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Operational Capacity Planning In Warehousing

Master's thesis in Engineering and ICT
Supervisor: Anita Romsdal
June 2023

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Preface

This thesis was written in the spring of 2023 and marks the completion of my master's degree in Engineering and ICT at the Department of Mechanical and Industrial Engineering at the Norwegian University of Science and Technology.

I would like to express my gratitude to my supervisor, Anita Romsdal, for her guidance, valuable feedback, and encouragement throughout the semester.
I also want to thank Andrea from Solwr and the warehouse manager, who wishes to remain anonymous, for the cooperation, interviews and sharing of information.

I would like to thank my friends, classmates, and roommates, for being there at the lowest of lows and highest of highs throughout the years.
I would also like to thank my family for their never-ending support, motivation, and occasional financial support.

Lastly, however, most importantly, I'd like to thank my wonderful girlfriend, Hannah, for being there for me every day, supporting me with all her love, and giving me confidence, strength, and ambition.

Abstract

Capacity planning is often challenging for warehouse managers due to fluctuating customer demands and a lack of essential information. Accurate information regarding the available workforce and workload demand is crucial for warehouses to plan their daily operations effectively.

The organization faces challenges in accurately determining the required number of employees for outbound logistics, due to demand fluctuations. Several challenges related to capacity planning for warehouses were identified, and suggestions for improvement using warehouse management systems were discussed.

To address these challenges, a decision support tool for short-term capacity planning is developed. The tool incorporates an assessment of WMS functionality and a workload determination model. The aim is to strike a balance between the additional labor costs associated with overcapacity and the organization's service level, which is impacted by undercapacity. The study uses the tool to analyze the situation of a Norwegian warehouse and its warehouse management system.

Overall, this tool offers valuable decision support for operational capacity planning in warehouses. It helps address the challenges arising from demand uncertainties, enabling the organization to make informed decisions and optimize labor allocation based on different scenarios.

Sammendrag

Kapasitetsplanlegging er ofte utfordrende for lager på grunn av svingende etterspørsel og mangel på viktig informasjon. Nøyaktig informasjon om tilgjengelig arbeidsstyrke og arbeidsbelastning er avgjørende for at lageret skal kunne planlegge sine daglige operasjoner effektivt.

Organisasjonen står overfor utfordringer med å bestemme antall nødvendige ansatte for utgående logistikk på grunn av svingende etterspørsel. Flere utfordringer knyttet til kapasitetsplanlegging for lager ble identifisert, og forslag til forbedringer ved bruk av lagerstyringssystemer ble diskutert.

For å takle disse utfordringene er det utviklet et beslutningsstøtteverktøy for kortsiktig kapasitetsplanlegging. Verktøyet inkluderer en vurdering av WMS-funksjonalitet og en modell for bestemmelse av arbeidsbelastning. Målet er å oppnå en balanse mellom de ekstra arbeidskostnadene knyttet til for mange ansatte og organisasjonens servicenivå, som påvirkes av mangel på arbeidskraft. Studien bruker verktøyet til å analysere situasjonen til et norsk lager og deres lagerstyringssystem.

Dette verktøyet tilbyr verdifull beslutningsstøtte for operasjonell kapasitetsplanlegging i lager. Det hjelper til med å håndtere utfordringene som oppstår på grunn av etterspørselsusikkerhet, og gjør at bedrifter kan gjøre informerte beslutninger og optimalisere arbeidsfordelingen basert på ulike scenarioer.

Table of Contents

List of Figures

List of Tables

Acronyms

AI Artificial intelligence.

EDI Electronic Data Interchange.

FMCG Fast Moving Consumer Goods.

JIT Just-In-Time.

ML Machine learning.

RFID Radio Frequency Identification.

WMS Warehouse Management System.

1 Introduction

Warehouse management is a critical component of supply chain management and is responsible for ensuring the efficient flow of goods within a warehouse (Ten Hompel and Schmidt 2008). Effective warehouse management requires making decisions about how to store, retrieve, and manage inventory, as well as decisions about the deployment of labor and resources (Bartholdi and Hackman 2019). In today's fast-paced and highly competitive business environment, it is essential for companies to make informed decisions about their warehouse operations to maximize efficiency and minimize costs (Andiyappillai 2019b).

Capacity planning in the Logistics 4.0 era is increasingly challenging due to complex delivery specifications and dynamic business environments (Kellermayr-Scheucher et al. 2023). The rise of e-commerce and omnichannel activities has made customer demand and order volumes more uncertain and volatile, posing a significant challenge for retailers (Kellermayr-Scheucher et al. 2023). Warehouse managers must address fluctuating workforce demands through effective capacity planning (Popović et al. 2021). Studies by De Leeuw and Vincent CS Wiers (2015) and Pooya and Pakdaman (2021) highlight the importance of capacity planning, including predicting manpower demand, forecasting supply, and managing the differences between supply and demand through workforce scheduling and staffing.

Efficient workforce scheduling, including task and job allocation, is crucial for optimizing warehouse operations and responding to demand fluctuations (Popović et al. 2021). However, the complexity of workforce planning is compounded by factors such as overtime, diverse working contracts, specific skills and tasks, sickness, and variations in employee productivity, as pointed out by Fowler et al. (2008) and Ladier et al. (2014). Weekly scheduling and daily planning become challenging processes due to these variables (Ganbold et al. 2020b).

Despite the complexity and criticality of workforce scheduling, many companies still rely on conservative planning methods (Häberer and Arlinghaus 2021). Even those using personnel management software often resort to self-made Excel tools for internal logistics processes. The studies of Kellermayr-Scheucher et al. (2023) indicate that Microsoft Excel remains the preferred tool for capacity planning among the surveyed companies. While some organizations utilize specialized software like SAP products for certain aspects of labor management, decisions are frequently based on Excel calculations (Häberer and Arlinghaus 2021).

The continued prevalence of Excel raises the question of why a suitable alternative has not been developed yet. To answer this, it is crucial to understand how retail companies currently plan capacity in warehouses and which systems they employ for this purpose (Kellermayr-Scheucher et al. 2023). Additionally, it is essential to identify the strengths and weaknesses of existing planning practices, reasons behind the lack of software adoption, and the specific features and functions required in an ideal solution (Kellermayr-Scheucher et al. 2023). Employing specialized software that supports capacity planning can provide a competitive advantage for retail companies (Ada et al. 2021).

Warehouse management systems (WMS) have become a critical component of modern supply chain management, providing organizations with the necessary tools to manage inventory, optimize space utilization, and streamline operations (Ramaa et al. 2012). However, with the growing complexity of warehouse operations, it has become increasingly challenging to manage these systems effectively (Andiyappillai 2019b). In particular, capacity planning and labor management have emerged as critical areas where the functionality of WMS can significantly impact warehouse performance (Rodler 2010).

To make informed decisions about warehouse management, it is essential to have access to accurate and up-to-date information (Andiyappillai 2019a). Gunasekaran et al. (2001) suggests that delays in fulfilling orders can lead to negative consequences and may result in limited time windows for preparing orders for shipment. However, over-staffing is not a viable solution due to the associated costs (Wruck et al. 2017). Given the high costs and risks involved, it becomes crucial to plan capacity as accurately as possible by considering all the available information (Friemann and Schönsleben 2016).

1.1 Problem statement

Despite the importance of WMS functionality in capacity planning, there is a lack of comprehensive research that examines these areas in detail. While there is a lot of literature on each of these topics separately, there is a need to explore the interrelationships between them. As a result, there is a significant gap in the understanding of how to design and implement an effective WMS that can be utilized for capacity planning.

In many warehouse environments, employees can perform tasks without needing specialized skills (Van den Berg 2007). However, unlike other staff scheduling problems, determining the optimal number of working hours for each employee to meet a specific workload remains challenging (Van den Berg 2007). It is crucial to have the best possible schedule for the upcoming planning period, and accounting for stochastic influences becomes necessary, particularly when even minor failures can have a significant impact (Wruck et al. 2017). Any inaccuracies in the scheduling process can result in lost sales, high labor costs from hiring external personnel on short notice, or even a loss of customers or competitive advantage (Wruck et al. 2017).

Labor costs are generally accepted as the largest operational cost in a warehouse accounting for somewhere between 50% and all the way up to 70% according to Remstar (2023). Meanwhile, the hourly compensation rates (2%) and labor hours worked (9%) are rising for the warehouse and storage sector while productivity is declining 4.4%, causing an increase of 8% in unit labor costs (Remstar 2023).

To minimize labor costs managing the workforce is crucial for maximizing the use of personnel while limiting downtime to ensure a certain service level (Van den Berg 2007). However, this is difficult due to the uncertainty of in and outgoing goods and therefore the amount of work during a day. To try and solve this problem I will study the functionality of WMS and how this tool can help with decision-making in capacity planning.

1.2 Objectives

The focus of this study was decision-making under uncertain conditions, specifically for scheduling and dispatching a mix of full-time staff, flexible workers, and external workforce in warehouses. In situations where labor shortages can significantly affect essential performance indicators, such as response times and delivery accuracy, it is important to understand and develop effective strategies to manage the workforce. The main objectives of this study were to provide a comprehensive understanding of capacity planning and WMS functionality and recommend solutions for decision support in operational capacity planning. Specifically, this study aims to:

1. Identify how capacity planning is done in warehousing and suggest potential improvements.

2. Evaluate the key features of WMS systems that are critical for effective capacity planning.

3. Provide recommendations for the design and usage of effective WMS systems for capacity planning in a modern warehouse.

1.3 Research questions

To achieve these objectives, the following research questions will guide the study:

RQ1: How are decisions regarding capacity planning made in warehouses today?

RQ2: What information is needed to support the decision-maker?

RQ3: What are the key features of a WMS and how can these be utilized for decision support in capacity planning?

1.4 Research scope

The scope of this study will be limited to a review of the literature on warehousing, WMS functionality, capacity planning, and decision-making. The study will include a qualitative analysis of a case study from a Norwegian WMS provider, as well as the warehouse that utilizes this system to identify the challenges warehouse managers face in capacity planning as well as critical features of effective WMS for this purpose. My study is focused on operational capacity planning deciding how many workers are needed for the day-to-day operations of a warehouse.

2 Research Methodology

2.1 Theoretical background

As part of my research on warehouse management and capacity planning, I conducted a thorough theoretical study to gather information on the key concepts and practices in this field. I utilized a variety of sources, including academic journals, industry reports, surveys, and online publications, to ensure that my research was comprehensive and up-to-date. The main search engines used for my research were Google Scholar, Science direct, Scopus, Oria, Scispace and Elicit. While the four first engines are well-known search engines for looking up academic articles, Scispace and Elicit are AI-driven platforms for exploring and understanding papers. Between them, they have over 4 million papers and the ability to upload pdf's for reading other articles at their platform. These platforms are very useful for research as they offer real-time AI assistance for summaries, discussion and explanations of mathematical formulas or unknown terms by simply markings text as you read shown in figure 1 and 2.

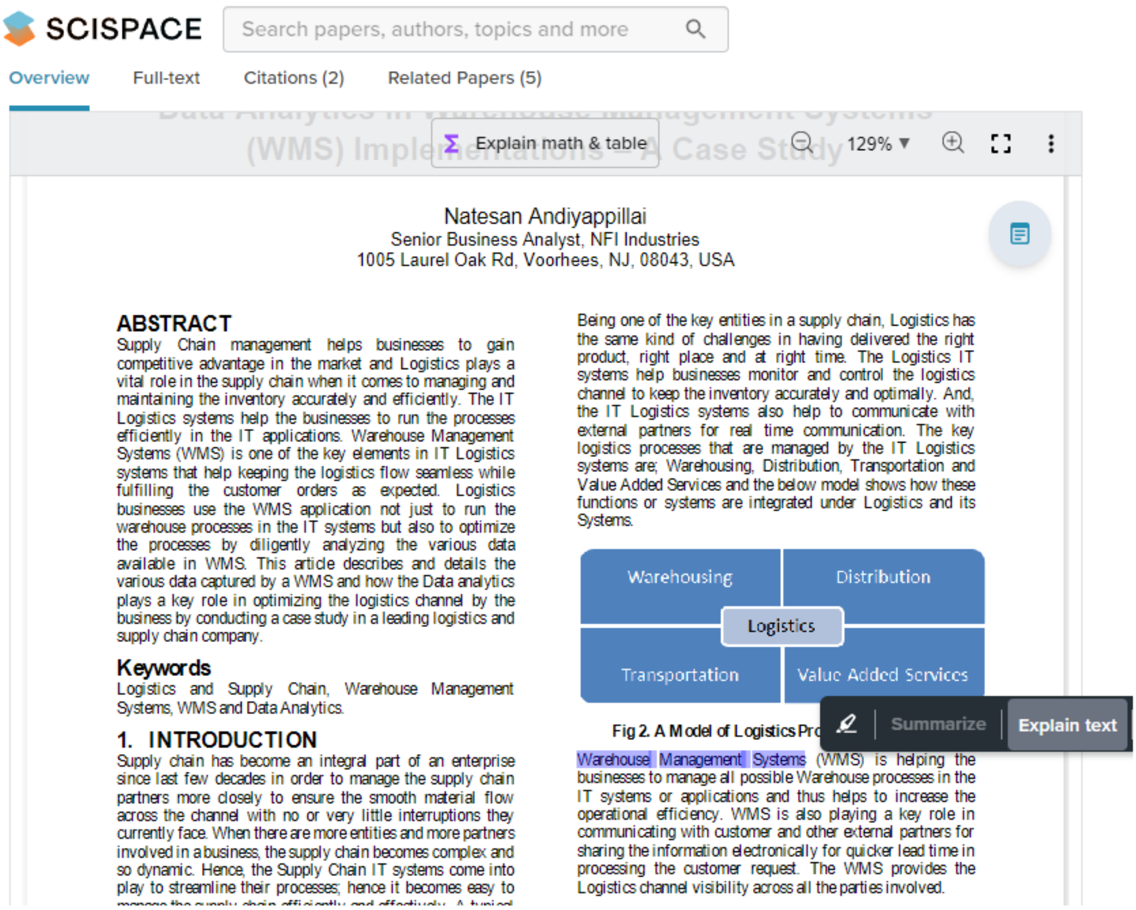

Figure 1: Example of highlighting text for explanation

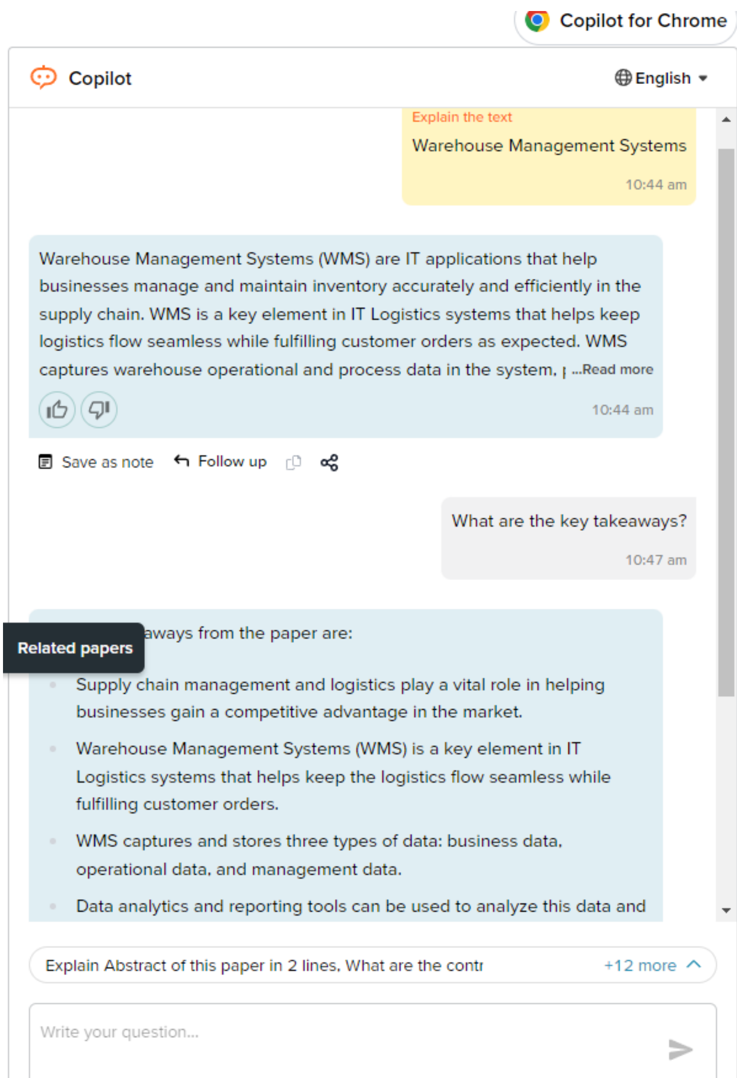

Figure 2: Asking the AI questions and getting a response

Initially, supply chain and warehouse concepts were studied to get a general overview. Next literature on Warehouse management and capacity planning was reviewed to better understand the subject. Various terms are used interchangeably in the literature to refer to parts of capacity planning. These include workforce planning, personnel scheduling, staff scheduling, workforce scheduling, labor management, and manpower planning. All these synonyms are related to the process of effectively organizing and managing the allocation of resources, specifically the workforce, to meet operational demands. While the specific terminology may vary, the underlying concept of efficiently planning and scheduling personnel remains consistent across these terms.

Table 1 shows how a combination of keywords was used to search for literature. A preference was given to peer-reviewed articles, newer articles to ensure relevancy for modern warehouses, and articles related to WMS and capacity planning. Scispace was used to quickly identify the abstract, findings, and conclusion of the papers which were read to narrow down the most relevant articles. The references these articles used for the most interesting points were then studied to find even more relevant literature.

Keywords set 1	Keywords set 2	keywords set 3
- Supply chain - Warehouse - Distribution center - Warehouse management system - WMS - Decision making	- Capacity planning - Labor - Workforce - Staff - Manpower - Operations - Machine learning - AI - Automation - Simulation	- Management - Costs - Tactical - Strategic - Operational - Strategies - Factors - Storage - Planning

Table 1: Keywords used in the theoretical study

Two of the key areas of my research was warehouse management and WMS. I found articles related to WMS and how it can be utilized for effective capacity planning (Friemann and Schönsleben 2016; Kim 2018; Ramaa et al. 2012; Tong et al. 2023). According to a study by Cognizant (2021), WMS can help warehouse managers to optimize their operations by providing real-time visibility into inventory levels and automating routine tasks such as order picking and packing.

I found several articles that discussed the challenges of capacity planning in warehouses where the environment is dynamic and uncertain, including fluctuations in demand and changing customer requirements (Friemann and Schönsleben 2016; Qazi 2020; Sazvar et al. 2021). According to Richards (2017), effective capacity planning requires a proactive approach that involves forecasting demand, identifying potential bottlenecks, and implementing contingency plans to ensure that the warehouse can handle fluctuations in demand.

One of the key findings in recent research on capacity planning is the importance of taking a data-driven approach (Fernández-Caramés et al. 2019; Friemann and Schönsleben 2016; Nada R Sanders 2014; Tanque and Foxwell 2018). Traditional approaches relied heavily on experience, intuition, or historical data, but newer methods leverage big data and advanced analytics to make more accurate predictions (Li and Liu 2019).

With the rise of new technologies such as Internet of Things (IoT) and Radio frequency identification (RFID), warehouses can now collect and analyze real-time data on inventory levels, order volume, and resource utilization to make accurate capacity planning decisions (Fernández-Caramés et al. 2019). This allows for more accurate and agile capacity planning that can respond to changes in demand quickly (Nada R Sanders 2014).

Two newer trends in capacity planning research are the use of simulation models and the use of artificial intelligence (AI) and machine learning (ML) algorithms to predict future capacity requirements (Baryannis et al. 2019; De la Fuente et al. 2019; Freile et al. 2020). Simulation models can simulate different scenarios and test the impact of changes to factors such as order volume, product mix, and resource allocation (De la Fuente et al. 2019). By using simulation models, warehouses can make more informed capacity planning decisions and identify potential bottlenecks before they occur (Freile et al. 2020; Friemann and Schönsleben 2016).

AI and ML have seen a massive increase in publicity due to the capabilities of analyzing large amounts of data and identifying patterns that humans might miss (Pournader et al. 2021). This is useful in capacity planning to increase the accuracy of predictions (Viswanathan, K. R. Kumar et al. 2022). AI and ML can also adjust to changes in demand more quickly than traditional methods, allowing organizations to be more responsive to market conditions (Baryannis et al. 2019; Min 2010)

Capacity planning research for warehouses also explores the implementation of automation technologies, specifically robotics and automated storage and retrieval systems (AS/RS). These technologies can help warehouses increase their capacity without needing to physically expand their space (R. B. De Koster et al. 2017). By automating tasks such as order picking and storage, warehouses can increase their throughput and reduce the need for manual labor (Manen 2019).

The utilization of cloud computing and virtualization technologies is also seen as significant areas of interest in capacity planing (Tanque and Foxwell 2018). These technologies enable organizations to dynamically allocate computing resources based on demand, allowing them to quickly scale up or down as needed (Hieu and Uyen 2021). This can help organizations avoid over-provisioning and reduce costs (Bhoir and Principal 2014)

Recent research has highlighted the importance of collaboration between different departments within an organization in capacity planning (Makaci et al. 2017). Effective capacity planning requires input from sales, marketing, operations, inventory management, logistics, and finance, among others (Friemann and Schönsleben 2016). By working together and sharing information, these departments can create a more accurate and effective capacity planning strategy (Andiyappillai 2019b).

Another important aspect of my research was the role of data in supporting decision-making in warehouse operations. I found several articles that emphasized the importance of collecting and analyzing data in order to make informed decisions about warehouse capacity planning, labor management, and inventory control (Friemann and Schönsleben 2016; Janssen 2015). According to a study by Kim (2018), data-driven decision-making can help warehouse managers to identify inefficiencies in their operations and implement targeted solutions to address them.

Finally, A gap between academic research and practical application existed in this area, resulting in a lack of studies on the use of decision-support tools to solve operational planning problems in real-world settings. By utilizing the information gathered from these sources, I identified potential areas for improvement and suggest new, effective solutions for warehouse management and capacity planning in my study.

2.2 Case Study

To gain in-depth insights into warehousing practices, capacity planning, and warehouse management systems, a single case study was conducted within a real-world context. The case company which wishes to remain anonymous was a large retailer in the Norwegian fast-moving consumer goods sector. The case study specifically analyzed a semi-automated warehouse facility in Trondheim, Norway.

A single case study has its own set of advantages and disadvantages. One advantage of a single case study is that it requires less time compared to conducting multiple case studies (Gustafsson 2017). It allowed me to delve deeper into the specific case and gain a comprehensive understanding of its intricacies. Through a single case study, it's possible to thoroughly investigate phenomena and describe them in greater detail (Gustafsson 2017).

On the other hand, a multi-case study offers the opportunity to explore differences and similarities among cases, contributing to the development of a more robust theory supported by empirical evidence from multiple cases (Gustafsson 2017). However, in my particular situation, I opted for a single case study due to time constraints and some trouble in finding a case company willing to cooperate. The case was also partly delayed due to a strike in the logistics sector in Norway.

Overall, while a multi-case study may provide broader insights, a single case study can still offer valuable in-depth analysis and understanding, particularly when faced with limitations in time and data availability (Meyer 2001).

Data gathering is a critical phase in any scientific study as it forms the foundation for analysis, interpretation, and conclusions (McNabb 2017). This process involves collecting relevant and reliable information to address research questions or hypotheses (McNabb 2017). It provides empirical evidence to support or refute research objectives and helps draw meaningful insights (Taheri et al. 2015).

Proper data collection ensures that research findings are based on accurate, representative, and valid information, enhancing the credibility and reliability of the thesis (Meyer 2001). Clear research objectives and well-defined research questions guide the data-gathering process (Taheri et al. 2015).

Researchers should have a clear understanding of the type of data needed to answer their research questions and achieve their objectives (McNabb 2017). This helps in selecting appropriate data collection methods and designing suitable instruments or protocols (Taherdoost 2021). It is crucial to ensure that the collected data is relevant to the research topic and aligns with the research questions (Taheri et al. 2015). Researchers must carefully select data sources and ensure that the collected data is reliable and valid (Cheung et al. 2017).

Interviews provide an opportunity to gather in-depth and qualitative data directly from participants (Meyer 2001). In my research, I conducted both structured and semi-structured interviews of a WMS provider and a warehouse manager. These interviews gave opportunities for the exploration of complex ideas and the collection of contextualized data. The qualitative and quantitative data gathered for my study can be found in table 2 and 3

Structure	Actors	Description	Date
Teams meeting	Wms provider	Initial discussion of master project and ideas	25.01.2023
Teams meeting	Wms provider	Discussion of problem statement and research questions	30.01.2023
Teams meeting	Wms provider and warehouse manager	Semi-structured interview to get an overview of the warehouse case	11.05.2023
Warehouse visit	Warehouse manager	semi-structured interview while touring the warehouse	19.05.2023
Structured interview	Warehouse manager	Interview after the visit	19.05.2023

Table 2: Collection method and date of Qualitative data

Data	**Actors**	**Date**
WMS Functionality	Wms provider	06.02
WMS data and tables	Wms provider	14.02
Capacity Planning Data	Warehouse manager	23.05
Layout Data	Warehouse manager	23.05

Table 3: Quantitative data type and date

3 Theory

3.1 Warehousing

A warehouse is a temporary place to store goods, such as raw materials, work-in-progress, or finished goods (Ten Hompel and Schmidt 2008). "Primarily a warehouse should be a trans-shipment point where all goods received are despatched as quickly, effectively, and efficiently as possible" (Richards 2017). Warehouses function as intermediaries in the supply chain and impact both costs and service, often serving as the final point for order assembly, value-added services, and dispatching products to customers (Faber, R. B. De Koster et al. 2018).

Warehouses are valuable to a supply chain in two primary ways, namely, storage and transportation (Richards 2017). Storage ensures that products are readily available when and where they are required, whereas transportation allows for efficient collection, sorting, and distribution of goods (Kay 2015). Moreover, Bartholdi and Hackman (2019) list various reasons for incorporating a warehouse in the supply chain, including matching supply to customer demand, limiting transportation costs, and providing a buffer for goods to facilitate quick responses to changes in demand.

The buffering effect is used to mitigate uncertainty and variability in demand or supply which reduce the risk of disruptions in the supply chain (Singh and Misra 2018). This can be an effective strategy for managing risk in a supply chain, but it also has costs associated with it, including the cost of maintaining inventory or excess capacity (R. B. De Koster et al. 2017). As such, it is important for companies to carefully balance the benefits and costs of buffering in order to optimize their supply chain operations (Ketchen Jr et al. 2008). Warehouses play a critical role within supply chains because they function as nodes that direct the flow of goods (Bartholdi and Hackman 2019; Ramaa et al. 2012).

According to Kay (2015), there is a fixed cost involved each time a product is shipped, such as by plane or train. A warehouse can store a large volume of goods concurrently, allowing shipments to be filled to their maximum capacity level, resulting in a reduction in the cost of shipping individual orders or products (Kay 2015). Each unique product stored in a warehouse is referred to as a stock-keeping unit (SKU) (Bartholdi and Hackman 2019). Items in a warehouse are stored in different storage locations, known as slots, which can refer to racks, bins, shelves, or floor areas (Bartholdi and Hackman 2019). Each storage location is allocated a unique address, and multiple units of the same SKU can be stored in the same location, subject to sufficient capacity (Pannu 2021).

3.1.1 Warehouse operations

Warehouse operations refer to the tasks and processes involved in managing a warehouse's daily activities (Ten Hompel and Schmidt 2008). These operations are critical to a company's supply chain and can have a significant impact on its overall performance (Lambert et al. 1998).

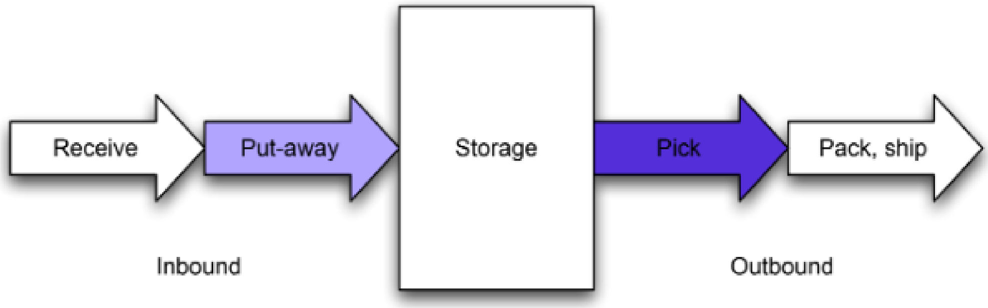

Figure 3: An overview of warehouse operations (Bartholdi and Hackman 2019)

The two primary functions of a warehouse are repacking and reorganizing products (Ten Hompel and Schmidt 2008). Often, products arrive in large quantities and need to be repacked into smaller units before leaving the warehouse(Bartholdi and Hackman 2019). Repacking is a crucial aspect of warehouse operations that can occur at various stages throughout the supply chain (Ten Hompel and Schmidt 2008).

Warehouse operations for reorganizing goods are typically divided into inbound and outbound processes (Ganbold et al. 2020a). Inbound processes include receiving and put-away, while outbound processes include order picking, checking, packing, and shipping. Generally, products should flow continuously through these processes in the specified order according to Bartholdi and Hackman (2019).

Inbound activities

Inbound activities in the warehouse begin with the arrival of shipments. The warehouse receives notification of the goods' arriving, enabling them to plan and coordinate the receiving activities with other warehouse operations in advance (Ganbold et al. 2020a). Typically, warehouses schedule truck arrivals within a 30-minute time window (Bartholdi and Hackman 2019).

Upon docking, pallets containing products are unloaded and placed in the inbound staging area (Bartholdi and Hackman 2019). From there, they are transported to the sorting workstation, utilizing a forklift or similar equipment. The products undergo manual counting, inspection for defects and damage, and then proceed to the goods receipt (GR) workstation (Ganbold et al. 2020a). At the GR station, workers scan the bar code or RFID of the products which are registered into the WMS, and inspections are conducted to identify any exceptions, such as damage, incorrect amounts, or other errors, which are noted and handled accordingly (Bartholdi and Hackman 2019). Putaway slips with storage bin information are generated for each pallet load (Ganbold et al. 2020a).

The WMS typically determines the storage location in advance using a specific storage policy (Bartholdi and Hackman 2019). After the goods receipt process, the products are ready to be put away in the designated storage area(s). A putaway worker follows the storage bin information on the putaway slip to place the pallet in its designated storage area (Bartholdi and Hackman 2019). This putaway activity marks the completion of the inbound process (Ganbold et al. 2020a).

Outbound activities

Outbound activities begin when order information is received in the WMS, and a pick slip is generated for each order (Ganbold et al. 2020a). Each pick slip is assigned to a picker. If the order picking involves large units such as pallets, it is typically automated, but if it involves smaller items, it requires more labor and time (Kay 2015).

Once the order picking process is finished, the items may require labeling before scanning (Bartholdi and Hackman 2019). If labeling is not necessary, the picked items are sent to the scanning station. There are two types of scanning methods: manual scanning and scanning through an auto-scanning tunnel (Ganbold et al. 2020a). The scanning activity ensures that all the items are matched against the order lists, and it generates slips that indicate items requiring packing together based on pallet or case dimension constraints (Ganbold et al. 2020a).

The picking lists contain details such as the type and quantity of goods and their storage locations (Bartholdi and Hackman 2019). Order picking includes traveling to and from storage locations, searching for the item to be picked, extracting the item from its storage location, and completing paperwork and other administrative tasks (Bartholdi and Hackman 2019). Order picking is an expensive and time-consuming process, accounting for up to 55% of total warehouse operating costs and 55% of the time allocated to warehouse activities (Valle et al. 2017).

The items are then packed into pallets and cases accordingly and a release worker transports the completed order to the outbound area (Ganbold et al. 2020a). From there, the order is loaded onto an outbound truck for shipment (Ganbold et al. 2020a). Shipping typically deals with larger units than picking, such as pallets and cases, resulting in less time and labor-intensive activities compared to the other warehouse processes (Bartholdi and Hackman 2019).

The outbound operations often face time constraints due to their customers' preference for just-in-time operations, necessitating deliveries on short notice (Bartholdi and Hackman 2019). On the other hand, their inbound processes experience comparatively less time pressure, as incoming goods are usually stored as safety stock without the need for individual handling, except in the case of cross-docked goods (Ganbold et al. 2020a). To ensure seamless operations, these warehouses must be flexible in managing their workforce to accommodate rapid demand fluctuations (Ganbold et al. 2020a). Accurate short-term workload forecasting and efficient labor management are therefore crucial in adapting to these dynamic conditions (Van Gils et al. 2017).

3.1.2 Warehouse strategies

To optimize warehouse operations, companies must strive to achieve high levels of accuracy, efficiency, and productivity (Shah and Khanzode 2017). To achieve this different strategies can be applied as seen in figure 4, 5, and 6. It is also essential to optimize warehouse layout and design by ensuring the efficient flow of goods within the warehouse (Shah and Khanzode 2017). This can involve using techniques such as ABC analysis to classify products based on their demand and value, and then assigning appropriate storage locations and retrieval methods based on those classifications (Bartholdi and Hackman 2019). Additionally, utilizing vertical space and implementing automated systems such as conveyors, sorters, and robots can help to increase efficiency and reduce labor costs (Karasek 2013).

Figure 4: Strategy 1 for transitioning materials through the warehouse adapted from (Kłodawski et al. 2017)

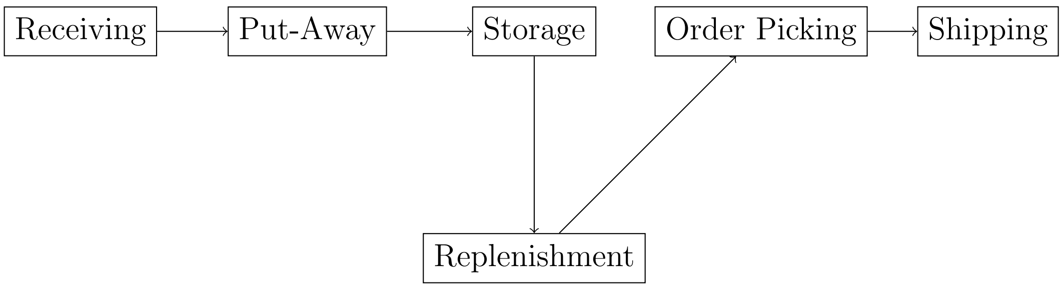

Figure 5: Strategy 2 for transitioning materials through the warehouse adapted from (Kłodawski et al. 2017)

Figure 6: Strategy 3 for transitioning materials through the warehouse adapted from (Kłodawski et al. 2017)

Stochastic models such as renewal processes, Markov models, and Martingale models are commonly employed for analyzing and evaluating warehouse operations (Kłodawski et al. 2017). These models enable the examination of various aspects related to the performance and efficiency of the warehouse (Kłodawski et al. 2017). By utilizing these models, it becomes possible to assess different operational scenarios and make informed decisions for improving warehouse processes. Additionally, these models facilitate the testing of different strategies and interventions to enhance overall warehouse performance (Kłodawski et al. 2017).

Warehouse operations can also benefit from the use of technology, such as warehouse management systems (WMS) and automation tools (Wruck et al. 2017). WMS can provide real-time visibility into inventory levels and streamline order fulfillment processes, while automation tools can help reduce manual labor and improve accuracy (Frazelle 2016).

3.1.3 Warehouse management

Warehouse management involves the planing and control of essential activities and operations mentioned earlier to ensure the smooth functioning of a warehouse (Ten Hompel and Schmidt 2008). While planning entails determining what actions should be taken and how they should be executed, control is the process of ensuring that the intended outcomes, as defined in the plan, are successfully achieved (Faber, M. De Koster et al. 2013). Especially storage and order picking are complex and frequently labor-intensive processes that significantly impact the overall performance of a warehouse (Faber, M. De Koster et al. 2013).

Efficient warehouse management enhances business productivity and efficiency, reduces expenses, and enhances customer satisfaction (Ten Hompel and Schmidt 2008). The structure of Warehouse management directly influences the decision-making process regarding material flow and resource utilization (space, equipment, and labor) within a warehouse on a daily basis (Faber, R. B. De Koster et al. 2018). Faber, R. B. De Koster et al. (2018) defines the structure of warehouse management as a blueprint of how warehouse management processes, including planning, optimization, and control, are formally organized and implemented.

One essential aspect of warehouse management is inventory management, which involves tracking and controlling the movement of goods within the warehouse (Bartholdi and Hackman 2019). Effective inventory management can help reduce stockouts, improve order fulfillment rates, and optimize storage space utilization according to Bowersox et al. (2013).

Warehouse management may also track resource utilization to identify potential bottlenecks in capacity (Ten Hompel and Schmidt 2008). By tracking resource utilization over time, warehouses can identify areas where capacity may be limited and make adjustments to improve efficiency and utilization (Ladier et al. 2014).

3.1.4 Summary

This section highlights the importance of warehouses as temporary storage facilities for goods in the supply chain. Warehouses mitigate uncertainty and variability in the supply chain by buffering stock, reducing the risk of disruptions. However, maintaining inventory or excess capacity comes with associated costs, requiring careful balancing of benefits and costs. Accurate short-term workload forecasting and efficient labor management are crucial to adapting to dynamic demand fluctuations.

3.2 Warehouse management systems

A warehouse management system (WMS) is a software application specifically designed to efficiently manage and coordinate the diverse activities and tasks associated with warehouse operations (Ramaa et al. 2012). It provides a centralized platform for managing inventory, optimizing storage space, tracking shipments, and improving order accuracy using features such as real-time inventory tracking, order and shipping management, and the ability to generate reports and analytics (Mao et al. 2018). WMS systems provide real-time data on inventory levels and usage patterns that helps organizations make informed decisions about their warehouse operations, reducing errors, increasing efficiency and ultimately improving their bottom line (Ten Hompel and Schmidt 2008).

The goal of a WMS is to ensure that all relevant information is consistently accessible or automatically gathered (Ten Hompel and Schmidt 2008). Capturing and utilizing the necessary data effectively is a crucial responsibility for logistics service providers (Andiyappillai 2019a). It enables them to address the challenges posed by faster product cycles, dynamic market behavior, high customer expectations, and cost optimization (Andiyappillai 2019a). This also leads to a reduction in errors and overstocks which reduces costs and increases the efficiency of the warehouse (Richards 2017). By ensuring timely and accurate order fulfillment the WMS also supports a high customer service level (Pannu 2021).

Another benefit of WMS systems is their ability to track shipments from the warehouse to the customer (Andiyappillai 2019a). With real-time tracking information, organizations can provide accurate delivery estimates to customers improving customer satisfaction (Ramaa et al. 2012). WMS systems can also improve order accuracy by automating the picking and packing processes, reducing errors, and improving overall efficiency (Ten Hompel and Schmidt 2008).

WMS Benefits
- Real-time stock visibility and traceability
- Improved productivity
- Accurate stock
- Reduction in picking errors
- Automatic replenishment
- Reductions in returns
- Accurate reporting
- Improved responsiveness
- Remote data visibility
- Improved customer service
- Reduction of paperwork

Table 4: The potential benefits of having a WMS in place (Richards 2017)

WMS are interconnected with various systems within a company (Andiyappillai 2019a). These systems include merchandising systems, information systems, production and enterprise resource planning systems, material flow and warehouse controlling systems, and other systems relevant to business-to-business or business-to-consumer operations (Karasek 2013). These interfaces allow for seamless integration and coordination between different aspects of the business, enabling efficient warehouse optimization (Karasek 2013). The data stored in a WMS can originate from various sources and remain accessible as long as required by the business (Andiyappillai 2019a). As the complexity of a business and the sophistication of the WMS increase, a greater volume of data can be extracted and analyzed to derive expected benefits in logistics and supply chain operations (Andiyappillai 2019a). se på plassering

3.2.1 Implementation of a Warehouse management system

Many types of WMS are available on the market, each with its own set of features and capabilities (Richards 2017). These systems are designed to work with a wide range of industries, from retail and e-commerce to manufacturing and distribution (Andiyappillai 2019b). To achieve a successful implementation of a WMS, it is necessary to complete the key components or milestones as depicted in Figure 7. WMS is often integrated with other systems and therefore the integration of Electronic data interchange (EDI) is vital in ensuring smooth communication flow through the different channels (Andiyappillai 2019b).

Figure 7: A model for successful implementation of WMS (Andiyappillai 2019b)

Implementing the right WMS is essential for optimizing warehouse operations (Richards 2017). The ideal WMS should simplify processes rather than complicate them, providing an intuitive and well-built application (Panday 2012). The study of Andiyappillai (2020) showed how successful implementation of a WMS led to a decrease in errors, and an increase in productivity, employee and customer satisfaction. Additionally, a robust WMS can efficiently manage seasonal employment, enabling temporary workers to quickly adapt during peak seasons (Panday 2012). Such a system should offer continuous tracking and visibility of the operations, achieving accuracy rates of 99% or more, reducing inventory shrinkage, and enhancing customer loyalty through timely shipments (Andiyappillai 2019b).

3.2.2 Warehouse metrics

Measuring warehouse metrics is crucial for providing managers with a clear understanding of potential issues and opportunities for improvement (Ramaa et al. 2012). These metrics are directly linked to the organization's business strategy, and the success of warehouse operations significantly impacts the financial results of the entire organization (Ramaa et al. 2012). To contribute value to the supply chain, warehouses must measure their performance using precise metrics (Ramaa et al. 2012).

According to Ramaa et al. (2012) warehouse performance metrics can be categorized into three main areas: order fulfillment, inventory management, and warehouse productivity. Establishing metrics to audit warehouse performance and assessing the potential of a WMS as a basis for investment justification is an essential initial step in any WMS project (Caplice and Sheffi 1995). Identifying suitable areas for improvement can also serve as an initial justification to assess potential returns on investment (Ramaa et al. 2012). The metrics found in table 5 complement the mentioned process.

3.2.3 Summary

This chapter provides an overview of warehouse management systems (WMS) and their key features. The integration of WMS with other systems and usage of these provides organizations with real-time data on inventory levels and usage patterns, enabling them to make informed decisions and improve warehouse operations. Key metrics related to order fulfillment, inventory management, and warehouse productivity are used to measure and improve warehouse performance. Overall, WMS can clearly benefit businesses of all sizes, helping them enhance their supply chain management.

Category	**Measure**	**Definition**
Order Fulfillment	On-time delivery	Orders delivered on time
	Order fill rate	Orders filled completely on first shipment
	Order accuracy	Order picked, packed, shipped ideally
	Line accuracy	Lines picked, packed, shipped ideally
	Order cycle time	Time from order placed to shipment
	Perfect order	Orders delivered without changes, damage, or invoice errors
Inventory Management Measures	Inventory accuracy	Actual inventory quantity compared to system-reported quantity
	Damaged inventory	Damage measure as a percentage of inventory value
	Storage utilization	Occupied space as a % of max capacity
	Dock to stock time	Avg time from carrier arrival until the product is available for order picking
	Inventory visibility	Time from physical receipt to customer service notice of availability
Warehouse Productivity	Orders per hour	Avg nr of orders picked and packed per person-hour
	Lines per hour	Avg nr of order lines picked/packed per person-hour
	Items per hour	Avg nr of items picked/packed per person-hour
	Cost per order	Total warehousing costs Fixed: space, utilities, and depreciation; Variable: labor/supplies
	Cost as a % of sales	Total warehousing cost as a % of total sales

Table 5: Performance metrics for a warehouse adapted from (Ramaa et al. 2012)

3.3 Capacity planning

Capacity planning is an important process for warehouse management, as it helps to ensure that a warehouse can handle the expected workload and meet customer demands (Richards 2017). One of the most common methods of capacity planning is to analyze historical data to identify patterns and trends in demand (Qazi 2020; Sazvar et al. 2021). By analyzing data on order volume, inventory levels, and resource utilization over time, warehouses can identify periods of peak demand and adjust their capacity accordingly (Kim et al. 2018).

With the rise of new technologies, capacity planning can be done more effectively and efficiently (R. B. De Koster et al. 2017). With the increasing use of IoT (Internet of Things) devices in warehouses, real-time data can be collected and analyzed to provide more accurate and up-to-date information on inventory levels, order volume, and resource utilization (Mostafa et al. 2020). This real-time data typically gathered by the WMS can be used to identify potential bottlenecks, optimize resource allocation, and plan capacity on an operational level (Cognizant 2021).

Machine learning and AI (Artificial Intelligence) technologies can be used to analyze large amounts of data and identify patterns and trends that may not be apparent through traditional analysis (Spiliotis et al. 2020). By using these technologies, warehouses can make more accurate predictions about future demand and adjust capacity planning accordingly (Baryannis et al. 2019).

Automated storage and retrieval systems (AS/RS) can be used to optimize the use of storage space and increase throughput without requiring additional physical space (R. B. De Koster et al. 2017). By automating tasks such as order picking and storage, warehouses can increase their capacity and improve efficiency (Richards 2017). Robots can be used to perform tasks such as order picking and packing, while automation technologies can be used to optimize the flow of goods through the warehouse (Manen 2019).

An important part of capacity planning is the management of labor in warehouse operations. Several articles discuss the challenges of managing a large workforce in a warehouse environment, including scheduling, training, and performance tracking (Fowler et al. 2008; Kim et al. 2018; Min 2006; Richards 2017; Rodler 2010). According to a report by Riemann (2022), effective labor management is critical for maximizing the productivity of a warehouse workforce and can be achieved through the use of performance metrics and incentives. The results of Kim et al. (2018) study show how warehouse management over-forecasts order sizes and suggests a bias for picking and loading to increase labor efficiency.

Typically, long-term capacity planning is based on sales forecasts, which incorporate historical data and an estimated growth percentage (Sazvar et al. 2021). These planned sales figures are then translated into the necessary hours required to process orders, taking into account employee vacations (Kellermayr-Scheucher et al. 2023).

To anticipate potential bottlenecks in the future, some companies consider the use of temporary employees in the medium term (Gutelius and Theodore 2019). Duty rosters are created to assign employees to specific shifts and tasks. In Kellermayr-Scheucher et al. (2023) survey companies mention monthly or weekly planning cycles. Additionally, last-minute adjustments are made on the respective day or week to determine worker availability and absences. This detailed planning may involve reassigning employees to different work areas at short notice (Kellermayr-Scheucher et al. 2023).

3.3.1 Capacity modeling

Capacity modeling involves using simulation models to predict future capacity requirements based on different scenarios (Gong and R. B. De Koster 2011). By simulating different factors such as order volume, product mix, and resource allocation, warehouse managers can make informed capacity planning decisions (Freile et al. 2020).

To tackle the uncertainty in labor demands, stochastic models are commonly employed in the literature to address staffing problems (Wruck et al. 2017). Sadjadi et al. (2011) focus on a period-wise staffing problem that involves hiring and layoff policies. Their objective is to minimize costs associated with hiring, layoff, labor shortages, and surpluses. Bard et al. (2007) develop a two-stage stochastic problem that incorporates recourse decisions. The first-stage decisions include full-time labor allocations and the amount of part-time labor, while the second-stage decisions involve the specific assignment of part-time employees to the schedule, with potential shortages managed through flexible labor. Liao et al. (2012) aim to maintain a constant staffing level throughout the planning horizon by incorporating uncertainty using random mean arrival times.

In situations where the system is highly sensitive to data variations, it becomes crucial to utilize sophisticated approaches (Wruck et al. 2017). Staffing policies that solely consider the "mean case" may not deliver satisfactory performance for most scenarios (Wruck et al. 2017). But caution is advised as the presence of forecast bias has been determined to lead to substantially higher organizational costs compared to forecast standard deviation (Nada R. Sanders and Graman 2009). Therefore, the varying and unpredictable demand patterns in warehouses emphasize the need for risk aversion tools (Wruck et al. 2017).

Bard et al. (2007) demonstrate in their work on staff scheduling in mail processing that allowing recourse decisions during the planning horizon can lead to 4% lower costs compared to solely optimizing expectations for the entire time horizon. Wruck et al. (2015) states that multistage stochastic models are a better solution for handling uncertainties in staffing problems.

3.3.2 Decision making in capacity planning

To make informed decisions in warehouse capacity planning, decision-makers must consider various available information (Kellermayr-Scheucher et al. 2023). As mentioned this includes analyzing historical data to accurately forecast future demand and adjust capacity accordingly. Understanding order volume, customer demand, and seasonal trends aids in making accurate predictions (Kim 2018).

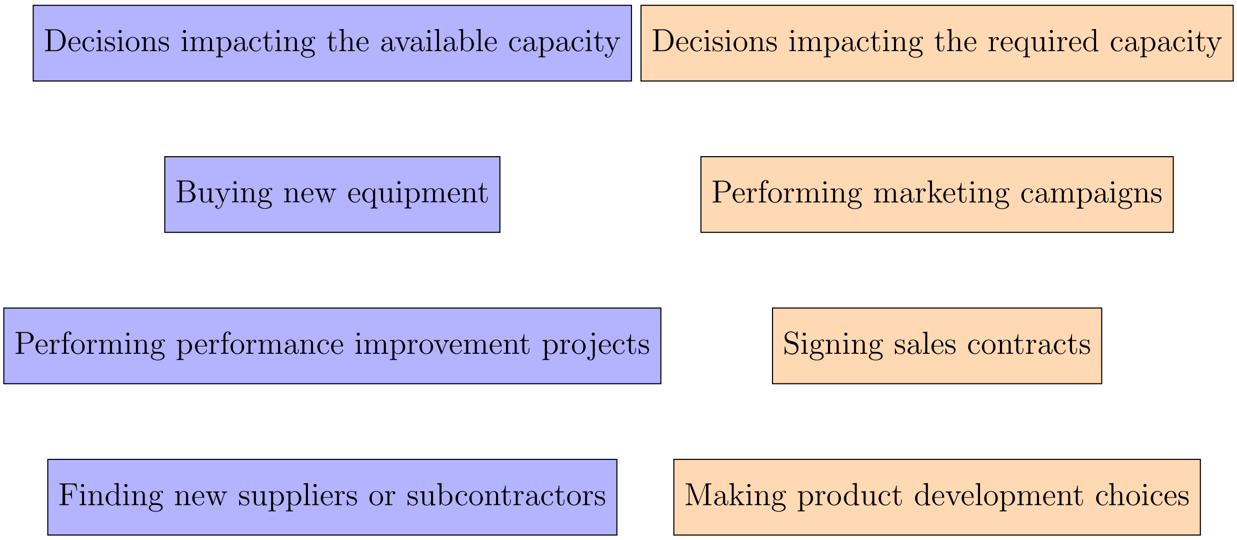

Figure 8: Decisions impacting the available or required capacity adapted from (Oger 2019)

Furthermore, decision-makers must have real-time knowledge of current inventory levels to assess the warehouse's capacity (Kellermayr-Scheucher et al. 2023). Resource utilization metrics, encompassing labor hours, equipment usage, and storage space utilization, which can be gathered from the WMS, are essential for identifying areas where capacity may be constrained and for implementing necessary improvements (Richards 2017). Considering future demand projections is equally important, as decision-makers require insights into market trends, sales forecasts, and other relevant data to anticipate future capacity requirements (Kellermayr-Scheucher et al. 2023).

Budgetary constraints must also be taken into account, as decision-makers need to understand any financial limitations that might restrict investments in new equipment or expansion initiatives (Fattahi et al. 2015). Finally, regulatory compliance plays a critical role, and decision-makers need to stay informed about any capacity planning regulations or labor laws specific to their industry and location (Friemann and Schönsleben 2016).

3.3.3 Labor management

A critical element of capacity planning is labor or workforce management, which involves managing employee schedules, training, and performance (Kellermayr-Scheucher et al. 2023). By utilizing labor management systems (LMS) or workforce management systems, companies can track employee productivity and identify areas for improvement (Mizrahi 2013). The system will gather all relevant data into a single location, allowing supervisors and team leads to more accurately anticipate the necessary number of employees to assign based on demand (Fernandes et al. 2020).

The primary objective of a labor management system is to determine the necessary number of operators for a projected workload on a specific day and allocate them to individual shifts (Rodler 2010). To accomplish this, it is crucial to measure and analyze the performance of operators in order to gauge their average work capacity within a given time frame (Gunasekaran et al. 2001). We previously saw the different performance metrics in table 5.

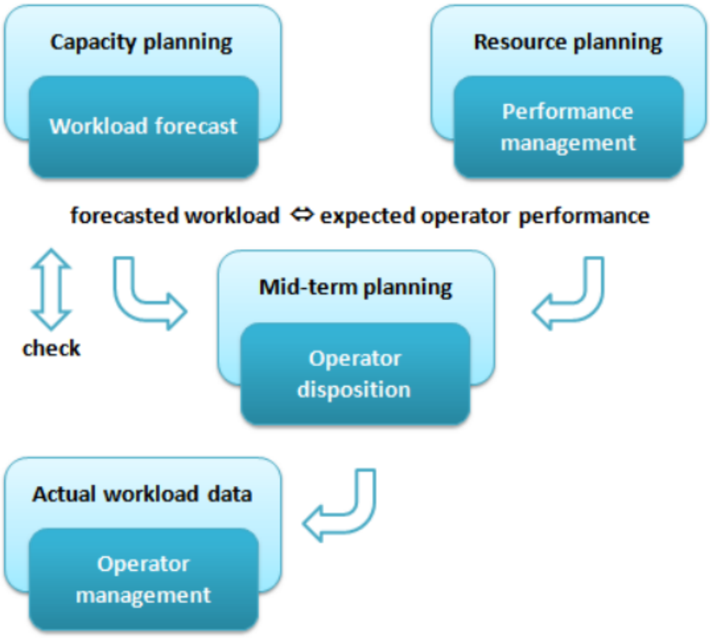

Figure 9: Modules for labor management (Rodler 2010)

According to the study of Rodler (2010) such a system must be developed step-wise or as different modules in the WMS. He suggests performance must be measured and analyzed first. Then he argues the expected workload needs to be forecasted based on historical data analysis. The results from these two modules need to be combined to calculate the required number of operators and suggest the optimal allocation of operators throughout the day, considering expected workload fluctuations (Rodler 2010).

Module	**Objective**	**Input**	**Output**
Performance	Calculate average performance per operator and hour	- Operator ID - Operator type - Date - Calendar week - Weekday - Hour of the day - Nr of units handled by each operator	Average performance per operator, average performance per operator type
Forecast	Estimate future workload situation for a specific week, day, and hour of the day	- Nr of processed units per hour - Date - Weekday - Calendar week - Hour of the day -Promotion adjustment	Workload forecast, Refinement of the workload forecast on a daily and hourly level, Presentation of both the typical weekly and daily workload patterns to the user.
Workforce disposition	Determine number of operators needed for a specific warehouse process and optimize the allocation of operators based on expected workload fluctuations	- Operator type - Shift pattern - Average performance values per operator type - Workload estimates	Weekly plan indicating the number of operators needed per shift for each type of operator
Operational planning	Present overview of possible scenarios based on the actual data available in the morning.	- Workload data - Average performance data	Divergence between forecasted and actual data, calculate possible scenarios and present them as a basis for decision-making, compare the workloads of all processes, and identify any employees who can be assigned to other processes.

Table 6: Process of determining required capacity (Rodler 2010)

3.3.4 Capacity planning strategies

Flexible planning

In situations where there is a sharp decrease in demand, there may be an excess of personnel capacity (Chopra and Sodhi 2004). In such cases, it becomes necessary to consider changes in capacity planning strategies (Martínez-Costa et al. 2014). Companies strive to plan their employees with fixed contracts in a flexible manner within the confines of their contractual agreements regarding hours and days off (Leeuw and Vincent C.S. Wiers 2015).

Flexible planning of standard contracts can be implemented through various approaches. One approach involves establishing a certain number of annual worked hours that can be flexibly distributed throughout the year (Leeuw and Vincent C.S. Wiers 2015). Alternatively, individual schedules can be adopted, where teams are divided into smaller subgroups that can adjust the duration of their work shifts (Leeuw and Vincent C.S. Wiers 2015). Flexibility can also be achieved by taking demand into account when scheduling holidays and non-working days (Stolletz 2010). Additionally, companies may choose to provide flexibility in employees' start times or offer flexibility in the number of hours they need to work within a given period (Stolletz 2010).

Implementing such flexible planning methods not only allows for accommodating changes in demand but also helps in achieving a better balance between personnel supply and demand (Leeuw and Vincent C.S. Wiers 2015). It can lead to reduced overtime, improved employee utilization, and quicker response times to customer needs (Martínez-Costa et al. 2014). Flexible planning also benefits employees by promoting a better work-life balance, which, in turn, can enhance job satisfaction and potentially reduce absenteeism, resulting in increased employee productivity (Autry and Daugherty 2003). As Leeuw and Vincent C.S. Wiers (2015) states "The more a company applies flexible planning in a warehouse the higher the utilization rate and productivity and the lower absenteeism and overtime."

Job rotation

Job rotation refers to the systematic movement of employees from one job to another (Malinski 2002). This practice requires employees to be competent in multiple tasks within a warehouse, making them multi-skilled (Leeuw and Vincent C.S. Wiers 2015). Many companies recognize its importance in fostering a dynamic, productive, and satisfied workforce, particularly during turbulent market conditions that demand flexibility (Collinson 2001).

One of the advantages of job rotation is that it introduces a more diverse workload for workers. As a result, boredom, work stress, and job absence tend to decrease (Michalos et al. 2010). Additionally, job rotation enables the fulfillment of orders with fewer employees, as multiple individuals can handle each process (Leeuw and Vincent C.S. Wiers 2015). This practice also fosters innovation, productivity, and loyalty among employees (Michalos et al. 2010). More usage of job rotation in warehouses leads to higher utilization rates and productivity of employees and lower rates of absenteeism (Leeuw and Vincent C.S. Wiers 2015).

However, in warehouse settings, job rotation may not always be feasible due to specific skill requirements (Ada et al. 2021). For example, not every employee may possess the ability to operate a forklift or handle incoming goods (Van den Berg 2007). Moreover, experienced and older staff members are often accustomed to their routines and are more likely to resist changes and learning new job skills (Leeuw and Vincent C.S. Wiers 2015).

Workload balancing

Workload balancing involves the strategic shifting of workloads between busy and quiet days, allowing for a reduction in overtime and idle times (Van den Berg 2007). By effectively managing the distribution of tasks, employees experience improved mood, enhanced physical fitness, reduced work stress, boredom, and job absenteeism (Jurkowiak et al. 2001). Additionally, workload balancing helps minimize costs associated with overtime and temporary staff (Leeuw and Vincent C.S. Wiers 2015).

However, during periods of highly fluctuating demand, calculating and implementing workload balancing can be challenging (Leeuw and Vincent C.S. Wiers 2015). Quick responsiveness to changing demands can be achieved through collaboration with clients and effective planning within the warehouse (Van den Berg 2007).

Enhancing collaboration in inbound processes, initiated by the arrival of goods, can help achieve workload balancing (Van den Berg 2007). For instance, warehouses have implemented time slots for incoming trucks, ensuring an available dock during specific times (Leeuw and Vincent C.S. Wiers 2015). This efficient operation reduces waiting times for suppliers, if they arrive on time, and prevents an imbalanced workload for warehouse employees (Boysen et al. 2010).

Distinguishing between immediate tasks and those that can be completed over a longer period, such as certain value-added activities, allows for further workload balancing (Leeuw and Vincent C.S. Wiers 2015). Postponing certain orders helps achieve balance, but it requires dedicated space in the staging area of the warehouse for both postponed and already picked orders (Van den Berg 2007).

3.3.5 Summary

This chapter highlights the importance of capacity planning in warehouse management. By considering the mentioned factors, decision-makers can make well-informed decisions in warehouse capacity planning, ensuring optimal utilization of resources and meeting operational demand. In situations of changing demand, flexible capacity planning strategies are necessary to accommodate changes and optimize personnel utilization. This enables them to maximize the utilization of resources while also meeting operational requirements, leading to optimal efficiency in warehouse operations.

3.4 Planning decisions

Based on the previous section, it is evident that planning capacity involves numerous interconnected decisions. In this section, I aim to organize these decisions within a hierarchical framework. Furthermore, I explore several performance criteria that can be used to assess different design alternatives.

3.4.1 Strategic planning

When making strategic decisions, the focus is on choices that have long-term implications, especially those involving significant investments (Rouwenhorst et al. 2000). These decisions primarily revolve around designing the flow of processes and selecting appropriate warehousing systems (Frazelle 2016).

At the strategic level, selecting the types of warehouse systems encompasses various systems that require substantial investments, including storage and sorting systems (Gu et al. 2007). The selection process can be divided into two sequential decision problems: one based on technical capabilities and the other based on economic considerations (Rouwenhorst et al. 2000).

In the first problem the storage unit, storage systems, and equipment must be suitable for the products and orders without conflicting with each other (Rouwenhorst et al. 2000). This warehouse design problem addresses both process flow design and the selection of the main warehouse system types (De Leeuw and Vincent CS Wiers 2015).

Input for this problem includes product and order characteristics, and the output identifies technically feasible combinations of warehouse systems that meet performance requirements (Rouwenhorst et al. 2000). Rather than providing a specific system or a few alternatives, the goal is to determine a limited number of possible combinations of warehouse systems that satisfy technical and performance criteria (e.g., throughput, response times, and storage capacity) (Rouwenhorst et al. 2000).

The second warehouse design problem focuses on process flow design and warehouse system selection based on economic considerations (Rouwenhorst et al. 2000). The objective of this optimization process is to minimize investment and operational costs within the range of system combinations determined in the previous phase (Rouwenhorst et al. 2000). It's important to recognize that each individual decision at this level imposes constraints and additional requirements on lower-level decisions (Rouwenhorst et al. 2000).

Several observations can be made regarding the relationships between these decisions:

Factor	Influence
Warehouse Investment Costs	Primarily depend on the number of resources.
Warehouse Storage Capacity	Mainly determined by the type and dimensions of the storage system. Storage policy (dedicated storage, class-based storage, or random storage) has a minor role.
Maximum Warehouse Throughput	Influenced by the type and dimensions of resources, as well as other factors such as the decision to have a separate reserve area, storage policy, batch policy, routing policy, and assignment policies (personnel, equipment, and docks).
Warehouse Response Time	Influenced by factors related to maximum throughput, but also affected by other organizational decisions like zoning policy, sorting policy, and dwell point policy.

Table 7: Factors Influencing Warehouse Operations adapted from (Rouwenhorst et al. 2000)

3.4.2 Tactical Planning

Tactical planning is a crucial activity that serves as a bridge between strategic planning and operations control (Carvalho et al. 2017). It involves solving the fundamental issue of allocating resources, including capacity, workforce availability, and storage, over a medium-range planning horizon (Bushuev 2014). Due to the constantly changing and fast-paced nature of the environment, many warehouses have a tactical planning horizon that is limited to days or weeks, rather than extending to months(Faber, M. De Koster et al. 2013).

This middle-level activity plays a critical role in ensuring efficient and effective operations within an organization (Bushuev 2014). During this level of planning, decisions regarding the acceptance or rejection of projects are made, and it is crucial to employ adequate capacity planning methods to assess the consequences of these decisions for the warehouse (Aslan et al. 2012; Zorzini et al. 2008).

Unfortunately, it is common for organizations to accept projects without adequately assessing their impact on resource capacity (Aslan et al. 2012). This can result in either resource shortage or overload, which can have negative effects on delivery performance and the profitability of the warehouse (Carvalho et al. 2017). Therefore, it is essential to carefully evaluate project acceptance decisions at this planning level to ensure optimal resource utilization and warehouse performance (Hans et al. 2007). The process of creating tactical plans can be time-consuming and should only be undertaken if they result in measurable performance enhancements (Faber, M. De

Koster et al. 2013).

Warehouse organizations face significant planning complexity, requiring the planning process to be broken down into more manageable components (Rouwenhorst et al. 2000). A model for hierarchical planning and control, based on three managerial decision levels (strategic, tactical, and operational), can aid in this process (Hans et al. 2007). To perform multi-project planning effectively, it is necessary to consider projects simultaneously at all planning levels, while also taking into account the varying objectives, constraints, degrees of aggregation, and capacity flexibility associated with each level (Hans et al. 2007).

Rouwenhorst et al. (2000) provides a framework and a classification for decisions in these three levels. The framework contains the tactical level which involves determining the dimensions of systems and their layout within a time frame of up to 2 years. Detailed control policies are generally categorized as operational decisions and affect the warehouses day to day operations (up to 1 year) (Rouwenhorst et al. 2000). However, it is important to note that most decisions are interrelated, and the hierarchical framework outlined in figure 10 reflects the horizon of the decisions (long-term, medium-term, short-term). Solutions chosen at a higher level provide constraints for lower-level design problems (Rouwenhorst et al. 2000).

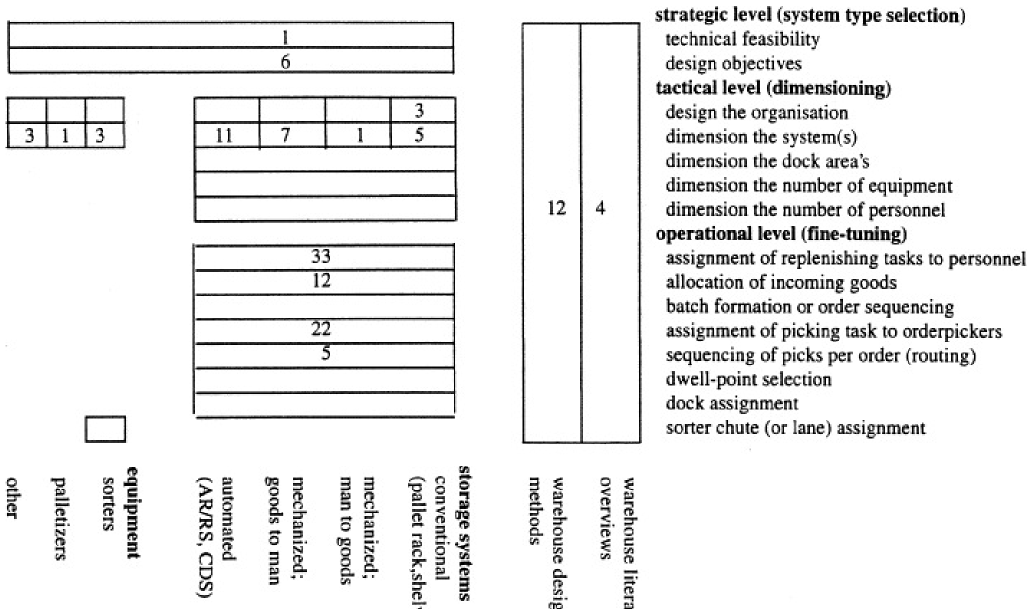

Figure 10: An overview of the classification (Rouwenhorst et al. 2000)

Tactical uncertainties in warehouse operations can arise from both internal and external sources within the supply chain(Gong and R. B. De Koster 2011). External sources include economic volatility, changes in resource costs, and labor availability (Chopra and Sodhi 2004). Meanwhile, internal uncertainties can stem from preemptive equipment maintenance and labor disputes (Gong and R. B. De Koster 2011). One common example of internal uncertainty is the Bullwhip effect, which can cause significant problems in warehouses (Chen and Lee 2012). This effect refers to how small changes in customer demand can result in amplified demand and inventory level fluctuations upstream in the supply chain (Chen and Lee 2012). As

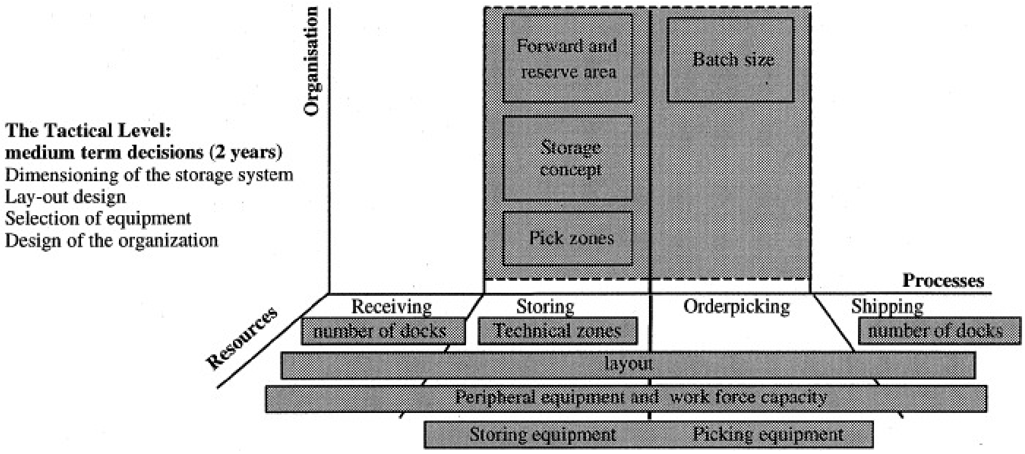

Figure 11: Design problems for the tactical level (Rouwenhorst et al. 2000)

Mangan and Lalwani (2016) noted, controlling the Bullwhip effect can lead to more effective and efficient warehouse operations.

To mitigate the Bullwhip effect, the study of Grean and Shaw (2008) shows how Wal-Mart has implemented measures to improve visibility of customer demand and inventory movement throughout their supply chain. This involves transmitting point-of-sale data from individual stores to the corporate information center multiple times a day and sharing the information with manufacturers such as Procter and Gamble. This approach helps to schedule shipments among Wal-Mart's distribution centers, stores, and suppliers' warehouses. As a result, the operations of the distribution centers are improved (Gong and R. B. De Koster 2011).

3.4.3 Operational planning

Operational planning involves sequencing, scheduling, routing of order picking, storage/retrieval operations, and making immediate adjustments and short-term decisions to assign workers to meet demand (Faber, M. De Koster et al. 2013). These decisions are typically made within a timeframe of days or weeks, depending on the planning horizon (Janssen 2015).

Within the operational level, processes must adhere to the constraints established by strategic and tactical decisions made at higher levels (Rouwenhorst et al. 2000). As the interfaces between different processes are typically addressed during the design phase at the strategic and tactical levels, this implies that policies at the operational level have less interdependence and can be analyzed independently (Rouwenhorst et al. 2000). The primary decisions at this level pertain to the assignment and control of personnel and equipment (Rouwenhorst et al. 2000). Furthermore, the assignment of arriving and departing trucks to docks is another control decision made at the operational level (Janssen 2015).

The design problems encountered at the operational level are represented in figure 12:

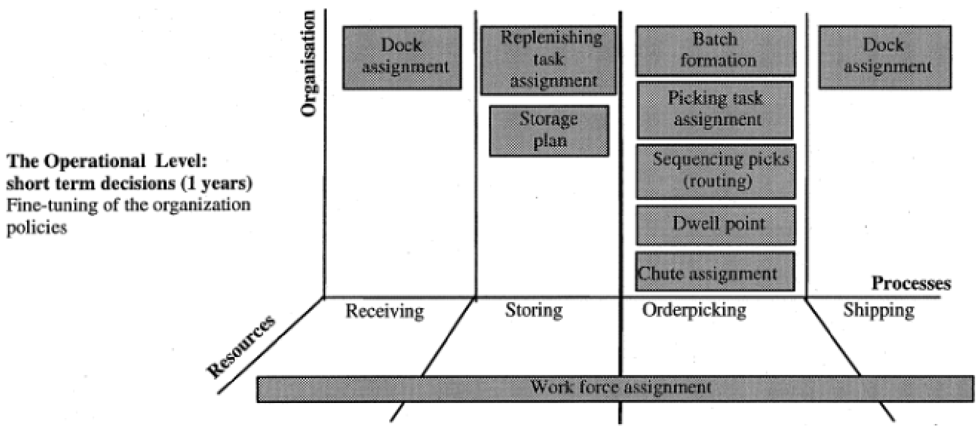

Figure 12: The operational level (Rouwenhorst et al. 2000)

Even with the perfect plan in place, unexpected events may still occur (Slack et al. 2010). Daily planing encounters uncertainties arising from equipment failures and facility maintenance (Gong and R. B. De Koster 2011). Traffic can cause shipment delays or staff sickness can cause labor shortages. Operational control is the ongoing process of adapting and managing these changes effectively (Slack et al. 2010).

By closely monitoring the actual operations and making necessary adjustments, control ensures that operations align with the objectives outlined in the plan, enabling the achievement of desired outcomes(Slack et al. 2010). Therefore, the core functions of operational control involve monitoring, analyzing, reporting, and taking necessary interventions (Faber, M. De Koster et al. 2013).

In order to effectively respond to deviations and changes, there is a limited time available making the speed at which data is transformed into actionable information essential (Faber, M. De Koster et al. 2013). The provision of accurate and timely information from the shop floor is crucial for effectively controlling operations (Faber, M. De Koster et al. 2013).

3.5 Big data as decision support

As seen in the previous section operational planning relies on data being transformed into information for decision-making. This chapter explores the rise and usage of big data for supporting decision-makers in capacity planning.

In the era of big data, supply chain management is increasingly embracing data-driven decision-making as a replacement for traditional solutions (Li and Liu 2019). The availability of vast amounts of data has opened up new possibilities for analyzing and leveraging information to make informed decisions and drive operational efficiency in supply chains (Kim 2018).

Companies are now using data analytics, machine learning, and predictive modeling techniques to extract valuable insights from the massive volume of data generated across the supply chain(Pournader et al. 2021). By leveraging data and analytics, supply chain professionals can make more informed decisions, mitigate risks, identify patterns and trends, and continuously improve performance (Janssen 2015). However, the traditional supply chain management strategies often impose limitations that hinder the full utilization of data (Li and Liu 2019).

In a study conducted by Gu et al. (2007), the decision-making process for warehouse operations strategies and policies is examined. The research involves a thorough analysis of scientific literature and proposes a classification based on the available information regarding incoming and outgoing shipments in the warehouse planning process. The study identifies three distinct scenarios for receiving and shipping operations:

Scenario 1: The operation planner has limited knowledge about incoming shipments, with no prior information about the contents until they arrive at the warehouse dock. Additionally, the demand is unknown, making it challenging to determine the most suitable storage policy for the given situation.

Scenario 2: The planner possesses partial statistical knowledge of incoming and outgoing shipments. This scenario is commonly encountered in supply chain warehouse planning. Historical data and possibly a demand forecast can be utilized to determine appropriate storage policies.

Scenario 3: The planner has access to perfect or nearly complete knowledge of incoming shipments' contents and outgoing order lists. This scenario enables detailed planning of warehouse operations and facilitates efficient allocation of goods to storage locations. Achieving this scenario requires enhanced collaboration across the supply chain through the use of information-gathering technologies and data exchange.

By considering these scenarios and the corresponding decision-making factors outlined in table 8, appropriate strategies can be developed for allocating resources effectively.

In the first scenario, where the operation planner has no prior knowledge other than the warehouse layout, decisions need to be made without knowledge of the incoming shipments or demand. This calls for strategies that can adapt to uncertain situations and optimize storage policies under such conditions (Gu et al. 2007).

In the second scenario, where the planner has partial statistical knowledge of incoming and outgoing shipments, historical information and demand forecasts can be utilized. This allows decision-makers to employ data-driven approaches to determine suitable storage policies that align with the anticipated demands (Gu et al. 2007).

The third scenario represents an ideal scenario where the planner has detailed knowledge of incoming shipments' contents and order lists of outgoing shipments. This level of information enables comprehensive planning of warehouse operations and facilitates precise assignment of goods to specific storage locations (Gu et al. 2007).

	Given
(1)	Information about incoming shipments, including their arrival time and contents.
(2)	Information about customer demands, such as orders and their expected shipping time.
(3)	Information about the layout of the warehouse dock and the available material handling resources.
	Determine
(1)	The assignment of inbound and outbound carriers to specific docks, which impacts the overall internal material flows within the warehouse.
(2)	The schedule for servicing carriers at each dock. This can be viewed as a machine-scheduling problem, where the arriving carriers are the jobs that need to be scheduled.
(3)	The allocation and dispatching of material handling resources, such as labor and equipment, to efficiently handle the operations.

Table 8: Basic decisions in warehouse operations (Gu et al. 2007)

Achieving this scenario requires enhanced supply chain collaboration and the utilization of advanced technologies for information gathering and exchange (Andiyappillai 2019b).

The study of Kim (2018) emphasizes the importance of data-driven warehouse management as a crucial factor in achieving efficiency in global supply chains. The rise of big data has led to data-driven smart manufacturing, offering both unprecedented challenges and opportunities for supply chain management (Li and Liu 2019). Embracing data analytics for decision-making can significantly reduce the inefficient allocation of resources within global supply chains (Kim 2018).

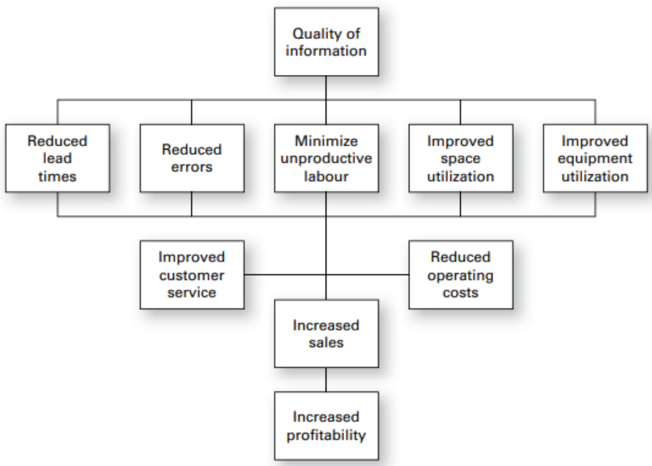

Figure 13: Advantages of quality information (Richards 2017)

Stage	Item	Volume	Velocity	Variety	Veracity	Value	Big data	Technology
Design & Develop	Consumer demand management	●	●	◑	◑	●	✓	POS, EDI
	Conceptual design	●	●	◑	●	●	✓	CAD, CAE
	Analysis of customer review	●	◑	◑	◑	◑		ROS, CRM
Purchasing	Source selection	●	◑	●	●	●	✓	EDI
	Contract management	◑	◑	◑	●	◑		
	Demand forecast	●	●	●	●	●	✓	EDI
	Collaborative purchasing	●	●	●	●	●	✓	EDI
Manufacturing	Production planning	●	●	◑	●	●	✓	EDI, ERP
	Quality control	●	●	●	●	●	✓	CAE, CAM, RF
	Efficiency management	●	◑	●	●	●	✓	CAD, CAPP, ERP
	Equipment management	◑	◑	●	●	◑		CPS
Logistics	Materials & Warehouse management	●	◑	●	●	●	✓	POS
	Transportation management	●	●	◑	●	●	✓	GIS, BC, RF
	Customer management	◑	●	◑	●	◑		
	Orders management	●	●	●	●	●	✓	CRM, EDI
Marketing & Sales	Market STP analysis	●	●	●	●	●	✓	POS
	Sales channel	◑	◑	◑	◑	◑		
	Brand management	●	●	●	●	●	✓	CRM
	User persona	●	●	●	●	●	✓	CRM
Customer service	Consulting service	●	◑	●	◑	◑		
	After-sales service	●	◑	●	●	●	✓	CRM, ERP, EDI

Figure 14: Big data useful for supply chain management (Li and Liu 2019)

Acronym	Full Form
PSD	Power Split Device
QS	Quick Response
POS	Point of Sale
CAD	Computer Aided Design
CAM	Computer Aided Manufacturing
CAE	Computer Aided Engineering
CRM	Customer Relationship Management
ERP	Enterprise Resource Planning
MRP	Material Requirements Planning
CAPP	Computer Aided Process Planning
BC	Binary-Coded Decimal
OEM	Original Equipment Manufacturer
NPI	New Product Introduction
EOL	End of Lifecycle
EC	Electric commerce technology
APS	Advanced Planning and Scheduling

Table 9: Acronyms and Full Forms

The complexity associated with order fulfillment often leads to inefficient utilization of labor (Kim 2018). To address this complexity, warehouses should adopt two approaches: first, by determining the optimal size of the labor force and incorporating a buffer to account for unpredictable variations in complex demand, and second, by designing efficient job sequences (Kim 2018).

Although numerous decision support models for warehouse operations have been proposed in the literature, their practical application still poses significant challenges (Gu et al. 2007).

4 Decision support tool for capacity planning

The primary objective of a capacity planning tool, specifically addressing short-term labor management, is to determine the number of operators required for a projected workload on a specific day and allocate them to individual shifts. To achieve this the proposed solution is a decision support tool to determine if the WMS has the needed functionality for capacity planning and can support operational planning for a specific warehouse scenario.

The tool incorporates the specification of the warehouse situation to provide clarity. By considering the impacts of uncertainties and constraints, the tool guides decisions on selecting the suitable planning strategy and calibrating it to meet the warehouse manager's specific needs.

The problem can be broken down into three distinct sub-problems based on the type of decision to be made. The first problem is assessing whether the WMS possesses the necessary functionality for capacity planning or if any modules must be added. This assessment is based on table 9 which also serves as guidance for implementing any missing modules. Step 1 of the tool accounts for this problem.

The second sub-problem involves capacity planning for a week, where the needed workforce is estimated, and how different tasks will be assigned to employees over the course of the week. The data in figure 14 and the functionalities described in table 6 serve as a basis for this step. As this is a tool meant for decision-support I do not go in-depth on how to perform the different calculations as the literature provides a lot of different approaches. The steps described in 2, 3, 4, and 5 are deemed necessary while steps 6,7 and 8 are optional but recommended for a more accurate capacity plan.

The third sub-problem is focused on operational planning during the day, where specific schedules are created and shifts are assigned to individual employees for a given day as described in 3.4.3. Adjustments to the initial capacity plan from the previous step are made based on real-time data. Throughout the day, planners have the ability to upscale or downscale the initial available capacity as needed, based on the available fallback plans. Accurate and timely information from the warehouse plays a critical role in effectively controlling operations.

By dividing the problem in this way, each decision can be addressed separately and the capacity planning can be optimized efficiently.

The three decisions are made in a sequential manner, where the output of each step serves as the input for the next. This sequential process ensures that each decision is based on the results and considerations of the previous step, creating a logical flow of information and actions. By structuring the decisions in this way, it's simple to effectively build upon the outcomes of each step and ensure a coherent and interconnected decision-making process.

4.1 Considerations

When building the decision-making tool, several factors should be considered: Firstly, historical data are required to create a reliable forecast. Secondly, the workload, derived from the forecast, needs to be allocated among different days based on demand percentages.

Thirdly, productivity targets are crucial to convert the workload per picking method into employee hours and determine the required workforce. The desired service level should also be taken into account to ensure labor capacity planning meets customer expectations.

Other factors that must be considered include promotions, seasonality, weather, holidays, or events sick leave, benefits, vacation, time compensation, and risk buffers. Factors that do not directly affect the workload are excluded.

4.2 Step-by-step explanation of the tool

Step 1: Asses WMS functionality

- Check if the WMS gathers the needed data for capacity planning and outputs the necessary rapports.
- If missing add the needed functionality.

Step 2: Define the Planning Horizon and Parameters

- Define the planning horizon (P) and fixed labor costs within that period.
- Specify variable costs (e.g., labor costs per hour) associated with workload assignment.
- Determine relevant values and parameters for the problem, such as constraints related to scheduling (e.g., multiple shifts, shift lengths, breaks).

Step 3: Gather and Analyze Historical Labor Data

- Collect historical data on key metrics, including order volumes, SKU data, labor productivity, and equipment utilization.
- Analyze the historical data to identify labor demand, potential shortages, trends, seasonality, and resource utilization.
- If no significant trends are observed, use a sufficiently large dataset to determine labor schedules for the future.
- If there are trends, employ an appropriate forecasting method that incorporates those trends to simulate future demands.

Step 4: Determine the workload

- Estimate the forecasted workload by considering factors such as order volume, the types of products being handled, and any seasonality or fluctuations in demand.
- there is a need to assess and analyze operator performance to understand the

average workload that a single operator can handle within a given time period.
- Determine the required skill sets of employees.

Step 5: Assess Resource Capacities

- Once the workload has been determined, decision-makers can estimate the number of employees needed to manage the workload.
- Consider factors such as the time required to process an order, the average number of orders per day or week, and the amount of time required for other tasks such as inventory management and equipment maintenance.
- Evaluate the current capacities of resources in the warehouse, such as storage space, equipment availability, and labor availability.
- The level of automation and technology used in the warehouse can also impact the number of employees needed.
- Consider any limitations or constraints associated with resources that may impact capacity planning decisions.

Step 6: Define Capacity Scenarios

- Develop different capacity scenarios based on potential changes in demand, operational processes, or resource allocation.
- Consider factors such as seasonal fluctuations, product launches, promotional campaigns, or changes in order profiles when creating scenarios.

Step 7: Simulate Capacity Requirements

- Utilize the gathered data and insights to simulate capacity requirements for each scenario.
- Assess the impact of each scenario on key metrics, such as order throughput, labor utilization, storage utilization, and customer service levels.

Step 8: Optimize Resource Allocation

- Determine the most efficient resource allocation strategies based on the simulated capacity requirements.
- Optimize labor allocation, equipment utilization, and storage space allocation to maximize efficiency and meet capacity demands.

Step 9: Identify available fallback plans

- Identify available options to address short-notice labor shortages, such as overtime, employing external labor, or postponement.
- Ensure that every labor shortage is accounted for and addressed.
- Define the costs and any limitations associated with each recourse option, considering constraints like overtime limits.

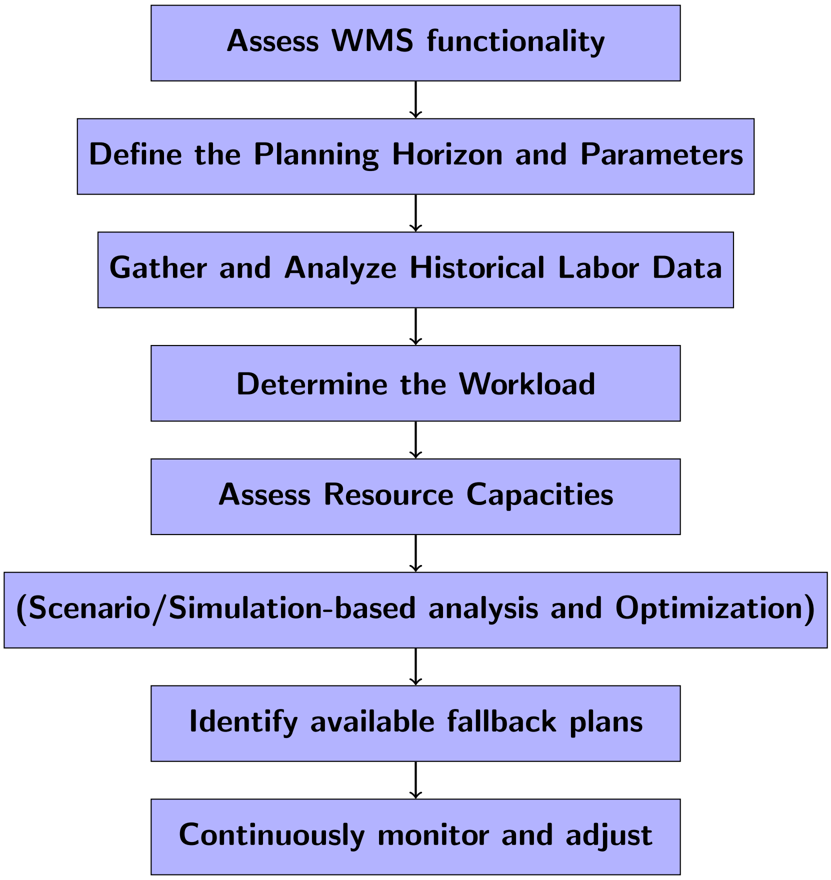

Figure 15: Decision support tool for operational capacity planning.

Step 10: Continuously monitor and adjust

- Even after determining the appropriate number of employees, decision-makers must continuously monitor the situation and adjust staffing levels as necessary.
- The strategies in section 3.3.5 can be utilized here.
- Consider skills of workers if necessary.

Figure 15 shows the proposed tool where steps 6,7 and 8 are gathered in scenario/simulation-based analysis and optimization.

5 Case study

The case study is of a retail company that operates a chain of grocery stores across Scandinavia. The company has established itself as one of the leading supermarket chains in the region. The company's core mission is to provide high-quality products at affordable prices, offering customers a wide range of choices in a convenient shopping experience. Efficient warehouse operations are crucial for any retail company, especially one this large and expansive.

This project focuses on capacity planning at a warehouse located in Trondheim, a city in central Norway. The Trondheim warehouse is 22000 sq meters and plays a pivotal role in supporting the company's regional distribution network, ensuring an efficient supply of products to 122 stores in and around Trondheim. With its strategic location, this warehouse acts as a vital link in the supply chain, serving as a critical distribution point for the region.

The main goal of the company is to deliver the best service at the lowest cost. In an interview with the warehouse manager having enough stock, delivering the right amount of high-quality products at the right time and at a low cost as well as predictability and flexibility were highlighted as the most important factors. Acting sustainably by filling up trucks and driving smart routes, acting responsibly by minimizing waste and preventing bad or infected goods from being sold, considering their worker's health, and having the right workforce at the right time were also mentioned as key values for the company.

The Norwegian grocery market stands out due to its unique structure, with three major companies Norgesgruppen (44%), COOP Norge (29.7%), and Rema 1000 (22.9%) controlling nearly the entire market (NielsenIQ 2022). Unlike many other markets that outsource logistics and distribution to third-party providers, the Norwegian grocery industry has chosen to maintain control over these operations. This decision allows them to streamline their supply chain as seen in figure 16. It also gives the company greater control over the flow of goods and information which gives them better opportunities to swiftly adapt to market changes and demand fluctuations (Vouzas and Katsogianni 2018). By coordinating logistics and distribution processes within their supply chains, the case company has successfully avoided the issue of increased complexity which is one of the biggest problems in supply chains of modern fast-moving consumer goods companies (Bala and D. Kumar 2011).

The company operates with its own dedicated wholesale and distribution service. In addition to its retail operations, the company is actively involved in the production of certain products. This centralized approach enables them to gather data across its entire supply chain, facilitating improved information flow and creating opportunities for further enhancements (Shamsuzzoha et al. 2020). However, it is worth noting that centralization also presents challenges, such as heightened complexity and the necessity for robust internal communication and coordination.

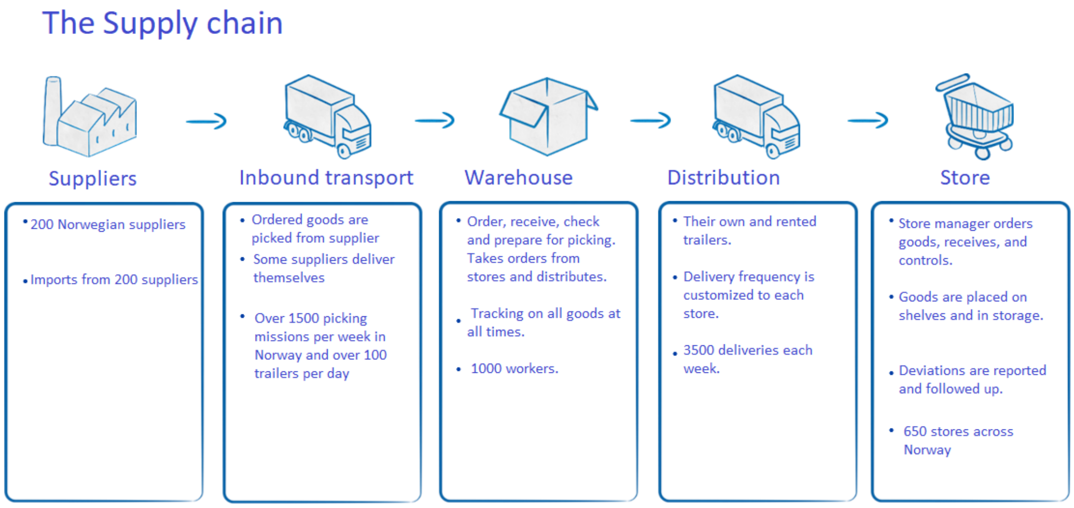

Figure 16: Supply chain of the case company

5.1 Warehouse operations

The warehouse receives shipments in the form of truckloads approximately 50 times a day. These truckloads are unloaded in the inbound areas, where the order information is uploaded to the WMS.

Incoming shipments from suppliers are unloaded in the inbound areas which the warehouse has two of to minimize distances. The contents are inspected for quality, quantity, and adherence to safety and regulatory standards. This involves verifying the condition of the shipment checking for any damage during transportation and counting that the right amount was received. The pallet comes with a bar code which is scanned into the WMS giving the system information on quantity and expiration dates. The WMS then assigns a specific storage location for the incoming goods. A warehouse operator is responsible for transporting the different SKUs to their respective assigned storage locations. The warehouse has three different forklifts for this purpose and the picking process which can hold one, two, and three pallets each.

During the storage process, various storage policies can be employed. The warehouse uses a mix of dedicated storage policy and correlated storage, which dictates that each product should be stored in a location predetermined by the WMS. The warehouse also uses a First in first out storage policy which is based on the shelf life of goods. Because the company operates as a chain from distribution and out to the stores the optimization of the storage process becomes limited.

Since the goods must be placed from pallets onto shelves in the stores, the warehouse has decided to group products with similar placements in the store. By picking products of similar characteristics at the same time they are also put on the pallet at the same time which means when they arrive at the stores retail workers spend less time traveling around placing the goods. This also helps reduce pallets cluttering the store as they spend less time on the floor. The warehouse manager argued that any time saved optimizing the product placement in the warehouse would be lost in the store and therefore not benefit the company as a whole.

Order-picking processes are more intricate and involve two main categories: picking mixed pallets and picking full pallets. Picking lists are generated based on customer orders and assigned to individual order pickers. The warehouse has a deadline for orders to make sure they have enough time to prepare the shipment. The stores wish to send in the orders as late as possible for increased control over their inventory while the warehouse prefers the orders as early as possible creating a dispute of interest. When picking full pallets, the order pickers retrieve entire pallets from their designated storage locations and transport them to the inbound and outbound areas.

On the other hand, when picking mixed pallets, order pickers are required to select cartons from various pallets and consolidate them together. The mixed pallets separate the different SKUs from each other on the pallets. The WMS chooses the best order to pick the goods and pickers are therefore unable to change the order. They can however utilize the space on the back of the forklift for building logical pallets. As stated by the warehouse manager the ideal solution would be to have all goods picked from the ground level, but due to the number of products in the warehouse assortment that is not possible. Before shipment, the mixed pallets need to be wrapped in plastic wrapping and labeled with new identifiers. Due to the additional tasks involved, picking mixed pallets is more labor-intensive compared to picking full pallets.

5.1.1 Warehouse layout

The warehouse is designed with aisles and storage racks to accommodate pallets. Three automated cranes are available for the movement of pallets within the warehouse transporting up to 60 pallets an hour each. The racks are arranged in an organized manner, allowing easy access for both the pickers and the automated cranes to retrieve and deposit pallets. This leads to a semi-automated warehouse seen in figure 17

The warehouse is separated into 3 sections; dry, cold and frozen goods as seen in figure 18. The staff has a preference to which section they like but since the tasks and skills required are similar they are able to work at every section.

5.1.2 Staffing

During business days, three shifts operate in the warehouse. The morning shift runs from 7:00 a.m. to 3:00 p.m. The evening shift operates from 3:00 p.m. to 10 p.m. while the night shift runs from 10 p.m. to 6 a.m. the following day each with a 30 min break during the shift.

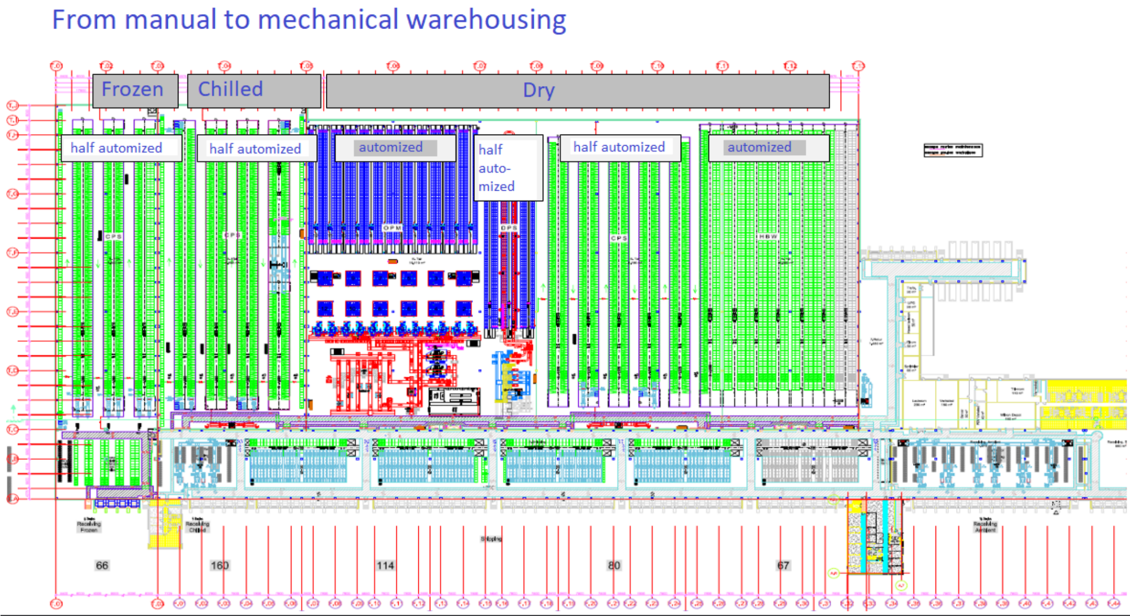

Figure 17: Warehouse

The total number of workers is fixed at 138. For the morning shift, 102 workers are assigned, while 10 workers switch between morning and evening shifts, and 6 workers are assigned to the night shift. 20 employees are part-time workers. The workload demand for a one-week period is known in advance, providing a basis for planning and allocation of resources.

To calculate the required demand ongoing data from the WMS is extracted for picking per line for dry, chilled, and frozen products. The number of items picked is based on previous year's sales data, calculating backwards from sales to item value and distributing it on a weekly level to allocate employees. This determines the target turnover.

Expected efficiency per hour determines the number of items to be picked based on efficiency and calculates the number of workdays required, accounting for differences between departments. Staffing is adjusted based on demand and expected volume. There are variations in demand from week to week impacted by several factors. Promotional campaigns, the weather and unexpected events such as strikes change the demand for certain goods and overall. Staffing needs are adjusted for specific weeks, such as Easter and growth rates are added to historical weeks. To handle these variations the company uses part-time employees and shuffles staff from the different section around based on the workload for each section on a day to day basis.

Data such as the number of picks are gathered from the WMS and manually entered into Excel sheets and used for capacity planning. Based on these calculations hiring is done in October and additional staff is hired based on results during the year.

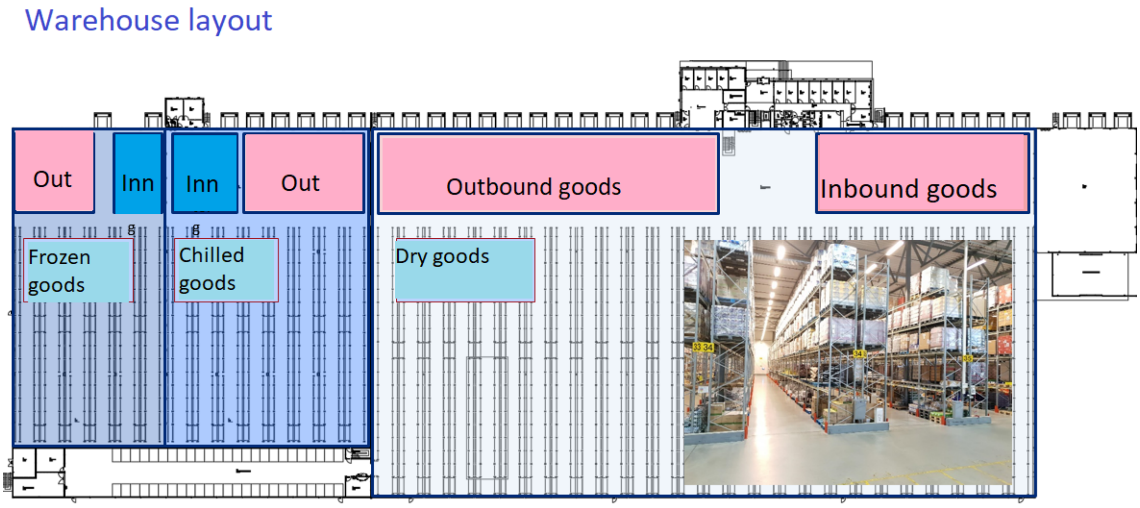

Figure 18: Warehouse Layout

5.1.3 Voice-guided picking

An example of modern utilization of the WMS is how the company decided to implement a voice-guided WMS for their picking process. The company partnered with a reputable WMS provider to implement the voice-guided picking solution. The first step involved analyzing the warehouse layout and product inventory to design an optimal picking strategy. The provider configured the voice-guided WMS to align with the specific requirements of the warehouse and integrated it with their existing warehouse management infrastructure.

To ensure a smooth transition, the warehouse conducted comprehensive training and onboarding sessions for its workforce. The training covered the functionalities of the voice-guided WMS, proper usage of wearable devices, and the new picking processes. The WMS intelligently assigns picking tasks based on factors such as order priority, worker availability, and proximity to items. This streamlined the assignment process, ensuring that workers were assigned tasks efficiently.

Workers receive picking instructions through their wearable devices, which included headsets with built-in microphones and speakers. The voice-guided system provided clear and concise instructions on item location, quantity, and any specific requirements, eliminating the need for paper-based instructions or handheld scanners.

As workers reach each storage location, the voice-guided system provides a number that belongs to the shelf, confirming the correct item and quantity. This real-time confirmation enabled accurate tracking of the picking progress, allowing supervisors to monitor productivity levels and make adjustments if necessary.

The voice-guided system enables workers to navigate the warehouse more efficiently, reducing travel time between storage locations. This has led to an increase in picking speed, resulting in higher order fulfillment rates and improved overall productivity. Also, workers have their hands free to handle items, improving ergonomics and reducing the risk of errors caused by manual handling or distractions. This has resulted in increased picking speed and accuracy.

5.2 WMS

A WMS provider develops and delivers the WMS used in the warehouse. The WMS offers many modules with functionalities for the smooth operations of a warehouse. One function is order management which allows orders to be processed or created. The solution can also be integrated with external purchasing systems through API, allowing seamless data exchange and integration between systems.

SMS (Store Management System) enables inventory management for warehouse employees by eliminating the need for traditional paperwork. It offers seamless support on both iOS and Android platforms, including rugged devices. Additionally, it facilitates barcode scanning using Scandit/ML Kit barcode scanner. With SMS, users can leverage the following key features:

Goods Receiving: Simplify the reception process by efficiently managing incoming inventory. This feature streamlines the task of receiving goods.

Goods Counting: Perform accurate inventory counts with ease. The counting task feature helps ensure inventory accuracy and enables efficient stocktaking.

Goods Picking: Optimize the picking process by efficiently locating and selecting items for customer orders. This feature enhances order fulfillment speed and accuracy.

Goods Moving: Seamlessly relocate items within the warehouse. The move feature allows for efficient organization and optimization of storage space.

Report Damaged Items: Quickly report any damaged or defective items. This feature enables prompt action to address shrinkage and maintain inventory quality.

Once the reception task is completed, an automated putaway task is generated if the designated location is a reception area. The putaway task is designed to facilitate the movement of goods from the reception area to the designated storage locations within the warehouse. This ensures that items are properly organized and stored in their appropriate locations for easy retrieval and efficient inventory management.

The admin has the ability to assign picking tasks as open tasks, which are then added to the task list of eligible employees who can perform the picking role. The administrator also has the authority to make modifications to the sales order quantities or cancel specific order lines while the picking order is being prepared for dispatch. In such cases, the assigned employee is promptly notified about any changes made to the order. This ensures effective communication and allows employees to stay updated on any modifications to the orders they are handling.

The system also has a feature called shift manager cockpit which provides a snapshot of production where you can easily see the status of the following modules:

Picking Overview: Displays information about the total number of units to be picked, remaining units, and the amount picked for a selected area on a chosen day.

Transport Information: Shows the percentage status of completed/picked units for a truck departure. Also indicates which areas still have units remaining to be completed.

Truck Overview: Provides an overview of the number of generated tasks, and allows prioritization of tasks based on task type.

Urgent Restocking: Refers to restocking a picking location that is empty or below a restocking threshold while a picking round for the same item has already been started.

Production Overview - Restocking: Generated when a picking location is empty or below an optional restocking threshold, but there are no active picking rounds for it.

Pallet Tasks: Involves picking full pallets, half pallets, 1/3 pallets, and 1/4 pallets.

Putaway: Generated when an item is registered as finished in a goods reception and is approved for transport into the warehouse.

Movement: Tasks are created when there is a need to move a pallet from one location to another within the warehouse, within the same temperature zone.

Goods Reception: Provides an overview of the number of pallets registered in a chosen day and how many of them have been transported into the warehouse. Also shows the staffing for the selected temperature zone.

Display: Allows the selection of a specific temperature zone to view information for a chosen day.

Staffing: Displays the number of users logged in and indicates which users are active or inactive. There is also the option to send a message to a selected picker and the ability to log someone out in case they have forgotten to do so.

Production overview gives a continuous overview of production for a specified time interval and area. It provides information on the total number of items to be picked, items already picked, items remaining to be picked, items partially picked, and items not yet sent for picking. It also indicates the number of logged-in users in different areas and estimated completion time. This information is presented in a graph with various viewing options, such as estimated optimistic speed and estimated pessimistic speed.

Staffing Planner is a tool for planning the workforce for production. Here, the staffing can be planned in advance, specifying the number of people scheduled to work at a given time. The number is used to calculate the estimated completion time for production in the corresponding interval.

5.3 Case analysis

The warehouse handles a diverse range of stock-keeping units (SKUs), each requiring specific activities to be performed. Due to space and workforce limitations, the warehouse struggles to maximize productivity by assigning workers appropriately. In addition to determining the number of workers required, it is important to carefully match specific workers with their respective tasks, taking into account their individual skills. When faced with high fluctuations in daily workload, it becomes crucial for warehouse planners to quickly obtain an optimal worker assignment. To tackle this challenge, the warehouse manager needs information for decision-making. The goal is to achieve the optimal assignment of workers to warehouse activities while ensuring compliance with operational requirements and worker skill constraints.

Applying the tool from the previous section we can start with step 1: By my assessment, the case company already has the necessary modules in their WMS for efficient capacity planning. However, they do not utilize all the available functionality and instead rely on Excel sheets and manual calculations. They do measure performance and use it in their calculations so the first consideration could be implementing performance-based pay to incentivize efficient work.

A forecast based on historic sales, campaigns and holidays shows the predicted demand for a period which is divided into days based on table 10. Then the predicted demand is divided by average picking to calculate the estimated workers for each day.

	Monday	Tuesday	Wednesday	Thursday	Friday	Weekend
2021	23.39%	21.93%	19.62%	18.97%	14.63%	1.45%
2022	22.29%	21.49%	20.40%	18.96%	15.49%	1.36%
2023	21.14%	22.03%	19.96%	19.17%	15.47%	2.23%
Permanent workers	22.4%	20.8%	19.5%	19-9%	17.4%	

Table 10: Percentages for capacity during a week

Overall and over time the forecast for the warehouse is pretty accurate but they struggle to predict the demand for individual weeks and days as seen in figure 19. Factors like promotions, seasonality, weather, and holidays impact the demand for different products leading to the workload varying up to 40% from the forecast on a weakly basis. While promotions and holidays are accounted for it's impossible to accurately predict factors like the weather way ahead of time. This was highlighted by the warehouse manager as one of the biggest challenges in operational planning as the weather largely impacts the demand for certain items on a day-to-day basis.

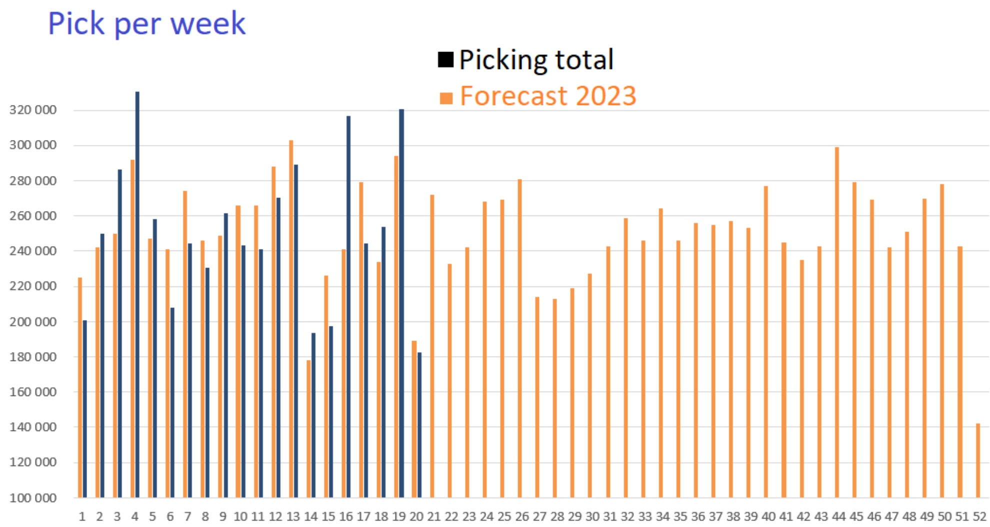

Figure 19: Picking forecast and actual workload

Another factor that recently has emerged is the impact of social media influencers. This was noticed in Norway in 2020 when stores saw a 128% increase in the sale of hockeypowder, a commonly low-selling candy after a video went viral (Nettavisen 2023). This led to the product being sold out in most stores further amplifying the craze. Events like this are impossible to prepare for which makes demand forecasting a challenging task.

In order to address the problem, it is necessary to handle the constraints related to the workforce. These constraints can be specific to individual workers, such as their skill set, or they can arise from the limitations of resources and operational rules within the warehouse.

For instance, the capacity of warehouse equipment imposes restrictions on the number of workers that can be assigned to certain activities. This means that there is an upper limit on the number of workers permitted to work simultaneously at each workstation or activity. This limitation is determined by factors such as the availability of material handling equipment and the number of scanning computers available.

The skills of the workers are similar for most operations except vertical work which is reliant on experienced workers. This means that excess capacity at one of the sections can be utilized to cover the fluctuating demand. But to efficiently manage this the operations manager needs information on the progress of orders and available capacity. This can be found in the shift manager cockpit described in the WMS section and seen in figure 20. If deemed necessary a skill matrix can also be added to this module but due to the cranes mostly being utilized for vertical work, it does not seem necessary. Instead, the experience of the planner can be relied on if manual vertical work is needed.

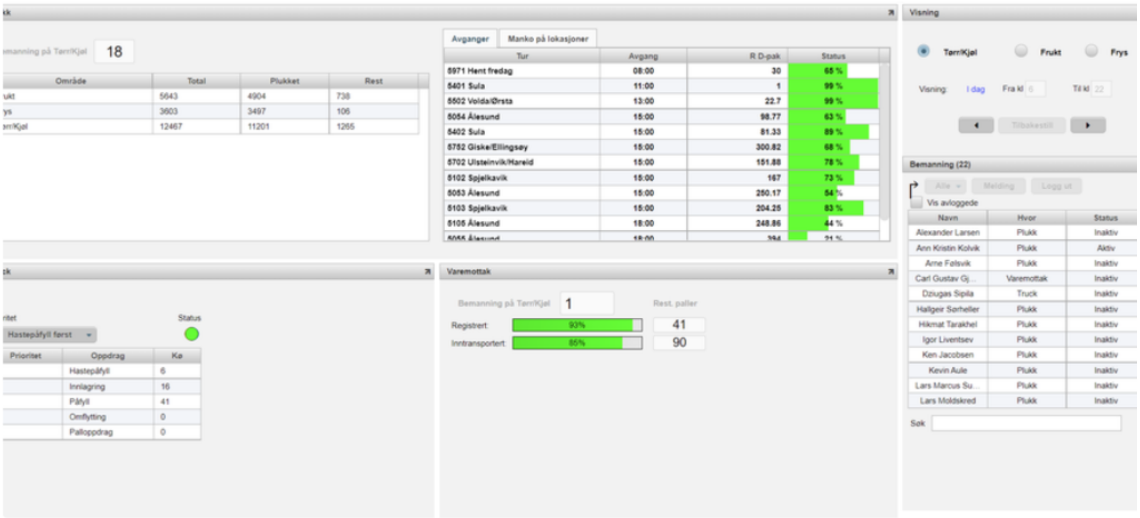

Figure 20: Dashboard

	Permanent staff pr 1.1.2023							
	Mo (and Su)	Tue	Wed	Thu	Fri	SUM	%	Change 22-23
Avg C/F	339,0	313,0	320,5	327,0	277,0	1576,5	47,3%	203,7
Avg DRY	406,1	380,6	328,8	336,1	304,5	1756,1	52,7%	63,3
Sum hours	745,1	693,6	649,3	663,1	581,5	3332,6		267,1
C/F	21,5%	19,9%	20,3%	20,7%	17,6%			
Dry	23,1%	21,7%	18,7%	19,1%	17,3%			
Sum hours	22,4%	20,8%	19,5%	19,9%	17,4%			

Step 2: The planning horizon is one week and the parameters and constraints for the capacity planning can be found in table 11

Step 3: Key historical data for demand and performance were gathered. Figure 21 and table 10 show the demand is typically highest at the start of and diminishes throughout the week. This presents a challenge in having enough capacity for Mondays while balancing for the lower demand on Fridays. The available solutions are mainly scheduling part-time workers and overtime for the days with high demand. Flexible contracts, job rotation, and workload balancing are also applicable strategies.

Step 4: In this step, the forecast of the company is deemed sufficient but with options for improvement. It is possible to implement AI and machine learning algorithms for a more accurate forecast. In a dynamic environment such as warehouses AI and ML algorithms can continuously learn and improve from new data, allowing for quick adjustments to the forecast as new information becomes available. This does however require substantial initial investment as the algorithms rely on large and high-quality data sets for training and validation.

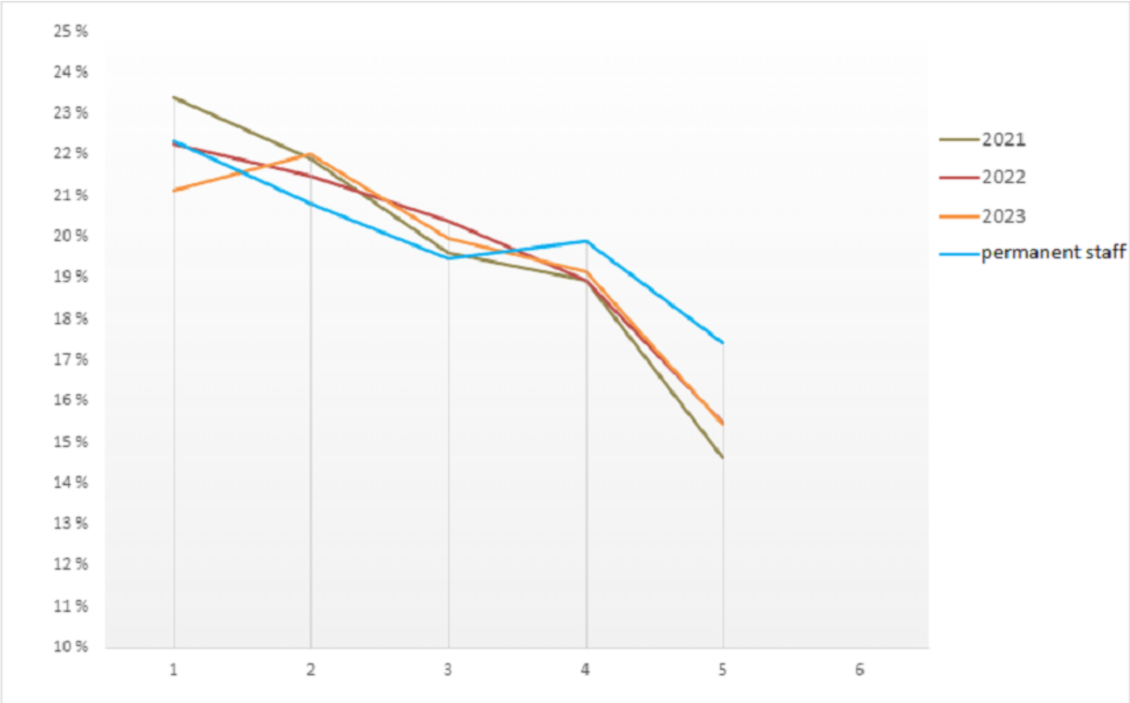

Figure 21: Capacity needed throughout a week

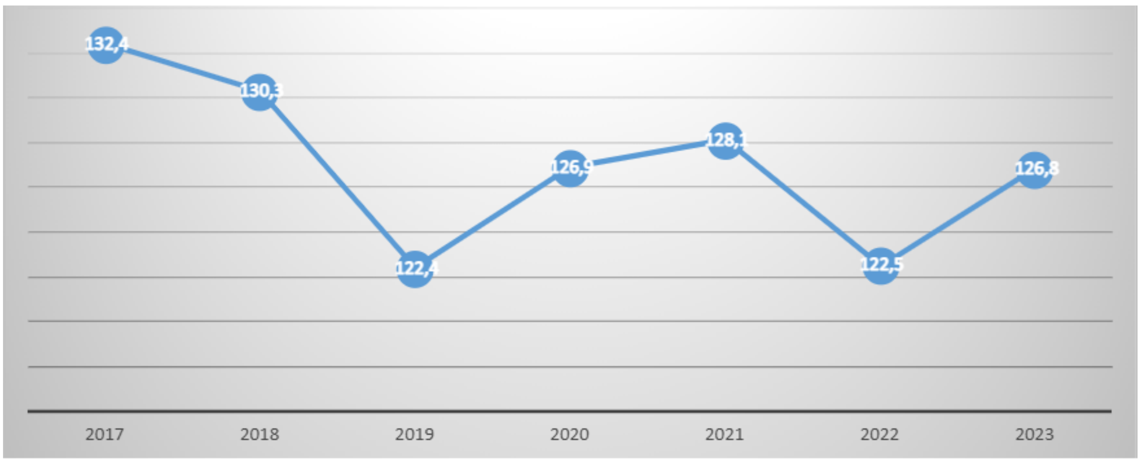

Figure 22: Avarage SKU picked per hour - Dry section

Permanent workers	118
Part-time workers	20
Operations	Receiving, picking, outbound
Shift model	h
Shift operating hours	7-15(122), 15-22(10), 22-06(6) (7workdays a week)
Shift break hours	1x30 min 2x10 min
Shift effective hours	430 min
Overtime model	50% after 17, 100% after 22, 60% night shift
Overtime limits	5 hours/day, 20 hours/week, 50 hours/month, 300 hours/year
Overtime payout policy	Payout or time off decided by worker, hours worked decided by manager
Holidays	5 weeks
Labor costs	257 NOK/hr
Traning lead time	22,5 hours
Retention time	3 months
Sickness estimate	8% per year

Table 11: Parameters for capacity planning

Step 5: In this step, decision-makers need to take into account various factors that affect workload, such as order processing time, order volume, and time required for other tasks like inventory management and equipment maintenance. These factors help in understanding the overall workload and resource requirements. The automated cranes which can move 60 pallets an hour must also be considered when estimating the required employees. No limitations in equipment were mentioned during the visit but it can be assumed there are limited forklifts.

Step 6: Let's consider a possible scenario where the demand rises 40% which we saw was possible in figure 19. A 40% increase on the biggest forecast of 300 000 units would lead to 420 000 Picks in 1 week. Can the warehouse handle such a scenario with the available workforce?

Step 7: With 118 permanent workers working 35 hours a week and an average of 127 units per hour we end up at 524 510 units per week at maximum capacity. Subtracting the sickness estimate of 8% gets us to 482 550 units per week. Considering stochastic variables such as the variation in picking speed seen in figure 23 we can get to about 400 000 units per week using the lowest possible avg speed of 105 units per hour. Still, we have not considered the part-time workers and the possible 2000 hours of overtime each week. It seems the maximum capacity of the company is rather resilient even in a worst-case scenario.

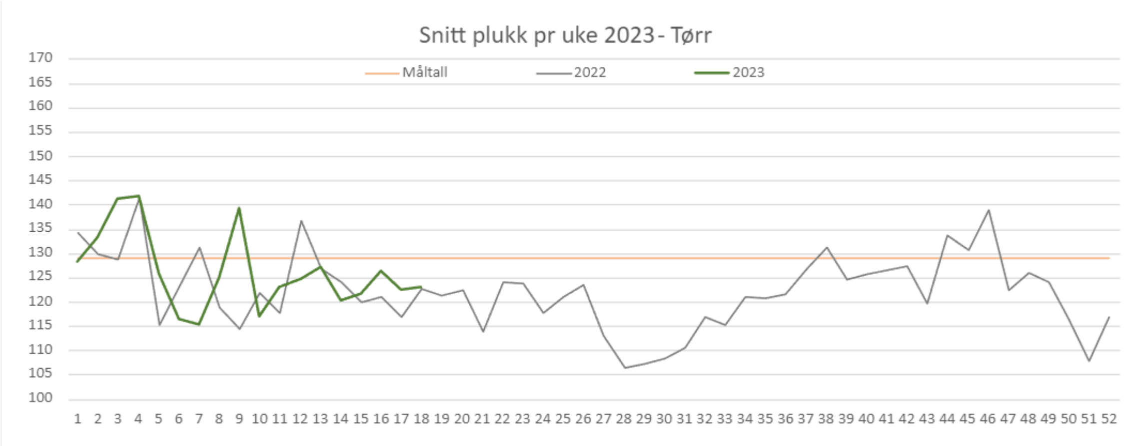

Figure 23: Variations in average picking per week

Step 8: No optimization is considered for this scenario as the capacity is sufficient even in a worst-case scenario.

Step 9: The warehouse does not hire external labor and therefore relies on part-time workers and overtime to deal with short-term labor shortages. Because of the limited options warning the operations planner early becomes crucial. Therefore a warning system should be added to the shift manager cockpit. Using information from the WMS on the available labor hours, performance metrics, picking orders, and deadlines calculations can be made to assess if the workload of the day is possible to achieve. Any large deviations should warn the manager as early as possible.

Step 10:

Proactive planning can minimize or even prevent last-minute issues when major adjustments are no longer feasible. Therefore, by improving the precision of the forecast, this stage can be enhanced. Consequently, the forecast can be converted into capacity requirements, quantified in terms of employee hours, and the corresponding workforce needed on a daily basis.

Even after determining the appropriate number of employees, decision-makers should maintain ongoing monitoring of the workload and make necessary adjustments to staffing levels. This flexibility allows for adaptability in response to changes in demand or the implementation of new technologies.

During the operational planning phase, tasks are further allocated within each day, taking into account any new data and allowing for more precise scheduling. The goal is to ensure that the operational planning aligns with the initial weekly timetable while accommodating necessary adjustments that may arise throughout the day.

For this purpose, I recommended utilizing the information from the dashboard in figure 20 instead of the currently used excel sheets.

5.4 Key findings

- The company has a modern WMS with the required functionality for operational capacity planning.
- Still, they use excellent sheets for planning likely due to comfort.
- Utilizing modules from the WMS can make planning more efficient.
- Challenges in managing high fluctuations in daily workload - Limited options in dealing with labor shortage.
- Real-time information and warnings become important for the operational planner.
- Historical data analysis reveals that demand is diminishing throughout the week.
- The available workforce, including permanent workers, part-time workers, and overtime hours, seems capable of handling increased demand scenarios.

6 Discussion

RQ1: How are decisions regarding capacity planning made in warehouses today?

Decisions regarding capacity planning in warehouses today are typically made through a combination of historical data analysis, simulation modeling, technological advancements, and consideration of various factors. Strategies such as flexible planning, job rotation, and workload balancing help accommodate changes in demand and achieve a better balance between personnel supply and demand. We have also seen a real-life example of a warehouse with a modern WMS capable of efficiently planning capacity who instead partly rely on traditional excel calculations.

Planning capacity in warehouses is crucial due to the fluctuating workload that warehouses often experience. These fluctuations can be anticipated in some cases, such as during seasonal patterns or sales promotions, while in other instances, they can arise unexpectedly. As a result, implementing effective strategies for capacity planning is essential to ensure optimal workforce allocation and productivity in warehouse operations.

Operational planning decisions are reliant on decisions made in higher levels of planning. To make accurate operational decisions the planer requires real-time information on warehouse inventory levels and process progress.

Adequate staffing levels and skilled personnel are essential for optimal capacity utilization. Analyzing labor requirements based on workload forecasts and implementing efficient labor management strategies, such as cross-training and flexible scheduling, can help make correct capacity decisions.

RQ2: What information is needed to support the decision-maker?

The proposed solution supports decision-makers in capacity planning by providing a structured approach to assess capacity planning needs and optimize resource allocation. Decision-makers can assess whether the Warehouse Management System (WMS) has the necessary functionality for capacity planning.

It provides guidance on the required data and how to transform that data into reports and information needed for capacity planning. Decision-makers can analyze this data to identify labor demand, potential shortages, trends, seasonality, and resource utilization. Warehouse managers can define the planning horizon and establish parameters for their own unique situation.

Decision-makers can develop different capacity scenarios based on potential changes in demand, operational processes, or resource allocation. Information on seasonal fluctuations, product launches, promotional campaigns, or changes in order profiles is needed when creating such scenarios. To assess the impact of each scenario information on key metrics such as order throughput, labor utilization, storage utilization, and customer service levels must be considered.

The solution helps decision-makers identify available options to address short-notice labor shortages, such as overtime, employing external labor, or postponement. To make such adjustments real-time data from the warehouse must be collected and presented for operational planners.

The issues addressed in this paper pertain to operational-level problems, where decisions must be made frequently and have a limited impact in terms of duration and scope. These decisions often require quick resolution. Consequently, the adoption of solutions that can consistently provide information within a reasonable timeframe is encouraged. Furthermore, from a managerial perspective, an ideal solution approach should be straightforward, intuitive, and dependable, minimizing expenses in the warehouse.

RQ3: What are the key features of a WMS and how can these be utilized for decision support in capacity planning?

In order to effectively utilize a WMS system for capacity planning, it is important to ensure that the system is properly configured and integrated with other systems and technologies. Additionally, warehouse managers should regularly review and analyze data from the WMS to identify areas for improvement and adjust capacity planning strategies accordingly.

By providing real-time inventory tracking and accurate data on inventory levels and usage patterns, a WMS can help decision-makers assess the current capacity utilization of the warehouse. This information can guide them in making decisions for operational capacity planning.

Furthermore, the reporting and analytics capabilities of a WMS outlined in table 6 and the benefits from table 4 highlight the most important features for capacity planning.

In summary, the key features of a WMS are real-time inventory tracking, order and shipping management, reporting and analytics, warehouse optimization, and integration with other systems, which can be leveraged for decision support in capacity planning. By utilizing the data and functionalities provided by a WMS, decision-makers can make informed decisions about inventory management, identify areas for improvement, optimize labor allocation, and ensure efficient utilization of warehouse capacity.

7 Conclusion

In the context of a warehouse, capacity planning presents challenges due to the variability in workload demand. Assigning workers optimally in such a dynamic system is a complex task. To address this problem, a decision support tool was proposed. This study provides a practical contribution to capacity planning in warehouses, offering warehouse planners and managers a valuable tool for assessing their WMS and allocating their workforce.

By utilizing the tool warehouse managers can effectively identify improved capacity planning strategies under dynamic daily workload conditions. The tool was developed based on modern research and its functionality was validated using real data from a warehouse in Norway.

The operational nature of the problems addressed in this paper necessitates a dynamic approach that continuously integrates new information about the operating environments. While some research has been conducted on the dynamic planning of warehouse operations, it is worth noting that dynamic problems receive considerably less attention compared to their static counterparts.

Warehouse management systems are an essential tool for organizations looking to improve their warehouse operations. As technology continues to evolve, we can expect to see even more advanced features and capabilities in WMS, further improving their ability to streamline warehouse operations and drive business success.

Future studies can focus on enhancing the flexibility of the proposed method by integrating a better initial solution selection. Also investigation and development of more sophisticated forecasting models that can accurately predict workload arrival and demand patterns in dynamic warehouse environments. This could involve the application of machine learning algorithms or AI. Incorporating a weather API that impacts demand forecast could also be interesting.

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