conducted, resulting in a total of 200 scenarios.

Experiment	Time Step (t)	Objective Function (€)	Transport Utilization (%)	Optimality Gap (10^{-5})	No. Work	No. rep. no solution
1	daily	n/a	n/a	n/a	n/a	n/a
2	weekly	36,584	99.88	8.4	748,910	35
3	bimonthly	35,397	98.74	8.3	564,945	15
4	monthly	33,241	98.04	7.5	374,540	8

5.3.1 Experiments: Time Steps

We conducted four experiments to assess the model's performance with inputs varying between daily, weekly, bimonthly, and monthly checkups. The results of these experiments are summarized in Table 5.4. Each experiment is replicated 50 times, maintaining consistent seed values for result comparison. Replication time was limited to 10 minutes per run. The daily check did not yield an optimal solution within this time frame, resulting in no available data. The following paragraphs elaborate on the outcomes of the performance metrics for the models.

Run Time. Reviewing Table 5.4, it becomes evident that increasing the frequency of checkups also increases the average workload. While the monthly model exhibits an average workload of 374,540, this metric rises to 564,945 for the bimonthly model and 748,910 for the weekly model. This trend can be attributed to the larger solution space associated with more frequent checkups. With additional time steps, there are more variable options, resulting in a broader solution space, which in turn leads to a higher workload and consequently longer runtime. As previously mentioned, each model is constrained to a ten-minute runtime to prevent excessive processing times. The number of experiments without a solution, as shown in Table 5.4, substantially increases with more frequent checkups. This indicates greater difficulty in finding a feasible solution within the given timeframe, particularly for the weekly model. This challenge is also why there is no available data for daily checks.

Objective Function / Transport Utilization. Comparing the results in terms of objective function and transport utilization across these experiments proves challenging due to significant variations in the number of replications where no solution is obtained. As the number of checkups increases, so does the frequency of replications failing to produce a feasible solution within the allotted time frame. Consequently, the objective function values presented in Table 5.4 for each model are derived from different numbers of replications, thereby complicating direct comparisons.

Optimality Gap. Upon examining Table 5.4, it is evident that the optimality gap widens with a more frequent checkup model. In the monthly model, the expected gap is 7.5×10^{-5} %, whereas in the weekly model, it increases to 8.4×10^{-5} %. This increase indicates the challenge that models face when addressing problems with a larger solution space. The lower optimality gap in the monthly model suggests that the best-known feasible solution for the monthly model is nearer to the optimal solution compared to the bimonthly and weekly models, yielding greater confidence in the solution's quality.
Because the more frequent checkup models lead to extended run times, we exclude the weekly and daily checkup models from subsequent experiments. We believe this is feasible due to the relatively low demand and extended lead time. It is not deemed optimal to place orders at such high frequencies.

5.3.2 Experiments: Storage Capacity, Forecast Accuracy & Lead Time

We conduct experiments to examine the influence of the storage capacity and the forecast accuracy on the model's performance. As previously discussed, we only consider the bimonthly and monthly checkup models for these experiments. We aim to understand how increasing storage capacity affects model performance, testing it under two settings: medium and high storage capacity. Furthermore, we explore the effect of enhancing forecast ability on performance, considering three scenarios: medium, low, and perfect forecast. We also investigate the interplay between these these variables, conducting a total of twelve experiments. The outcomes of these experiments are summarized in Table 5.5.

Run Time. As discussed in Section 5.1.2, we include an extra column to depict the frequency of replications where the model failed to find an optimal solution within the given time frame. Table 5.5 illustrates the reduction in frequency with a lower forecast error and lower storage capacities. Particularly, scenarios featuring medium forecast errors and high storage capacities exhibit the highest average workload and, consequently, the longest runtime. This explains why the number of runs where no replications are found is also significantly higher in these scenarios. It is noteworthy that the

Table 5.5: Results of the experiments varying maximum storage capacity and forecast accuracy for a monthly and bimonthly model. Two storage capacity scenarios are introduced: medium (M) and high (H), along with three forecast accuracy scenarios: medium (M), low (L), and perfect forecast (P). Based on a monthly and bimonthly checkup model, with 12 experiments and 50 replications conducted, resulting in a total of 600 scenarios.

Experiment	Forecast Error (FE_{jt})	Storage Capacity (I_j^{MAX})	Objective Function (€)	Transport Utilization (%)	Optimality Gap (10^{-5})	No. Work	No. rep. no solution
Monthly Model							
1	M	M	33,241	98.04	7.5	374,540	8
2	M	H	33,255	98.05	7.7	666,410	11
3	L	M	32,621	97.49	6.5	304,225	2
4	L	H	32,603	97.56	7.6	252,970	3
5	P	M	31,826	99.83	8.8	467,823	0
6	P	H	31,826	99.83	8.8	737,734	0
Bimonthly Model							
7	M	M	35,397	98.74	8.3	564,945	15
8	M	H	35,475	98.65	7.3	534,846	17
9	L	M	34,973	98.87	6.0	381,987	6
10	L	H	34,973	98.78	5.5	341,392	6
11	P	M	34,857	98.71	7.0	276,418	0
12	P	H	34,857	98.71	6.0	246,566	0

averages in these scenarios are derived from a smaller number of replications. Subsequently, in the next paragraph, we delve into the implications of comparing these observations on the objective function and utilization. In summary, introducing greater storage capacities leads to increased runtime owing to the expanded solution space, a phenomenon similarly observed with less accurate forecasts.

Objective Function / Utilization. Figure 5.2 shows the results in terms of total cost from six experiments varying in medium, low, perfect forecast accuracy. The figure illustrates the superior performance of the perfect forecast accuracy. Upon examining Table 5.5, several key findings emerge:

- *Forecast Accuracy:* The experiments conducted assuming perfect forecast accuracy (experiments 5, 6, 11, 12) consistently demonstrate superior performance in terms of both total cost and transport utilization metrics. Conversely, the model assuming medium forecast accuracy and high storage capacity performs relatively poorly in these metrics.

- *Conclusion Forecast Accuracy:* The experiments underscore the significant impact of enhanced forecast accuracy on both overall costs and transport utilization. For example, the expected costs decrease from approximately €33, 255 with medium forecast accuracy to around €31, 826 with perfect forecast accuracy, representing a notable reduction of approximately 4.30%. Even with an improved but not perfect forecast accuracy, a cost reduction of 1.96% is observed, highlighting the importance of accurate forecasting in minimizing costs and optimizing operational efficiency.

- *Impact Storage Capacity:* Contrary to expectations, when forecast accuracy remains constant, a minor increase in expected cost is observed with high storage capacity compared to medium capacity. This unexpected result challenges the

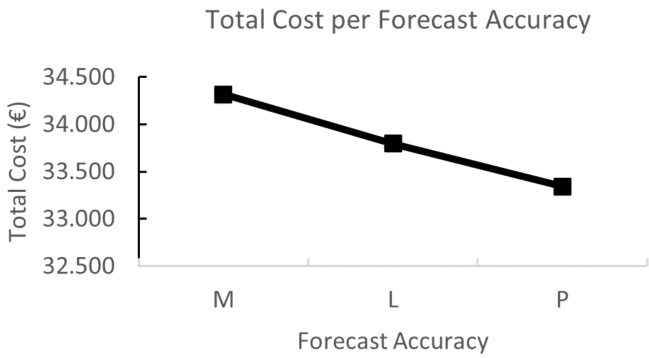


Figure 5.2: Comparison of the expected total warehouse and distribution costcheckup model across medium, low, and perfect forecast accuracy. It is based on six experiments, each replicated 50 times, resulting in a total of 600 scenarios.

assumption that increased total capacity would lead to cost minimization or at least consistent costs. Upon closer examination, it becomes apparent that the number of experiments failing to solve within the given time frame increases with higher storage capacity, directly influencing the expected total costs of the model.

- *Conclusion Storage Capacity:* The performance comparison per replication indicates equivalent performance between experiments 1 and 2, as well as between experiments 3 and 4, 7 and 8, 9 and 10. Consequently, it can be inferred that increasing total storage capacity does not necessarily enhance model performance under the current settings.

Optimality Gap. The highest optimality gap is noted in scenarios featuring a perfect forecast error, whereas the lowest optimality gap is observed in instances characterized by medium storage capacities and low forecast errors. Although there is a discrepancy between the two extremes, the variation is not substantial; the highest observed gap stands at 8.8×10^{-5} %, while the lowest is recorded at 6.0×10^{-5} %.

Influence Lead Time Reduction. When reducing the lead time from two to one month, we observe no changes in the objective function and transport utilization compared to the results presented in Table 5.5. Notably, the number of work, which indicates computational time, decreases by an average of 82%. Although there is a small change in the optimality gap, it is negligible. These findings suggest that reducing the lead time does not immediately impact total costs, as the same orders are simply placed later in the new model. The costs and constraints thus overshadow the lead time reduction in this specific model.

5.4 Comparative Analysis to Current Situation Partner X

To assess the performance of our proposed VMI model, we employ two benchmarks. Firstly, we compare the actual schedule and metrics for 2023 with a model where we input the actual demand for 2023. Additionally, we simulate the current ordering method, which closely resembles the just-in-time principle.

5.4.1 Actual Performance 2023

Calculation of the Actual. We aim to contrast the actual ordering schedule and the associated performance in 2023 with the outcomes of our model proposal. We input the actual sales figures for each item into the model and manually compute the total costs of the actual ordering strategy in 2023. Actual costs are determined retrospectively. However, GBD lacks documentation regarding the transportation mode for each order placed in 2023. Consequently, we presume they utilized the most suitable mode for each shipment. For instance, if an order could fit in a 20-foot container, we assume they did not use a 40-foot container unnecessarily. Additionally, in cases where multiple orders were picked up on the same day, we assume they were consolidated. Partner X provided an overview of the inventory levels throughout the year, making it possible to determine the total holding costs. It is important to note that the supply planners at Partner X review the need for placing an order on a more frequent basis, often leading to multiple order placements within a single month.

Results. Table 5.6 presents the comparison between the model's performance and the actual performance of the partner in 2023. The most significant difference lies in the number of orders placed. Throughout the year, the partner placed a total of 27 orders, accompanied by the utilization of 17 20-foot containers and 7 40-foot containers. Although determining the exact utilization retrospectively is challenging, given these figures and the relatively modest order quantities, it can be inferred that the transportation utilization is approximately 53%. Moreover, in the existing scenario, only 87% of the total order volume is comprised of full pallets, with the remaining 13% consisting of single pallet layers and broken layers. However, in the VMI system, we assume ordering only whole pallets to mitigate any packing errors in the warehouse. By utilizing the VMI approach, there exists an opportunity to reduce the overall warehouse and distribution costs of this partner by 34.78%.

Acquiring Initial Stock Level: Moreover, as detailed in Section 5.2, the VMI model avoids placing any orders in the final months, as the planning horizon is limited to a year. In our input data, we accounted for an initial stock level adequate to fulfill demand for the succeeding two months. However, it is important to note that acquiring this initial stock incurs costs in real-world scenarios. We assumed a planning horizon of one year, where orders for the upcoming year would typically be placed at the year's end, constituting the initial stock level for the model. Notably, our model did not generate any orders in the final months, which diverges from reality, where orders for the following year are commonly initiated during this period. Consequently, the costs associated with obtaining this initial stock are not factored into the total cost in our model, potentially leading to an underestimation of costs compared to actual scenarios. Hence, for a more comprehensive comparison, it is imperative to factor in the estimation for obtaining the initial stock levels. Initially, 96 pallets were introduced, equivalent to €1,283 for warehouse expenses. These pallets can be transported using three 40-feet and one 20-feet container, incurring transportation costs of €7,960. Thus, the total expenditure for acquiring the initial stock stands at €9, 243. Consequently, the overall cost for the model amounts to €42, 232, still representing a reduction of 16.5%.

Table 5.6: Comparison between the actual performance of Partner X in 2023 and the model's performance with the actual sales as input. Based on the monthly checkup model and medium forecast accuracy, with 1 experiment and 50 replications conducted, resulting in a total of 50 scenarios. Note that the costs for acquiring the initial stock level are not included.

	VMI Model	Actual
Cost		
Total Cost (€)	32,989	50,581
Holding Cost (€)	1,687	2,845
Transportation Cost (€)	26,100	39,620
Order Cost (€)	500	2,700
Warehouse Cost (€)	4,702	5,416
Order Schedule		
Total no. orders	5	27
Total no. 20ft	0	17
Total no. 40ft	12	7
Total Order Quantity	352	375

5.4.2 Just-in-Time Model

We also simulate a similar ordering strategy to that of Partner X to compare the performance of our model against it. This ordering strategy bears some resemblance to the JIT principle. Examining their 2023 ordering schedule, we observe a high frequency of orders, often for non-full containers and pallets. Given the frequent urgent orders and the associated risk of stockouts, it is evident that they do not maintain extremely high inventory levels. Consequently, we opt to model a more JIT-oriented approach for comparison with the VMI model. In this model, we remove the constraint of a minimum transport utilization of 95% and introduce lower maximum stock levels per item. As a result, the partner is unable to maintain inventory levels as high as those in the VMI model. Table 5.7 summarizes the outcomes of the experiments. We evaluate the JIT model under three scenarios; medium forecast accuracy, low accuracy and perfect forecast. 297

VMI vs. JIT performance. The VMI model demonstrates reductions of 4.5%, 4.1%, and 3.0% in overall warehouse and distribution costs compared to the JIT model with medium, low, and perfect forecasts, respectively. Figure 5.3 shows the difference in total cost for the six experiments. In terms of average utilization, VMI achieves 98.45%, while JIT reaches 98.39%, with the difference being negligible. The JIT models exhibit a higher number of tasks, leading to longer runtimes. However, the disparity in the number of experiments failing to produce a solution is not significant.

Order Schedule. Upon examining the order schedules of a single replication for both models, we can evaluate differences in ordering patterns at a more detailed level. Table 5.8 presents the outcomes of both models when tested with identical inputs,

Table 5.7: Comparison of VMI and JIT performance under different forecast accuracy levels, denoted as FE_{jt}: medium (M), low (L), and perfect (P). Based on the monthly checkup model, with 6 experiments and 50 replications conducted, resulting in a total of 300 scenarios. The final line illustrates the 2023 actual costs for comparative analysis.

Experiment	Model	Forecast Error (FE_{jt})	Objective Function (€)	Transport Utilization (%)	Optimality Gap (10^{-5})	No. Work	No. rep. no solution
1	VMI	M	33,241	98.04	7.5	374,540	8
2	VMI	L	32,621	97.49	6.5	304,225	2
3	VMI	P	31,826	99.83	8.8	467,823	0
4	JIT	M	34,718	98.11	8.3	903,581	9
5	JIT	L	33,974	98.05	7.1	687,764	3
6	JIT	P	32,791	99.00	0	916	0
	Actual	M	42,232	53.00	n/a	n/a	n/a

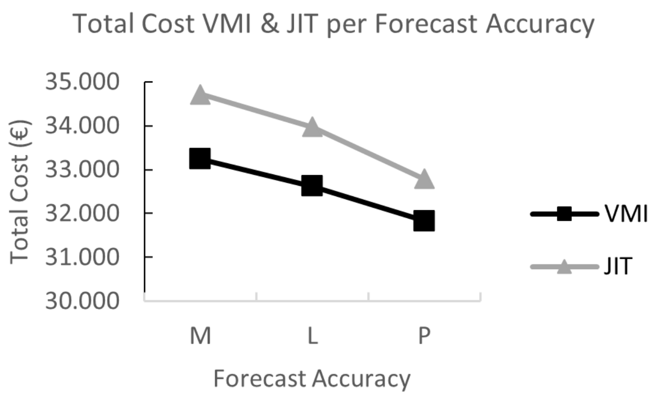


Figure 5.3: Comparison of the expected total warehouse and distribution cost between the VMI and JIT model across medium, low, and perfect forecast accuracy, demonstrating the superior performance of the VMI model. Based on the monthly checkup model, with 6 experiments and 50 replications conducted, resulting in a total of 300 scenarios.

achieved by introducing identical seed values. It shows that the VMI model places five orders, whereas the JIT model places nine orders on average. As anticipated, the holding costs in the JIT model are lower compared to the VMI model. However, this reduction in holding costs does not offset the other costs where the VMI model outperforms the JIT model.

Table 5.8: Comparison between an order schedule based on the VMI model and the JIT-based model. Based on the monthly checkup model and medium forecast accuracy, with 2 experiments and 50 replications conducted, resulting in a total of 100 scenarios.

	VMI	JIT
Cost		
Total Cost (€)	34,364	36,662
Holding Cost (€)	1,640	962
Transportation Cost (€)	27,535	29,710
Order Cost (€)	500	900
Warehouse Cost (€)	4,689	5,090
Order Schedule		
Total no. orders	5	9
Total no. 20ft	1	1
Total no. 40ft	12	13
Total Order Quantity	351	381

5.5 Summary

In this chapter, we established the experimental setup, where experiments were conducted varying time steps, forecast accuracy, and storage capacity as variables. Initially, we successfully tested the model's output and validated it to ensure it accurately reflects real-life scenarios. Here are the key findings from the results section:

- Increasing the monthly checkup frequency raised workload and processing times, some exceeding ten minutes. Comparing models across various intervals becomes challenging. Daily and weekly intervals are dismissed from further experimentation because of their considerable processing times. This choice seems feasible due to low demand and ample lead time. Ordering at higher frequencies isn't deemed optimal.

- The storage capacity agreed upon with Partner X was found to be adequate, and increasing it did not significantly impact performance.

- Improving forecast accuracy has the potential to reduce costs by up to 4.3%.

- Adapting the VMI model to 2023 data could potentially result in expense reduction of up to 16.5%.

- In all experiments, covering medium, low, and perfect forecast accuracy, the VMI model consistently outperformed the JIT model, achieving improvements of 4.5%, 4.1%, and 3.0% respectively.

Chapter 6

Conclusion & Recommendation

We formulated the main research question of this study as "How can GBD optimize the order profile of the partners to minimize the total distribution and warehouse costs while maintaining service levels?". In Section 6.1 we draw our conclusion and discuss these in Section 6.2. Then, we make some recommendations to the company in Section 6.3 and propose areas for future research in Section 6.4.

6.1 Conclusion

The primary aim of this study was to develop an effective strategy for minimizing the distribution costs of GBD by refining the ordering practices of their partners, specifically in terms of frequency and volume. In this section, we address the sub-research questions outlined in Chapter 1.

How does the current situation of the JDE export process look like? The current practices among the partners involve frequent orders, often comprising incomplete pallets and failing to utilize full container capacities. This leads to inefficiencies in distribution and increases overall warehouse and distribution costs.

What inventory management strategies can be employed to address cost minimization challenges associated with enhancing the order profile? Existing literature highlights the successful implementation of Vendor Management Inventory (VMI) across various contexts. VMI grants the company greater control over its partner's inventory management, thereby streamlining the ordering process and enhancing supply chain collaboration.

How can we apply these modeling techniques to the GBD case and adjust it to improve its performance? In this research, we developed a model for VMI involving a single retailer and vendor, managing multiple items. This model considers both constant lead time and variable demand, aiming to optimize total warehouse and distribution costs. At each time step, decisions are made regarding whether to place an order and, if so, which transportation mode offers the most cost-efficient solution.

How does the newly proposed solution perform, reviewed on total distribution costs and transport utilization, compared to the current way of GBD? We applied the model to a case study with Partner X, demonstrating its effectiveness in refining both the timing and size of orders. The key findings regarding the implementation of the VMI model at Partner X include:

- *Cost Reduction:* The model significantly cuts down on total costs related to warehousing and distribution by consolidating orders, leading to fewer but larger shipments and increased transport utilization.

- *Potential Savings:* Adoption of the VMI model to 2023 data shows potential expense reduction by up to 16.5%.

- *Transport Utilization:* Transport utilization increases to approximately 98%, a significant improvement compared to the current average utilization rate of only 53%.

It is worth noting that while higher transport utilization is generally desirable, it does not necessarily guarantee lower overall costs. Across all experiments, transport utilization remains above 95%; however, beyond this threshold, increased transport utilization does not necessarily correlate with decreased overall costs. Relying solely on transport utilization as a metric is therefore not adequate.
Additionally, notable findings emerged concerning the optimal container size and the frequency of checkups. Various intervals (monthly, bimonthly, weekly, daily) were explored to evaluate performance based on the objective function, optimality gap, and runtime:

- *40-foot Containers Preferred:* The model suggests predominantly using 40-foot containers over 20-foot containers due to cost-effectiveness.

- *Monthly and Bimonthy Checkup Model:* Increasing the monthly checkup frequency raised workload and processing times, some exceeding ten minutes. Comparing models across various intervals becomes challenging. Daily and weekly intervals are dismissed because of their considerable processing times. This choice seems feasible due to low demand and ample lead time. Ordering at higher frequencies isn't deemed optimal.

We also conducted experiments to examine how the total warehouse capacity and forecast accuracy influence the model's performance:

- *Warehouse Capacity:* Increasing capacity did not improve the objective function, suggesting existing capacity was sufficient.

- *Forecast Accuracy:* Enhanced forecast accuracy could reduce overall costs by 4.3% with a perfect forecast and 1.9% with halved standard deviation.

- *Lead Time.* Reducing the lead time does not immediately impact total costs, as the same orders are simply placed later in the new model.

Lastly, we compared the performance of our VMI model with that of a JIT-based model, given its similarity to the current ordering method.

- *Superiority of VMI:* The performance of the VMI model was compared with the JIT model across various forecast inputs, including medium, low, and perfect forecasts. The VMI model consistently outperforms the JIT model in terms of objective function, showcasing reductions in overall costs across all scenarios: 4.5%, 4.1%, and 3.0%, respectively.

- *Neglible Transport Utilization:* Minimal disparities were observed in transport utilization between the VMI and the JIT models.

6.2 Discussion

The implementation of the VMI model offer valuable insights into an optimal order frequency and volume. However, certain considerations need to be addressed to reassure the realism and effectiveness of the model.

Static Lead Time: Assuming a static lead time may not align with real-world dynamics. Unforeseen events, like the ongoing disruptions in the Red Sea, can significantly impact lead times. Therefore, it would be beneficial to consider introducing a variable lead time to better reflect real-life scenarios. Additionally, transportation costs are often influenced by such events. Thus, incorporating monthly variable transportation costs could provide a more accurate representation of the dynamic nature of supply chain operations.

Exceptional High Demand: Events characterized by exceptionally high demand, such as supply chain disruptions or unforeseen market trends, might not be adequately accounted for in the existing model. Currently, our model assumes that actual demand follows the forecast via a forecast error, where the occurrence of such events is highly unlikely. This distribution is derived solely from historical data where such events did not manifest. In reality, there exists the possibility of encountering a significant outlier in demand. Therefore, it is imperative to enhance the model's flexibility to accommodate such scenarios and better capture the variability inherent in real-world demand patterns. Additionally, the forecast error in our model relies on the forecast accuracy from the previous year, without distinguishing between errors stemming from human oversight or unforeseen market shifts. Consequently, significant efforts to enhance forecast accuracy may not be promptly reflected in the model's performance. It is essential that improvements in forecast accuracy are integrated into the model's inputs, ensuring that the model accurately reflects the evolving forecasting capabilities.

Information Sharing: The effectiveness of VMI depends significantly on information sharing encompassing inventory levels, actual demand, and forecasts. Typically, computer programs facilitate the exchange of updates on these aspects. However, since we recommend GBD to adopt only a partial VMI approach initially, immediate access to such programs, for sharing information via EDI messages, may not be available. Nevertheless, as long as GBD and the partner agree on an alternative method for complete information sharing, the functionality of the model would remain unaffected.

6.3 Recommendations

Implementation Partial VMI: Based on the favorable outcomes of the model, we recommend that GBD considers implementing a partial VMI approach in their operations. This approach ensures that not all responsibilities are shifted to GBD; rather, they can collaborate with their partners on order frequency and volume suggestions. The initial step involves creating awareness among partners regarding their current ordering practices, highlighting the costs incurred and how they can be minimized through the new approach. This awareness alone can significantly impact overall costs, as many partners may not fully realize the effect of their order profiles. Following this, we advise GBD to closely collaborate with partners on order timing and quantities, emphasizing the importance of information sharing on stock levels, actual demand, and forecasts for successful VMI implementation.

Improving Forecast Accuracy: Furthermore, our experiments demonstrate that improving forecast accuracy greatly enhances the model's performance. Therefore, we suggest GBD focuses on enhancing the forecasting capabilities of their partners, providing support where necessary and evaluating forecasts at an early stage. Storing and analyzing this data allows for continuous improvement and learning from past mistakes.

Minimum Order Quantity to Pallet: An assumption in this model is that partners can only place orders in full pallets rather than in individual boxes or pieces. However, in the current system, partners have the flexibility to order single pieces or boxes of an item. This practice incurs additional warehousing costs as goods need to be repackaged, leading to increased error rates. We recommend that GBD raise the minimum order quantity of each item to one pallet to streamline operations and mitigate these challenges.

More Partners: To achieve a substantial reduction in warehouse and distribution costs, it is beneficial to expand the VMI approach to more partners. While implementing it with one partner impacts costs, scaling it to all partners significantly amplifies its effect.

Reduction of Lead Time: Moreover, once VMI is successfully implemented with a partner, attention can be directed towards reducing lead times. Currently, GBD operates on a make-to-order paradigm with lead times typically around eight weeks, depending on the partner. Many partners express a desire to shorten these lead times. By gaining insight into partner order schedules through VMI, GBD can make more accurate forecasts. This insight presents opportunities for GBD to transition from a make-to-order to a make-to-stock process, thereby improving efficiency further. While our model indicates that reducing the lead time does not have an immediate impact on performance, in reality, prioritizing lead time reduction is of considerable significance. It enhances the responsiveness of the company, improves customer satisfaction, and increases flexibility. Moreover, it supports lean practices by enhancing efficiency, eliminating waste, and reducing bottlenecks. Therefore, despite its minimal impact in the model, reducing lead time remains a valuable strategic initiative.

6.4 Future Research

For further research, exploring the transition from a make-to-order to a make-to-stock paradigm could offer insights into reducing lead times. An integrated production and distribution model would be valuable to ascertain how production can be optimally planned in alignment with the expected demand by our VMI model. Thus, research into methods for aligning GBD's production with expected demand by introducing inventory to reduce lead time would also be beneficial.
Furthermore, partners encountering heightened demand rates and increased stochasticity may necessitate more frequent check-ups. Hence, the introduction of a meta-heuristic capable of addressing such large-scale problem instances could yield significant benefits.

Appendices

Appendix A

Full Model

A.1 Sets & Indices

T = number of simulation days
J = number of items
Item $j \in \{1, 2, 3, \ldots, J\}$ = set of all items
Day $t \in \{0, 1, 2, \ldots, T\}$ = set of all days

A.2 Parameters

F_{jt} = forecast of item j for day t
FE_{jt} = forecast error for item j at day t, normally distributed with mean and standard deviation
d_{jt} = demand rate of item j on day t, equals $F_{jt} * (1 - FE_{jt})$
I_{j0} = inventory level of item j at the beginning of day 1
I_j^{MAX} = maximum inventory level for product j
K_{20}^{MAX} = total capacity of a single 20 feet container
K_{40}^{MAX} = total capacity of a single 40 feet container
k_j = space occupied by one unit of item j
K_{20}^{MIN} = minimum number of pallets for a single 20 feet container load
K_{40}^{MIN} = minimum amount of pallets for a single 40 feet container load
T_{20} = fixed transportation cost of a 20 feet container
T_{40} = fixed transportation cost of a 40 feet container
O = fixed order cost
V = warehouse tariff charged per pallet shipped
h = holding cost per item per day
y_{jt} = number of pallets of item j in transit at day t
I_{jt} = inventory level of item j at the end of day t
FE_{jt} = forecast error for item j at day t, normally distributed with mean μ and standard deviation σ

A.3 Decision Variables

Q_{jt} = order quantity of product j on day t
z_t = binary variable indicating whether a replenishment order is placed on the day t
N_t^{20} = number of 20 feet containers needed for the order on day t (integer)
N_t^{40} = number of 40 feet containers needed for the order on the day t (integer)

A.4 Objective Function

$$\min TC = \sum_{t=1}^{T} (z_t(N_t^{20} T_{20} + N_t^{40} T_{40}) + z_t O + \sum_{j=1}^{J} (z_t Q_{jt} V + hE[I_{jt}])) \tag{A.1}$$

A.5 Constraints

$$\sum_{j=1}^{J} Q_{jt} k_j \leq N_t^{20} K_{20}^{MAX} + N_t^{40} K_{40}^{MAX} \qquad \forall t \tag{A.2}$$

$$\sum_{j=1}^{J} Q_{jt} k_j \geq N_t^{20} K_{20}^{MIN} + N_t^{40} K_{40}^{MIN} \qquad \forall t \tag{A.3}$$

$$I_{jt} = I_{jt-1} + Q_{j,t-L} - D_{jt} \qquad \forall j,t \tag{A.4}$$

$$I_{jt} \leq I_j^{MAX} \qquad \forall j,t \tag{A.5}$$

$$\frac{I_{j,0} + \sum_{i=1}^{t-L} Q_{jt} - \sum_{i=1}^{t} \mu_{D_{jt}}}{\sqrt{\sum_{i=1}^{t} \sigma_{D_{jt}}^2}} \geq \phi^{-1}(1-\alpha) \qquad \forall j,t \tag{A.6}$$

$$y_{jt} = \sum_{i=t-L}^{t} Q_{jt} \qquad \forall j,t \tag{A.7}$$

$$\sum_{j=1}^{J} Q_{jt} \leq M * z_t \qquad \forall t \tag{A.8}$$

$$Q_{jt}, I_{jt}, y_{jt} \geq 0 \qquad \forall j,t \tag{A.9}$$

$$N_t^{20}, N_t^{40} \geq 0 \qquad \forall t \tag{A.10}$$

$$z_t \in \{0,1\} \qquad \forall t \tag{A.11}$$

Appendix B

Forecast

Table B.1: The forecast of 2023 of Partner X for each SKU on a monthly basis.

		Month											
Item	Description	Jan	Feb	Mrt	Apr	Mei	Jun	Jul	Aug	Sep	Okt	Nov	Dec
0	PDO FORZA 1KG	5,9	5,5	6,3	7,5	13,5	11,8	10,7	10,2	10,0	12,0	7,6	5,7
1	PDO INTENSO 1KG	0,3	0,3	0,6	0,4	0,6	0,7	0,6	0,8	0,8	0,7	0,4	0,4
2	DE DARK ROAST 1KG	1,2	1,0	1,3	2,2	1,9	1,8	1,9	1,6	2,1	1,8	1,4	1,4
3	JACOBS ROYAL EL.1KG	5,5	5,5	5,5	12,0	11,4	10,0	10,0	12,0	11,6	8,8	4,1	4,5
4	JACOBS BANKETT 1KG	0,0	0,7	1,9	5,0	1,4	2,0	2,5	2,7	1,6	2,2	1,2	0,5
5	L'OR CAPS FORZA	0,2	0,2	0,5	0,7	0,6	0,4	0,5	0,8	0,6	0,8	0,3	0,2
6	L'OR CAPS DECAF	0,1	0,1	0,2	0,2	0,2	0,1	0,2	0,2	0,1	0,2	0,1	0,1
7	L'OR CAPS RISTRETTO	0,1	0,1	0,1	0,3	0,3	0,5	0,3	0,3	0,2	0,3	0,1	0,1
8	CAFÉ MILK 2L	1,2	2,5	7,8	17,9	22,5	17,6	18,0	18,6	19,9	18,0	6,7	5,3
9	CAFÉ MILK 0.75L	0,1	0,2	0,5	2,0	1,1	0,7	0,6	0,9	0,8	0,9	0,5	0,5
10	PROMESSO MILK 1.4L	0,2	0,2	0,2	0,3	0,3	0,4	0,4	0,4	0,2	0,3	0,2	0,2
11	J INSTANT MILK 1000G	0,0	0,0	0,1	0,1	0,2	0,1	0,1	0,1	0,2	0,2	0,0	0,1
12	PW ENGLISH	0,4	0,4	0,3	0,2	0,0	1,3	1,2	1,1	0,9	0,8	0,7	0,6
13	PW GREEN TEA PURE	0,3	0,3	0,2	0,1	0,4	1,5	1,4	1,3	1,1	0,9	0,8	0,6
14	PW EARL GREY	0,3	0,3	0,3	0,2	0,1	0,4	0,3	0,3	0,2	0,1	0,0	0,0
15	PW MINT	0,4	0,4	0,4	0,3	0,1	0,8	0,7	0,6	0,4	0,2	0,1	0,1
16	PW CHAMOMILE	0,7	0,7	0,6	0,5	0,2	1,1	1,0	0,9	0,7	0,9	0,8	0,6
17	PW LEMON	0,5	0,5	0,5	0,5	0,4	0,6	0,5	0,4	0,4	0,3	0,2	0,2
18	PW FOREST FRUIT	0,3	0,3	0,2	0,2	0,1	0,4	0,3	0,3	0,2	0,1	0,1	0,0
19	PW STRAWBERRY	0,4	0,4	0,4	0,3	0,2	0,5	0,3	0,3	0,2	0,1	0,0	0,0

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