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Developing a Decision Support Tool for Increased Warehouse Picking Efficiency

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Abstract

Title: Developing a Decision Support Tool for Increased Warehouse Picking Efficiency

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Problem description: Warehousing is central in order to achieve a competitive supply chain, and considered essential for the success, or failure, of businesses today. In general, warehouses account for a large share of the company logistics costs. Consequently, there is a need for warehouses to operate smoother, faster and more accurate. Within warehousing, the most labor-intensive and costly warehouse operation is order picking, this is mainly due to the large amount of travelling involved. All articles included in this study agree that order picking account for at least 50 percent of warehouses' total operating costs. Warehouses thus carry great potential to justify the expenses they bring through reducing the time spent on activities that are not value adding.

Purpose: The overall goal in this thesis is to provide guidance for how a warehouse can operate more efficient by improving its picking performance, which also includes reviewing the closely interlinked warehouse operations storage allocation and routing.

Research questions: How can a decision support tool for reviewing the choices of storage allocation, order picking, and routing methods in manual warehouse operations be put together in a structured way? Which features should be considered in the decision support tool for choosing methods for improving warehouse operations?

Methodology: The guidance for improved picking performance was framed into a decision support tool building on a thorough review and analysis of the research available in the area. A case study on picking efficiency was conducted in order to create a deep understanding for the issues and challenges that prevail in warehousing, and also to ensure that the final recommendations and the answers to the research questions have good support in academia. Once the tool was created, an illustrative example was used to demonstrate the use of the tool on a more detailed level and to test its comprehensibility and usability.

Conclusions: In many areas, the resulting tool manages to provide unequivocal guidance for how to improve a warehouse’ picking operations. Multiple features are identified as important for the decision process; among those are demand skewness, seasonality among different SKUs, total demand variation and pick list size. Company objectives and priorities were also identified as a central feature due to the interrelatedness of the decisions connected to picking and their well-known tradeoffs. The research is however sometimes scarce, and further studies need to be carried-out in order to complement and level the strength of the tool.

Keywords: Order picking, picking efficiency, routing, storage allocation, warehouse operations, warehousing

Sammanfattning

Titel: Utveckling av beslutsverktyg för effektivare plockhantering i lager

Författare: Elina Gildebrand, Kristina Josefsson

Handledare: Joakim Kembro, Institutionen för teknisk ekonomi och logistik, Lunds universitet.

Problembeskrivning: Lagerverksamhet utgör en central del i att uppnå en konkurrenskraftig försörjningskedja och betraktas som direkt avgörande för ett företags framgång, eller utebliven sådan. Det är en dyr verksamhet, och en stor del av ett företags totala logistikkostnader kan hänvisas direkt till lagret. Följaktligen finns det ett behov för lager att prestera jämnare, snabbare och mer precist. Orderplockning är den tveklöst kostsammaste och mest resurskrävande lageraktiviteten. Den huvudsakliga anledningen är att orderplockning till stor del består av transporter mellan platser, vilket inte i sig tillför något värde och därmed enbart är resurskrävande. Alla vetenskapliga artiklar som är inkluderade i studien är eniga om att minst 50 procent av ett typiskt lagers driftkostnader kan härledas till orderplock. Lagret har därmed stor potential att rättfärdiga sina kostnader, genom att reducera den andel tid och resurser som läggs på icke värdeskapande aktiviteter.

Syfte: Det övergripande målet med uppsatsen är att skapa vägledning för hur lager kan öka sin effektivitet genom att förbättra sina plockprocesser. Detta inkluderar även de närliggande beslutsområdena lagerplatsallokering och ruttplanering.

Forskningsfrågor: Hur kan ett beslutsverktyg för att granska metodval för lagerplatsallokering, orderplockning och ruttplanering vid manuell lagerverksamhet sättas ihop på ett strukturerat sätt? Vilka egenskaper bör beaktas i ett beslutsverktyg för att välja metoder som förbättrar lagerverksamheten?

Metod: Beslutsverktyget skapades utifrån en grundlig genomgång samt analys av den forskning som finns inom området. En fallstudie om effektivisering av plockhantering genomfördes med syftet att skapa en djupgående förståelse för de problem och utmaningar som förekommer i en lagerverksamhet, liksom att säkerställa att de slutgiltiga rekommendationerna och svaren på forskningsfrågorna var väl förankrade i akademin. När verktyget var skapat användes ett illustrativt exempel för att demonstrera dess användning på en detaljerad nivå, samt för att testa hur lätt det är att förstå och använda.

Slutsats: Beslutsverktyget som skapats lyckas ge tydliga rekommendationer och vägledning inom många områden för hur ett lagers plockprocesser kan förbättras. Flera egenskaper identifieras som särskilt viktiga att beakta i beslutsprocessen; bland annat skevhet i efterfrågan, säsongsförknippad efterfrågan mellan olika lagerplatsenhet, total variation i efterfrågan samt längden på plocklistorna. Företags egna mål och prioriteringar identifieras också som centrala i beslutsverktyget eftersom alla beslut är tätt sammanvävda och generellt innebär ständiga kompromisser. Inom flera områden relaterade till plockhantering visade sig forskningen emellertid vara otillräcklig, och ytterligare studier krävs för att stärka beslutsverktyget.

Nyckelord: Effektiv plockhantering, lagerhantering, lagerplatsallokering, lagerverksamhet**,** orderplockning, ruttplanering

Preface

This thesis was conducted during the spring of 2014 as the final part of our education in Industrial Engineering and Management with master specialization in Supply Chain Management at Lund University, Faculty of Engineering. The research process has been very interesting and we have gained insights and knowledge both about the field of warehouse operations and the ups and downs of managing a half-year project. Team effort has been a key ingredient; it is evident that the Swedish saying “shared joy is a double joy, shared sorrow is a half sorrow” also goes for academic writing.

The project was initiated by the Thule Group and we could not have tested the theoretical tool and reached the same level of the result without their participation. We would like to thank Carl Risholm for the opportunity to perform this assignment with Thule, and would also like to express our gratitude to our company supervisor Rickard Andersson and the other Thule managers who have given us valuable support and information throughout the project. Last but not least, we would like to thank our supervisor at Lund University, Joakim Kembro, for all feedback and suggestions, which successively have improved the quality of our thesis.

Finally, we would like to thank our families and friends who have supported us during these five years at Lund University.

“The greater the obstacle, the more glory in overcoming it.”
Molière

Lund, June 2014

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Glossary of Terms and Abbreviations

Abbreviations

3PL	Third-Party Logistics provider
AS/RS	Automated Storage and Retrieval Systems
CBS	Class-Based Storage
COI	Cube-Per-Order Index
DC	Distribution Center
ERP	Enterprise Resource Planning
I/O	Input/Output
KPI	Key Performance Indicator
LTH	Lunds Tekniska Högskola – Faculty of Engineering at Lund University
SCM	Supply Chain Management
SKU	Stock Keeping Unit
TSP	Travelling Salesman Problem
VBS	Volume-Based Storage
VLM	Vertical Lift Module
WMS	Warehouse Management System

Explanation of Terms

3PL	A firm that provides multiple logistics services for use by customers.
ABC-classification	Term used to categorize SKUs within warehousing. It suggests that SKUs are not of equal value/importance, and should be managed accordingly.
Batching	Refer to the picking of multiple SKUs from separate orders in one route, as opposed to single picking.
Case picking	Order picking of cases or cartons containing a specific number of individual items from a pick location.
COI	Ratio of the maximum allocated storage space to the number of storage/retrieval operations per unit time. The SKUs with the lowest COI are stored in the most desirable locations. Using COI, both popularity and space requirements are taken into account.
DC	A type of warehouse or storage location where the main functions are buffering and storage, as well as additionally distribution of the goods.
ERP	Business management software used to store and manage data from every part of a business. A system for managing and coordinating all the resources, information, and functions of a business.

Flow rack	Storage rack with shelves equipped with rollers or wheels that allow products to "flow" from the back of the rack to the front. Suitable for small-quantity order-picking.
Forward area	Limited area located close to the I/O points where SKUs are stored for easy retrieval by an order picker; it usually contains smaller amounts of fast-moving SKUs and is replenished from the reserve.
Item	The individual article of a certain product or SKU.
Lean	Philosophy in production and SCM that all expenditure of resources should create value for the end customer, i.e. add something to the product or service that the customer is willing to pay for. All non-value adding actions are considered waste and should be eliminated.
Order	A type of request for goods or services, e.g. customer order, purchase order, sales order, work order.
Order line	Each entry in an order. Usually contains the item and quantity requested. In this study each order line is considered an individual pick. At Thule several identical order lines can exist since each represent unique picks.
Order picking	The process of retrieving a number of items from their storage locations to fill a number of independent customer orders.
Order picking method	The way the picking of SKUs in an order should be organized. Might also be referred to as order picking process, policy, and strategy, although not in this thesis.
Order size	Number of SKUs per order.
Order volume	Number of pallets per order.
Pareto principle	A concept that states that for many events, roughly 80 percent of the effects come from 20 percent of the causes, also known as the Pareto law or 80/20 rule. Often used for sorting data.
Partial pallet picking	Order picking of less than a full pallet, see also Case picking and Piece picking.
Pick density	This term has several different definitions, this thesis uses the following: Ratio of number of SKUs in an order out of all SKUs in the warehouse.
Pick location	Location where a SKU is picked directly to meet an order. In the illustrative example in the thesis, all pick locations are on the floor level.
Piece picking	Order picking of individual items from a pick location, also known as broken case picking.
Product	Type of good, e.g. bike carrier.
Reserve area	Area where SKUs are stored in the most economical way i.e. in bulk or full pallets.
Routing	The process of selecting paths to specific destinations, e.g. determining how to move in a warehouse to retrieve all SKUs on a pick list.
SCM	“The integration of key business processes from end-user through original suppliers that provides products, services, and information that add value for customers and other stakeholders” (The Global Supply

	Chain Forum, 1994-2014).
Seasonality	Regular or semi-regular fluctuations in demand that result in overall cyclic variations, e.g. periodic demand variations that create a high season with high demand some part of the year and a low season with low demand another part of the year. Seasonality can also refer to the individual variations in popularity for season related SKUs.
SKU	A product kept in stock, its individual articles or items share the same product/item/article number.
Slotting	See Storage allocation.
Slotting measures	Criteria used to determine the order or ranking of the SKUs about to be slotted/allocated.
Storage allocation	The process of assigning a certain SKU to a certain storage location.
Storage allocation method	The strategy of where to place and store different SKUs in a warehouse, according to which pre-requisites, in order to facilitate the order picking.
TSP	Combinatorial optimization problem the determines the shortest possible route, i.e. given a set of nodes to visit in a network and their distances it determines the shortest patch that visit each node exactly once, and then returns to the point of origin, often used in planning and logistics. Computationally difficult, so the TSP is often used as a benchmark for the large number of optimization heuristics that also exist.
Unique pick line	Unique number given to each row in the order data, it should correspond to each individual picks made in the warehouse, although it sometimes contains multiple pallets which obviously is more than one pick.
VLM	High density storage system for small parts, where they are stored vertically in AS/RS carousels.
Warehouse	Storage location where the main function is buffering and storage.
WMS	Computer system used to control the movement and storage of materials within a warehouse and process the associated operations.

1 Introduction

This initial chapter will describe the background to the research area addressed in this master thesis. The problem at hand, as well as the purpose and research questions will be discussed. An introduction to the company serving as illustrative example will be presented, and the target group of the report described. Finally the structure of the report will be provided.

1.1 Background: The Increasing Focus on Warehouse Operations

Supply Chain Management (SCM) is a concept that has gained more and more attention during the last thirty years, as business leaders have started to understand the competitive advantage of a well-performing supply chain. A competitive supply chain is achieved through the integration of both internal and external business functions such as purchasing, production, sales and distribution (Christopher, 2011). One of the aims of the integration is to minimize the inventory throughout the supply chain, which usually is achieved through smoother, faster and more accurate distribution (Frazelle, 2002). A large part of the distribution is warehousing, especially in terms of costs. Several studies have found that warehousing typically account for between 20 and 25 percent of companies' logistics costs (De Koster, et al., 2007; Establish Davis Logistics Costs and Service, 2013), or between 2 and 5 percent of total cost of sales, depending on company size and type of industry (Frazelle, 2002; Establish Davis Logistics Costs and Service, 2013). Consequently, there is a need for the warehouses to operate smoother, faster and more accurate just like the whole distribution chain. They are even considered essential for the success, or failure, of businesses today (Baker & Canessa, 2009).

Many companies have therefore increased their focus on improving their warehouse operations, often with the aim of reducing inventory and increasing turnover of stock, and thereby freeing capital, but also to increase customer satisfaction. This is achieved both by avoiding and resolving issues related to warehousing that might cause late or inaccurate deliveries, which have a direct, negative impact on customer service (Huertas, et al., 2007), and by offering value-adding services. As a result, the role of warehouses has changed: From having the single purpose of storing or buffering products between points of origin and points of consumption, they now also provide activities such as consolidation of goods from different manufacturing facilities, returns processing, and spare part services (Frazelle, 2002; De Koster, et al., 2007). Another focus area is the warehouse operations connected to manual handling. Receiving store keeping units (SKUs) from production or suppliers, put-away of SKUs, storage, order picking (retrieving the SKUs according to customer orders) while following a certain picking route, and finally shipping of goods to customers, are all performed by human labor in most warehouses, and labor means wages and high costs (Frazelle, 2002; Gu, et al., 2007). The most labor-intensive and costly warehouse operation is order picking, mainly due to the large amount of travelling involved. All articles included in this study agree that order picking account for at least 50 percent of warehouses' total operating costs, the most cited figure concluded by Tompkins et al. (1996) is 55 percent.

However, warehouses also carry great potential to justify the expenses they bring, for example through reducing the time spent on activities that are not value-adding (Theys, et al., 2010). This is a challenge for most companies due to the complexity of the area of warehousing. All warehouse operations are interconnected, and will be affected by previous steps and decisions. Moreover, the links between the different warehouse operations mean that resources such as space, labor, and equipment need to be allocated to each function in a coordinated way to avoid sub-optimization. Hence, decisions regarding improvement of the warehouse efficiency and the establishment of warehouse methods need to consider both the insertion (store) and extraction (order picking) methods (Le-Duc & De Koster, 2005; Gu, et al., 2007).

1.2 Problem Discussion

Current SCM trends that demand higher customer service at reduced costs (Frazelle, 2002), together with increased demand volatility, makes it necessary for the warehouse to stay flexible and adaptable. The high requirements on warehouse operations leave almost no room for errors; smaller orders are to be delivered rapidly within tight time windows while larger warehouses should keep more make-to-stock items but smaller buffers (Le-Duc & De Koster, 2005; De Koster, et al., 2007; Chackelson, et al., 2011). Altogether this makes it extremely complex to improve the overall performance of a warehouse. At the same time, it increases the need of ensuring that the most suitable method always is used i.e. updating the operation procedures as the external factors change. Order picking will be the main focus of this thesis, since it is the undisputedly most labor-intensive and costly warehouse operation.

Most of the current research in order picking is centered on a specific situation or decision problem, but a solution to one situation is seldom applicable to another. De Koster et al. (2007) argue that there is a lack of general design procedures for order picking. They also claim that the design of real order picking systems often is complicated due to a wide spectrum of factors such as demand patterns, mechanization level, information availability, which impact design choices (De Koster, et al., 2007). The complexity might, according to Gu et al. (2010), be the reason why research on the actual selection process is so scarce. There is no doubt that additional research within the area of warehouse performance would be valuable. However, by reviewing the research that does exist, Gu et al. (2010) conclude that prevailing decision support tools mainly compare picking methods by considering the order structure. Other important factors such as storage allocation and detailed implementation of the order picking methods are assumed fixed. Warehouse operations and systems are however highly interdependent, so in order to improve the order picking one must also consider other aspects. Especially important are the design of the storage allocation, and the choice of routing method; which determines order picking sequence and path. This is in line with Gu et al.'s statement that there is "a need for research focusing on the operational management of warehousing systems, where the different processes in the warehouse are considered jointly, the problems are placed in their dynamic nature, and multiple objectives are considered simultaneously" (Gu, et al., 2007, p. 17). Similarly, Chan and Chan (2011) recognize that more combinations of factors should be included in the study of improving the performance of order picking. This master thesis will adhere these recommendations through expanding the area of picking to include also the closely interlinked areas of storage allocation and routing.

In many warehouses the current operations can be improved by e.g. adapting to changed circumstances through redesigning and updating its methods. This update of processes is not only important when successive change take place or due to new logistics trends, but should also be contemplated when a company experience cycling changes such as seasonality. Consequently, a review of warehouse methods should be conducted on a regular basis.

The starting point in this thesis is an existing warehouse with given premises and limitations such as warehouse dimensions, racks, warehouse management system (WMS), and product characteristics, and stretches from the storage operations to the activity of sorting. Decisions to make in an updating process will be summarized along with related possibilities. Further, it will provide theoretically anchored decision support for which choices to consider in a given situation as well as which parameters to base them on. Beyond generating guidelines, the aim is also to encourage a holistic and unified view of the warehouse processes. It is especially important to emphasize the features connected to warehouse operations that have the greatest effect on performance. Identifying these features is central in order to avoid unnecessary, time-wasting data collection and analysis that are likely to occur when a problem is not sufficiently framed.

1.3 Purpose

The overall goal in this thesis is to provide guidance for how to operate more efficient by reviewing the warehouse picking performance. Due to its resource demanding nature, large gains can be expected from improving the picking methods and the closely interlinked decision areas of storage allocation and routing. The guidance will be structured into a decision support tool with hands-on recommendations, created from the most recent and relevant research within the field. The tool will be designed in a simple and structured way to encourage a continuous review of the current processes. The scope of the thesis is presented in Figure 1.

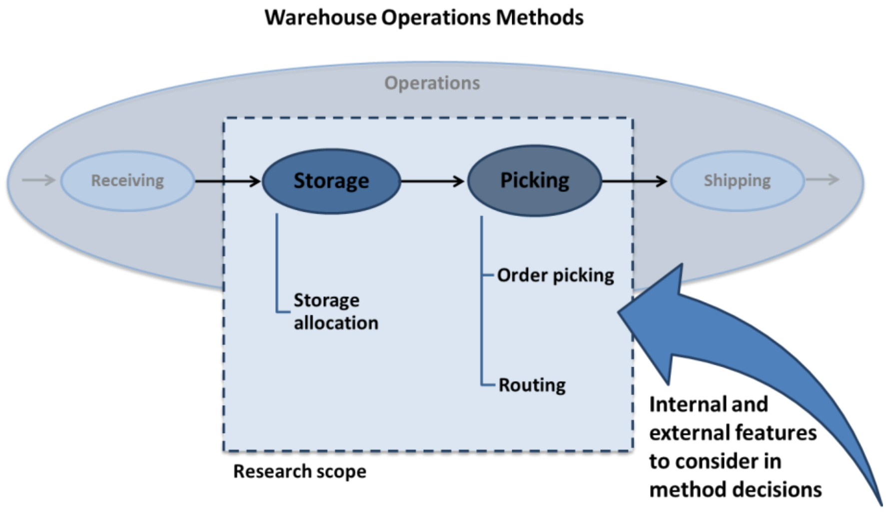


Figure 1 Focus areas for improving warehouse picking operations by creating a decision support tool (Gildebrand & Josefsson, 2014).

1.4 Research Questions

The following research questions are created to capture the purpose:

1. *How can a decision support tool for reviewing the choices of storage allocation, order picking, and routing methods in manual warehouse operations be put together in a structured way?*

2. *Which features should be considered in the decision support tool for choosing methods for improving warehouse operations?*

1.5 Illustrative Example: The Thule Group

The Swedish company Thule Group initialized this research on warehouse operations. It wanted advice on which order picking methods to use in its planned distribution center (DC) in Huta, Poland, a decision that also affects the choice of storage allocation and routing methods. The methods should consider physical constraints and multiple order characteristics, especially the strong seasonality of the products. In order to provide advice that could be applicable for other companies as well, the problem and research questions described in the previous chapters were identified along with a need for a research based decision support tool. In the process of developing the tool, data from a real company was needed for some basic testing of its usability and to see what the outcome might be. It was also vital in order to get realistic input from practitioners regarding company objectives, constraints and requirements etc. The Thule Group's Huta DC was therefore used as an illustrative example to show how to use the tool and what to consider when updating or designing the methods to use in storage allocation, order picking and routing. The warehouse in question is estimated to open for business in December 2014. It is thereby not yet possible to measure its performance,. Instead, recommendations are designed from what is known to date. Starting from scratch is usually not an option in warehouse operations design, which is why the tool created in this thesis primarily aims to be applicable in already existing warehouses and why some factors will be considered fixed also in the illustrative example. The Huta DC is more thoroughly described in chapter 5. Illustrative Example; Empirical Data.

1.6 Delimitations

The study has not considered research on automatic warehouses, since it is the human labor intense operations that are the focus in this thesis. The decision support tool is designed on a general level, to be applicable on any manually operated warehouse, and therefore does not use calculations and simulations of different scenarios. Consequently it is up to each company using the method to do the succeeding steps of actually determining which SKUs to put where, how to form zones or batches, the actual picking route etc.

Further, differences among warehouses are not put as constraints. Most of the research articles simplify the circumstances and make generalizations about travel time, warehouse layout etc. Hence, the facts used and compared are not performed in identical settings. The authors believe the results to be valid as long as they are not contradictive. This is strengthened by the fact that the researcher themselves do not seem to stress the discrepancies among different settings studied. Many areas are interlinked to those of order picking and storage allocation. Three that are excluded from the scope of this study are replenishment, inventory levels and safety stock. This was both because of time limitations; to be able to make a more comprehensive study of a narrower field, and most of the previous research did not seem to look at such a wide area.

The data used when creating the illustrative example in this study was limited to one year of Thule’s order history. It was still considered representative due to the large amount of information, small but probable changes such as added products or some extra orders would not impact the general picture it provides. The same reasoning lies behind the delimitation of data input also conducted on the illustrative example: spare parts and SKUs to be stored in a vertical lift module (VLM) were not included. The spare part storage was to be managed separately by Thule, and do not stand for an extensive part of the orders. Thule considers the VLM storage to be optimal for small and infrequently ordered SKUs, and want to store as many SKUs as possible there. The company performed the selection of these SKUs themselves so storage decisions regarding the VLM were thereby not included in the study. Consequently related picks were not included in the analyzed order data either, but it was assumed that travel connected to these items would not affect the overall performance of the picking since the VLM is positioned close to the input/ output (I/O) points, and thereby not cause any detours. However, to get a complete picture of the situation all SKUs and storage areas should be included when using the decision support tool. Moreover, suspicions that method choices are based on non-representative order data increase the motives for doing an update i.e. using the decision support tool.

1.7 Target Group

Research on isolated or narrow aspects within warehouse operations are easy to find. If however interested in recommendations covering combinations of decision problems, the sources are scarce. The purpose with this thesis was, as mentioned in 1.3 Purpose, to collect excising research to build a decision support tool for improving warehouse order picking. The findings thus primarily aims to be of relevance for warehouse managers with an interest in how picking performance can be improved and guidelines for how to update current procedures when external factors, like order characteristics, change. The outcome should be of particular interest to the Thule Group since the research focus derived from them, and the result was developed through their specific case. For academia, the main contribution was a review of the literature and research available in the field. It established a ground and a starting point for further research, both through identified gaps in the research within picking optimization and through emphasizing the complexity of the problem and the need for a broader scope in research to develop hands-on applicable methods.

1.8 Structure of the Thesis

This master thesis has the following outline:

Chapter 1 Introduction includes a background to the research area, a problem discussion as well as the purpose of the study summarized in the two research questions. An introduction to the company serving as illustrative example will be given, and the target group of the report described. Finally the structure of the report will be provided.

Chapter 2 Methodology describes and motivates the methodological choices made regarding research philosophy, approach, strategy and methods in this study, before describing the research procedures performed in seven steps. Lastly, the trustworthiness of the research is discussed.

Chapter 3 Frame of Reference provides the theoretical framework connected to choosing warehouse operations methods. The physical design of a warehouse, and storage allocation, order picking, and routing methods are described in detail and evaluated based on different criteria, connected to company's priorities in warehousing.

Chapter 4 Developing the Decision Support Tool takes its starting point in two existing decision support models for redesigning warehouses, before combining them and the aspects identified in the evaluations in chapter 3 in to a basis for developing the decision support tool. It continues with presenting the created conceptual model for how to make the right choices when updating and improving the storage allocation, picking and routing methods in a warehouse, which is then explained in the succeeding sections step by step.

Chapter 5 Illustrative Example; Empirical Data presents the information about the Thule Group needed in order to provide an illustrative example of how to use the decision support tool presented in chapter 4.2. The empirical data includes all information needed to update the warehouse operations for the Huta DC: the physical warehouse constraints, product characteristics, and order characteristics.

Chapter 6 Applying the Decision Support Tool provides an illustrative example of how the decision support tool can be used in practice by applying it on the Thule Group. The indications of each step are analyzed and concluded, before the final recommendations for the Huta DC are summarized.

Chapter 7 Analysis of Decision Support Tool analyses the theory that compose the tool, as well as the tool itself; structure, strengths and weaknesses.

Chapter 8 Conclusions summarizes the outcome of the master thesis and answers the research questions. Finally suggestions for further studies are presented with aspects of interest for both researchers and practitioners.

The very last part of the thesis consists of References and Appendix A-F.

2 Methodology

This chapter will describe the methodological choices to make regarding research philosophy, approach, strategy and methods. It will discuss and motivate the choices made for this study, before describing the research procedures performed in seven steps. Lastly, the trustworthiness of the research will be discussed.

Making a well-informed choice regarding research strategy and design is essential for the process of answering the research questions. This is central for the continued work, hence need to be accompanied with a plan, containing clearly defined objectives and constraints for how to the answers will be reached (Saunders, et al., 2009). There are several important choices to be made when deciding on a suitable and logically designed research methodology. In order to structure the decision-making, the ‘research onion’ by Saunders et al. (2009) was used as a framework. Figure 2 illustrates an expanded version that includes the final alternative adopted in each layer for the Thule study. The choices were made step by step, starting on the outside and gradually, layer by layer, getting closer to the core –the actual data collection and analysis. This chapter is structured in the same way by stepwise describing the different layers, including motivation of each choice for the procedure used in the thesis.

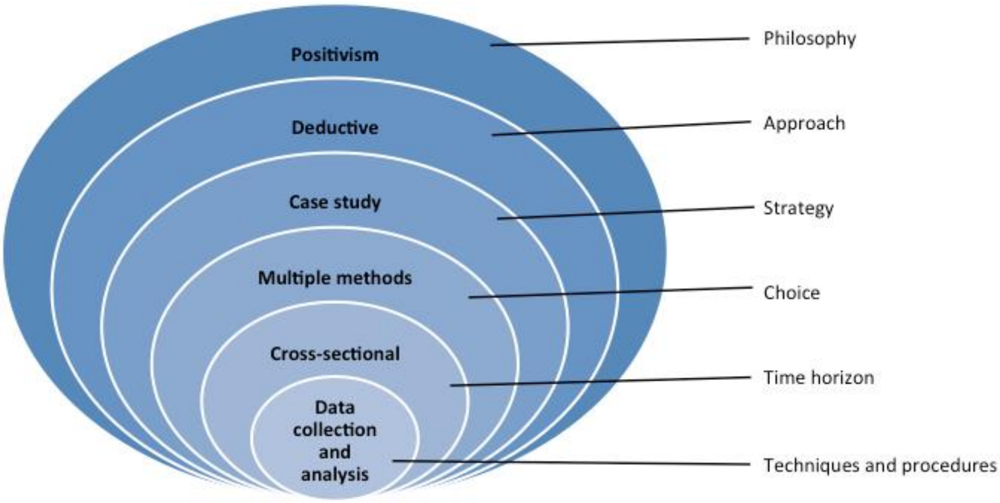


Figure 2 Methodological research choices presented in an adapted version of Saunders et al.’s research ‘onion’ (2009).

2.1 Research Philosophy

The first step according to Saunders et al. (2009) is to determine which philosophy to adopt throughout the research, which is what is considered knowledge and how new knowledge is developed. The research questions in this thesis are about finding improvement methods and making decisions mainly based on hard, observable facts. The aim is that the resulting decision support tool should be applicable for many types of companies, although alterations might be needed depending on the circumstances. Hence, a positivistic research philosophy is suitable. Positivism is the typical view within natural sciences and it is based on observability and objectivity, meaning that the input should be observable facts rather than impressions, and the result should be the same even if the researcher is replaced (Saunders, et al., 2009; Patel & Davidsson, 1994). The goal is to be able to generalize the outcome by empirically proving different hypothesis, and ultimately create universal laws and mathematical formulas that can describe cause and effect (Patel & Davidsson, 1994). This choice is in line with many other logistical researches since positivism is the most common philosophical stance in logistics research (Gammelgaard, 2004).

2.2 Research Approach

The next layer in the research ‘onion’ (Saunders, et al., 2009) depicts which research approach to use. There are several suitable methodological approaches to scientific research, depending on the field of studies, the context and the personal opinions of the researchers. For this study, the phrasing of purpose and research questions together with the use of an illustrative example indicated that the base of the study would be already established theories regarding storage allocation, order picking and routing, although adapted to a new setting. This approach corresponds to Kovács and Spens (2005) description of the deductive research; it takes its starting point in existing theories, moving from a general law to a specific case. The deductive research process aims to identify and explain causal relationships between specific variables (Saunders et al., 2009). Hence, it is more suitable for testing already existing theories than for creating new science, and for this reason the deductive approach dominates the relatively young field of logistics (Kovács & Spens, 2005). Deductive research requires that it is possible to control variables and that the methodology used is structured and replicable to get a reliable result. In order to be able to generalize the outcome it is important to ensure that the size of the sample studied is sufficient (Saunders, et al., 2009). The aim of this master thesis was to identify the relationships between different order characteristics and warehouse operation methods. The starting point was an extensive literature review, which is used to decide the method that is the most suitable in each specific situation. In order to be able to follow the deductive research requirements, the methodology used is thoroughly described in this chapter. The included articles are thought to strengthen the research foundation by using both simulations and case studies to demonstrate and prove their main ideas. The outcome should therefore be applicable to specific situations.

Arbnor and Bjerke (2009) also describe two other major research approaches: the inductive and the abductive. The inductive approach was not an option since no new theory was to be developed through the empirical case data (Kovács & Spens, 2005). The abductive research approach has a more cyclic nature (Fischer, 2001) and can be viewed as a combination of the other two approaches: The first part of an abductive study is inductive and develops new theories. The theories are then tested in the second part by using them in deductive research to forecast and conclude different observations (Arbnor & Bjerke, 2009). The time constraints of this study prohibit such an extensive study. The abductive process also requires that the researchers are very experienced in the relevant field to succeed, and this was not thought to be the case. Figure 3 shows the deductive approach in comparison with these two other research approaches. In the context of this study, *theories* refers to the frame of reference, while *forecasts* can be compared to the decision support i.e. the answer to the research questions. *Facts/observations* is the evaluated outcome of using the decision support which is a state the illustrative example do not reach, i.e. the deductive half-circle is not fully completed.

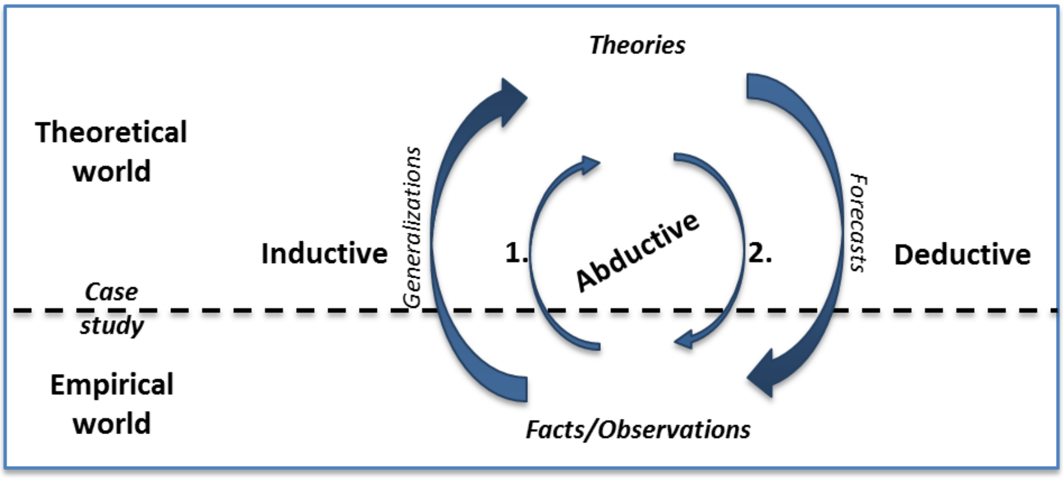


Figure 3 Comparison of different research approaches (inspired by Arbnor & Bjerke (2009), and Fischer (2001))

2.3 Research Strategy

The next methodology decision to make, the third layer of the research onion, concerns the research strategies. There are many strategies when it comes to doing research; common examples are experiments, surveys, archival analyses, histories and case studies. When deciding what method to use, there are several factors to take into account according to Yin (2009). Initially, the form of the research questions should be analyzed. One way to categorize them are depending on the purpose of the research and which of the questions *who*, *what*, *where*, *how* and *why*, they answer. For example, if a research question answers how or why, it is usually explanatory and will likely result in the use of case studies, histories and experiments. With this background, it is obvious that the defining of the research questions is a crucial step in the early research process (Yin, 2009). An overview over when to use different research and in connection to what research question depending on the goal or purpose of the study can be found in Table 1.

Table 1 Relevant research strategies for different situations (Yin, 2009).

Research purpose	Question type	Suitable research strategies
Exploratory - develop pertinent hypotheses and propositions for further inquiry	what	survey, archival analysis, case studies, histories, experiments
Predictive - describe the incidence or prevalence of a phenomenon or predict outcomes	who, where, how many, how much	survey, archival analysis
Explanatory - establish cause-effect relationships	how, why	case studies, histories, experiments

The aim of this master thesis was primarily to create a decision support tool that highlights the methods for storage allocation, order picking and routing, which have the strongest support in research for bringing improvements regarding picking efficiency within a specific warehouse. This includes identifying and using cause-effect relationships so the research is explanatory to its nature, which is further strengthened by the first research question, which asks *how*. Explanatory researches often use case studies, histories or experiments depending on the degree of control of events. This study uses all three alternatives to some extent, although partly from a secondary source. The literature review in chapter 3 Frame of Reference is based on previous research conducted by using both actual companies and simulation models i.e. histories, case studies and experiments. The literature study ends with two examples of existing decision support models for redesigning warehouses. These parts of the literature review were then both used to create the resulting theoretical decision support tool, which was then illustrated by following the procedures in a real life company setting. The process described is a case study of the subject *methods for increasing picking efficiency*, from which a conceptual model evolved. Typically, a case study combines several data collection methods such as archives, interviews, questionnaires and observations (Eisenhardt, 1989). The purpose when choosing a case study is to gain a thorough understanding within a specific area. In this thesis, it is also about mapping the existing research within the targeted area in order to create value for warehouses that wish to improve their operations in the future. The main criticism regarding case studies is that it provides a weak basis for generalization due to its narrow focus. Over time the value of learning from specific cases has been better recognized and its prevalence is successively increasing in many scientific disciplines (Dubois & Gadde, 2002). This is not considered an issue in this master thesis, since the method provides a strong theoretical tool that intends only to provide a starting-point for future research and adjustments, which eventually could serve as subject for generalization. For further discussions in this matter, see chapter 2.7 Trustworthiness of the Research.

An experimental outcome or an evaluating test of the performance of the decision support tool tested on the Thule case was unfortunately not possible due to the limited scope of the project. Further, the warehouse settings in which the operations eventually will take place are not expected to run until December 2014, when this research already will be finished. Hence, it was not possible to test, isolate and measure in that environment, which would be required if doing an experiment.

2.4 Research Choices

The fourth layer for decision-making regarded the area of research choices (Saunders, et al., 2009), choosing the method to use for answering the research questions. This can be referred to as choosing mono method or multiple methods, i.e. using either a single data collection technique with corresponding analysis procedure, or using more than one data collection technique and analysis procedure. This research study uses a case study of the subject *methods for increasing picking efficiency* including a wide scope of research articles, order data analyses and interviews; hence the research choice was a multiple methods. The reason for this choice was to get a broader perspective on the studied problem, and to increase the trustworthiness of the research. For further elaborations on this matter, see chapter 2.7.

2.5 Time Horizons

Another important decision, according to Saunders et al. (2009), to make prior to the research start regards the time horizon of the study. Should it capture a snapshot of the situation, from now on referred to as cross-sectional studies, or a longer period of time, so called longitudinal studies? The choice between these are highly related to the kind of research one are to perform, and does not relate to the research strategy. The longitudinal studies have a great strength in the possibility to study the development over time, but also research with time constraints can contribute with change analyses if utilizing already performed studies as a foundation for the further research (Saunders, et al., 2009).

Due to the limited time frame and scope of this master thesis, longitudinal studies were not possible to conduct; hence cross-sectional is the best description. The collected historical data used in the illustrative example cover one year of Thule's order history, which can be considered a short period of time in a fast growing company with significant seasonality. Further, the interviews only represent a snapshot of the situation. The literature used in chapter 3 Frame of Reference is from different years, stretching over longer periods of time but most of them are also to be considered as separate cross-sectional studies and do not provide a longitudinal study if considered together.

2.6 Research Techniques and Procedures

The core of the research 'onion' concerns research procedures and techniques, or rather how the data should be collected and analyzed (Saunders, et al., 2009). This master thesis studies methods for increasing picking efficiency by doing an extensive literature review and combining the different recommendations in to a decision support tool in the shape of a conceptual model. The theoretical framework is analyzed by comparing the different recommendations and their implications for companies in terms of when each method is suitable. The tool is tested on a real life setting through an illustrative example by doing a trial run with data from the Thule Group. The actual application is then analyzed based on performance and usability; implementing and analyzing performance of the decision recommendations is left for further studies.

More detailed descriptions of the data collection and research analysis, is provided in the following sections through a seven-step multi-stage rocket, illustrated in Figure 4.

Figure 4 Research process in seven steps (Gildebrand & Josefsson, 2014).

2.6.1 Step 1: Determining Project Scope

The initial step in this study was to determine the scope and establish a project plan, which was done together with the supervisors at LTH and the Thule Group iteratively. By doing a broad literature search with key words like "warehousing" and "order picking" the researchers' basic knowledge of the research area was enhanced. Some gaps in current research could be identified, leading to the problem discussion, purpose and research questions presented in chapter 1 Introduction. The execution of the project was planned in order to meet the limited time frame of the master thesis of totally 20 weeks.

2.6.2 Step 2: Determining Research Methodology

The next step was to decide on research methodology using Saunders et al.'s research 'onion' as a framework (2009), according to previous chapters 2.1 to 2.5.

2.6.3 Step 3: Literature Review and Creating a Frame of Reference

Once the research structure and methodology was determined, the next step was to conduct an extensive literature review in order to address the purpose and research questions. By finding, reading and summarizing relevant research articles a frame of reference was constructed. The actual search process was performed by using different databases: EBSCOHost, Elsevier, JSTOR, Scopus, and Web of Science. The main key words used were *warehouse*, *warehousing*, *picking*, *order picking*, *storage allocation*, *storage assignment*, *classification*, and *seasonality* in different combinations. When needed the search result was further narrowed down by putting constraints on times cited and/or publication date. The aim was to find the most recent research in order to conclude the state of the art within the topic of order picking, which meant focusing on recently published articles. However, the selection of suitable articles was not that extensive. For this reason, un-cited scientific articles, as well as frequently cited articles from as long back as 1989, also were included in the study.

When promising articles were found, a brief browsing and reading of the abstract was done in order to determine their relevance to the project at hand. If they were judged as relevant and to be from a reliable source they were put in the internal project library, otherwise they were discarded (for more information about the source evaluation see chapter 2.7 Trustworthiness of Research). The references in the relevant articles were examined in order to find additional relevant articles. This was mainly done based on author name, article title or the piece of information referred to. In fact, the main part of the literature included in the frame of reference was not found directly through the databases, but rather through backtracking the reference lists in relevant articles. The retrieval of these articles was often done with the assistance of the search engine Google Scholar.

The next part of the literature review was to read through the articles i.e. the content of the project library and categorize them based on main topic. The categorization was done according to what the browsing indicated would be the structure of the frame of reference: literature review and frameworks, general about warehouse operations, order picking and storage allocation. The final structure of the literature review was however achieved iteratively by writing and getting supervisor feedback.

2.6.4 Step 4: Determining a Decision Support Tool

The fourth step was to evaluate the key factors found in theory for determining order picking methods. As the last part of the literature review, it meant summarizing different research result and comparing their statements on how certain characteristics influence the storage, order picking, and routing decisions. The idea was to identify important relations that determine how decisions should be conducted, and compile them into a decision support tool: A stepwise instruction of which warehouse, product, and order characteristics to consider and how to consider them when deciding on methods to use in ones warehouse operations. It should provide guidance for updating these procedures, while taking different pros, cons, and tradeoffs connected to company objectives in to account. Some factors were not satisfyingly examined in current research, why the tool is not comprehensive but can be further developed and expanded.

2.6.5 Step 5: Illustrative Example; Empirical Data and Applying Decision Support Tool

When the decision support tool was finalized from a theoretical point of view, next step was to apply it on a real case, provided by the Thule Group. The purpose was to get practical input to the theory-based tool by using information about the Thule Group and its Huta DC as an illustrative example. In this step, the data collection and analysis sometimes overlapped which gave the researchers a head start in the analysis and also allowed them to take advantage of flexible data collection (Eisenhardt, 1989).

The basic company and warehouse information was received through the company website as well as through unstructured interviews with the company representative Carl Risholm (Project Manager Supply Chain) during company visits. Short semi-structured qualitative research interviews were also carried out with three of Thule's managers involved in warehousing and the new DC: Rickard Andersson (Vice President Supply Chain, Sweden), Marcus Hunt (Supply Chain Manager, UK), and Monika Janas-Kaszuba (Project Manager, Poland). The purpose was to collect support for how Thule wished to prioritize its warehouse objectives and thereby should act in the tradeoff situations. The semi- or unstructured interview approach means that the interviews were non-standardized and used an explanatory approach were the interviewee and its answers affect the questions asked. The difference between the two is that the semi-structured interviews use a predetermined list of questions to cover, but some may be omitted and others added depending on the nature of the interview. Unstructured interviews on the other hand are completely informal; the goal is to explore a research area in depth by letting the interviewee talk freely. No predetermined questions are set, but it is important for the interviewer to have a clear idea of what to achieve through the interview (Saunders, et al., 2009). Here, the interviewees were e-mailed the interview guide, found in Appendix A, and initially also answered in writing. Then follow up interviews were held to clarify some points with Janas-Kaszuba on Skype on 2014-03-20, and with Andersson in Malmö on 2014-03-28. The quantitative order and product data to use in the different decision steps was collected through the company's ERP system and compiled in Excel-files provided by Risholm (2014). It contained all orders from July 2012 to June 2013 of SKUs to be stored in the Huta DC. To conclude, the empirical data collected from the Thule Group was both primary and qualitative (interviews), and secondary and quantitative (order history).

Next, the decision support tool was gone through step by step to determine the suitable warehouse operation methods regarding storage allocation, order picking and routing to apply to Thule's Huta DC. In the initial phase Yin (2009)'s recommendation to start the analysis process with playing with the collected data to find appropriate strategies to proceed with was used. This process included filtering and sorting the information as well as analyzing the outcome, all based on the parameters the tool suggests to be able to follow its recommendations. Sometimes lack of or inadequate theory called for assumptions, e.g. regarding where exactly to draw the line between A, B and C SKUs, as well as how to determine the size of the corresponding zone. Similarly, assumptions were made when the data provided from Thule were ambiguous, e.g. regarding number of unique picks. This step was conducted both to test the theoretical tool and show how it should be used, and to identify problems and discrepancies between theory and practice.

2.6.6 Step 6: Analyzing the Decision Support Tool

The next step was to analyze the decision support tool itself, its theoretical foundation, guidance and ease of use. The main idea was to compare different research results, their common opinions and their extensiveness before moving on to evaluating the applicability of the tool. How cohesive, clear and comprehensible was the implications from research? Was the advice understandable and did the outcome seem reasonable? What about gaps or indecisiveness? And how did the tool perform in reality in terms of usability? Which reasons determined the structure of the tool? Any alternatives? Did the tool recommend different methods for different time periods and storage areas? Which features settled the decisions? Did this outcome seem reasonable?

2.6.7 Step 7: Conclusions and Further Studies

The last step in this master thesis project was to conclude the outcome in terms of the final decision support tool and answering the research questions. The process of doing this also involved a final review, and an opportunity for the authors to summarize their own reflections and ideas regarding the study. This process involved identifying and expressing improvement areas and suggestions for further studies related to the topics of warehouse operations and picking efficiency.

2.7 Trustworthiness of the Research

There are several criteria for judging the quality of research designs. Yin (2009) presents four widely used tests to ensure that research is trustworthy:

- *Construct validity* identifies correct operational measures for the concepts being studied.
- *Internal validity* seeks to establish a causal relationship (for explanatory or causal studies).
- *External validity* defines an area to which a study’s findings can be generalized (not always the purpose).
- *Reliability* ensures that the operations of a study can be repeated, with consistent results.

2.7.1 Validity

The first three bullet points regarding validity are concerned with whether the findings really are about what they appear to be about or not. Is it really the intended variable that is measured? Is it the identified relationship between two variables casual? And can the findings be applied outside the area in which the study was performed? Raising these questions is an important step in ensuring validity, but it is also important to be aware of possible threats. It can be participants dropping out of studies, participants changing behavior *due to* them being measured or that conditions change during the study that affect the outcome. The external validity is of particular concern if developing theories aiming to be generalizable i.e. possible to use for other organizations or in other situations. This type of research calls for further, larger studies, and it is of importance that the objects studied are representative –either by being a larger sample or by not being markedly different. Research performed in a small setting or one company only is usually not enough to make generalizing conclusions, and as long as there is no claim that the result is applicable in other settings than the one studied there is no reason to evaluate the external validity (Saunders, et al., 2009).

The validity of this master thesis is closely connected to the trustworthiness of the information collected in the literature review. The search process used well-known databases recommended by academia and the articles found were published in international journals used by both researchers and practitioners. The frame of reference is therefore considered valid. The relations between order characteristics and storage and picking strategies found in them are based on both simulations and case studies, thereby enhancing the research foundation of the project. The casual relations were thoroughly examined and it was made evident that most researchers had found the same indications. Consulting different sources and comparing their views is sometimes referred to as data triangulation, which also helps validate the findings (Denscombe, 2010). However, analyzing the prerequisites and compiling different research results in the decision support tool was performed by the researchers, which leave room for misinterpretation. The risk of such faults was decreased by the test of the tool, together with the iterative feedback sessions with the LTH supervisor. Moreover, the iterative process of collecting the research result used in the decision tool made sure the statements was examined multiple times in order to categorize them correctly. Consequently, less room should be left for errors.

The aim of the resulting decision support tool is to be applicable to many types of settings i.e. generalizable to some extent. This external validity of the project might be questionable due to the somewhat limited literature supply on the subject. The outcome is based on several research projects and consequently more extensive than if the authors of this report only had based the outcome on self-manufactured primary data. However, many of the cited researchers work together on different research papers and frequently use and cite each other’s result. Hence, there is a risk that many of the different research articles that point in the same direction, actually base their statement on the same original research. There is also a risk that the individual researchers choose not to question the prevailing theories, due to the small size of this research community. For further discussions of this issue see chapter 2.7.3 Criticism of Sources. Two other limitations to fully generalizing the research result are that this study only concerns certain types of warehouses (manual with fixed layout) and that more adjustments based on industry practice and case studies are needed to anticipate more real life warehouse and demand situations.

Another issue that affects the validity of the result is connected to the extensiveness of the research within this area. Many aspects of how order characteristics affect the storage and picking methods have not been examined in the research, which is why the summary used when constructing the decision support tool in this master thesis contains some gaps. This cannot be resolved within the scope of the project, but is something in need of more research, see discussion in chapter 8.3 Suggestions for Further Studies.

Lastly, when studying the empirical data from Thule in term of the quantitative order data and qualitative interview answers it is important to remember that this data only was used for testing the theoretical result, i.e. the decision support tool. Hence, it was a complement to the theoretical research and its validity is therefore not as fundamental when observing the validity of the entire master thesis. Nevertheless, it is important to make sure that the facts from the illustrative example used in the analysis chapter are valid and that no misinterpretation of the order data or interview answers were done. To avoid this, the initial semi-structured interviews were conducted via e-mail, which meant the interviewees were able to read the questions themselves, think them through, and answer in their own words. Both the outcome of the interview answers, and of the order data analysis in terms of different order characteristics were verified by follow-up questions and feeding the answers back to the concerned Thule personnel.

2.7.2 Reliability

One way of assessing the reliability can be to raise three questions. Will the measures yield the same results on other occasions? Will other observers reach similar observations? And is there transparency in how interpretations were made from the data? These questions are also in line with the overall positivistic research philosophy of the study. Another way to assess the reliability is to raise awareness of its four common threats:

- *Subject or participant error* can occur when handing out questionnaires without realizing that the time of the day, day of the week etcetera will influence the result.
- *Subject or participant bias* is a risk, for example if interviewees provide answers they feel that they are expected to give. This is more likely to occur in organizations characterized by an authoritarian management style or when employment insecurity is high.
- *Observer error* is always a risk when the researcher has to interact in a situation. In interview situations, it may be that different persons or ways of asking questions bring out completely different answers.
- Finally, *observer bias* is a threat when data or information needs to be interpreted, since this highly depends on the person conducting the analysis (Saunders, et al., 2009).

A similar concept used to ensure trustworthiness is the combined qualities of credibility, transferability, dependability and confirmability. Credibility has the same meaning as internal validity. In the same way, transferability should be interpreted the same way as external validity, and dependability can also be described as reliability. Confirmability can be described as objectivity, meaning that the findings should represent the results of the study rather than the researchers bias (Halldórsson & Aastrup, 2003).

The reliability of this study can be considered high. The resulting decision support tool is based on scientific articles and research already published and accessible in the same way for any researcher. Hence, the theoretical outcome should be more or less identical if repeated no matter by whom. However, the parts that require interpretations and adjustments due to tradeoffs input from practitioners and judgment of what different order characteristics imply might come out differently. The human factor is present, although tried to keep at a minimum, why an exact research replica is impossible.

The order characteristics yielded from processing the order data received through the illustrative example are judged as very reliable since the order figures are hard facts; static figures only processed with mathematical tools in Excel to provide averages rather than about 200 000 individual orders distributed over one year. Consequently the data itself was not altered and another observer would thereby get the same results as the authors of this master thesis. Interviews, however, are always unique events and cannot be repeated exactly in the same way. Still, the main questions the Thule Group warehouse managers were asked can be found in Appendix A, hence the interview itself can be repeated and should yield similar answers. Interviews were conducted by two persons to avoid subjectivity, and verified by collecting each answer both verbally and in text.

2.7.3 Criticism of Sources

A huge part of determining the trustworthiness of this report and its result depends on the reliability of the sources used. The main source for chapter 3 Frame of Reference was research articles, but some books were also included. The research articles were primarily or secondarily found through scientific databases accessed through Lund University Libraries and recommended by the LTH supervisor as well as other LTH professors. Moreover, they were published in reliable, well-known international research journals evaluated and used by both academia and practitioners, such as the European Journal of Operational Research, the International Journal of Production Economics, the International Journal of Physical Distribution & Logistics Management, and the International Journal of Production Research. Some of the articles are fairly old and others are published in smaller journals, they are however still considered reliable. The content of the first kind still seem valid though they are referred to in new articles, and the references used in the latter are the same as in articles published in more prestigious journals. This is also true for the books cited; they were both validated by LTH supervisor and cited in articles from reliable journals. Hence, the cited works and their content are considered trustworthy, especially since many of the authors are reoccurring, both as authors and in the reference list.

This proof of trustworthiness has, however, also a negative aspect. Multiple sources indicate the same result, but as mentioned above, the total number of researchers is fairly small, which mean more influence on each other. This is evident when reading through the reference lists; the same authors appear over and over again and in different constellations. Many of them know each other and work together, which mean there is less chance of them questioning previous results. Moreover, they all refer to each other, which means that something that seem like a well-proven fact due to appearing in paper after paper, might turn out to refer back to one single study.

3 Frame of Reference

This chapter will provide the theoretical framework connected to choosing warehouse operations methods that support the overall goal of improving the picking process. The physical design of a warehouse, and the storage allocation, order picking, and routing methods will be described in detail and evaluated based on different criteria connected to company's priorities in warehousing.

There are many aspects to consider when making warehousing decisions in order to increase picking efficiency. Le-Duc and De Koster (2005) have established five main factors that affect the performance and efficiency of the order picking in a warehouse:

- Warehouse layout and physical design
- Storage allocation method
- Batching or order picking method
- Routing and sorting method
- Demand pattern

In accordance, Bottani et al. (2012) identified warehouse layout, storage allocation and order picking methods as particularly relevant for this purpose. These three common elements have been used to set the structure of this frame of reference and form the base illustrated in Figure 5. Le-Duc and De Koster's two remaining factors are also included in the figure and form two chapters, although the amount of available research within these areas generally is considerably smaller than within the other three. Further, Figure 5 depicts the interconnection between the factors by having the four triangular shapes of the warehouse factors form a larger triangle together if considered jointly. The omnipresent demand pattern is illustrated as a cloud in the background, to illustrate its influence on all the other decision areas. The outcome in terms of effect on picking operations, if treating the factors correctly, is depicted as an arrow pointing forward to symbolize an increased picking efficiency.

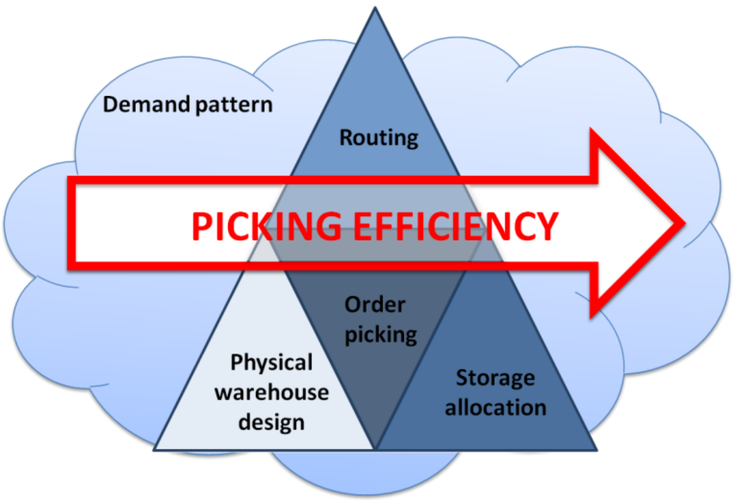


Figure 5 Overview of factors affecting picking efficiency covered in frame of reference (Gildebrand & Josefsson, 2014).

Since warehouse layout is considered a given factor, chapter 3.1 only aims to introduce the complexity of the area, and its impact on performance. The following three chapters continue by in detail describe the different methods for storage allocation, order picking and routing and they will end in comparisons of when to use different methods. Lastly, chapter 3.4 will give some input to research's view on how to deal with changing demand patterns and seasonality.

The authors use the term storage allocation method to refer to the strategy of where to place and store different SKUs in the warehouse in order to facilitate the order picking, i.e. according to which pre-requisites. Order picking method refers to the way the picking of the SKUs in an order should be organized. Other terms used in research, but not adopted in this thesis, instead of method are process, policy, and strategy.

3.1 Physical Design of the Warehouse

Research within warehousing usually aims at improving different parts of the operations and providing decision support for warehouse managers. According to Baker and Canessa (2009) there are many articles that analyze isolated aspects of warehouse design. First and foremost order picking method, but also layout, choice of equipment etc. However, focusing on separate parts easily leads to sub-optimization since all areas of the warehouse are interrelated (Rouwenhorst, et al., 2000). The physical layout as well as the warehouse operations are interdependent and interact, see Figure 6. This means design decisions such as the overall structure, sizing and dimensioning of a warehouse, the department layout, operation strategies and choice of material handling equipment, racks and shelves, affect each other as well as the choice of warehouse operations methods. Consequently the decision-making in warehousing consists of a large number of decisions whereof many constitutes of combinatorial problems that are very difficult to optimize. The problem gets even more complex when considering all other factors that affect travel time, throughput and costs in a warehouse: demand, order and product characteristics etc. Every decision puts constraints or requirements on subsequent levels. This makes it important to simultaneously consider related issues in order to balance the tradeoffs.

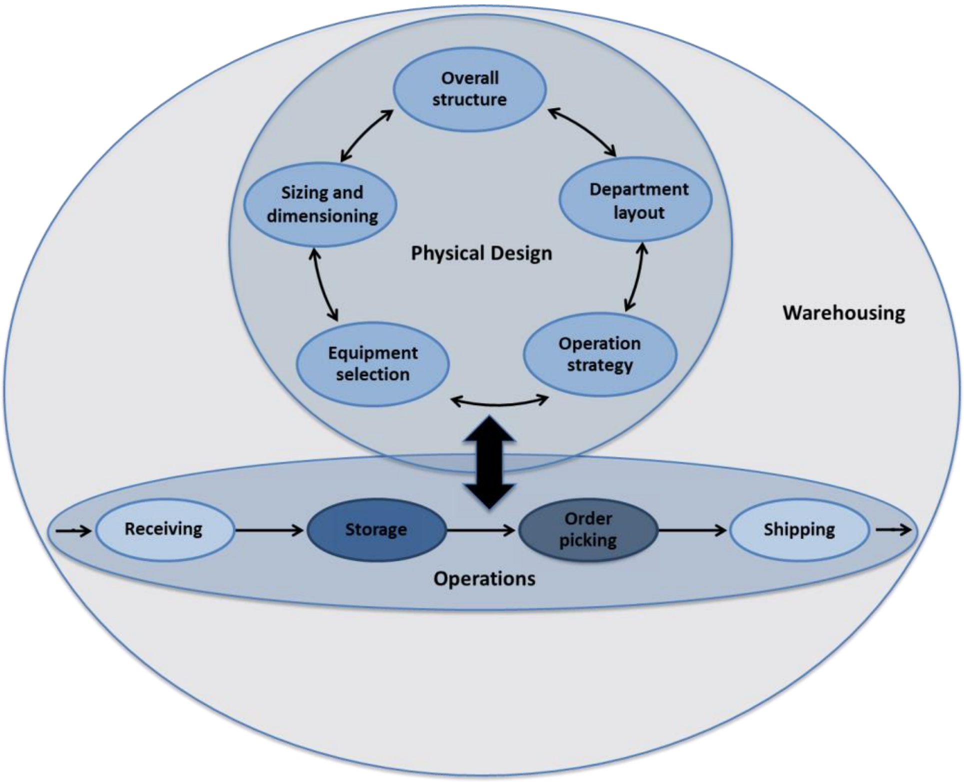


Figure 6 Framework for warehouse design and operation problems derived from Gu et al. (2007).

One strategy when clustering design problems for optimization is to base the partition on the time horizon of the outcome i.e. long, medium or short term. Many of the long-term decisions are connected to the physical design of a warehouse. That includes decisions connected to the overall structure, size, layout, and equipment, and they often also bring on high investments (Rouwenhorst, et al., 2000). The goal is to increase the utilization of the physical space and decrease the travelling distance and time, as well as material handling and associated costs. It is important to emphasize such operational measures in the design phase, since operational efficiency is strongly affected by the design (Huertas, et al., 2007). The layout of the warehouse facility thus plays a crucial role in the business success of the company. It stipulates and put the boundaries to many of the other design-choices. For example, the size will limit the volume of goods that can be stored in the warehouse while its dimensions, door locations and design of aisles will limit what flows of material that are possible, and it can be very costly or impossible to change the layout once the warehouse is built (Huertas, et al., 2007). This means that analyzing expected demand and establishing operating methods preferably should be done before determining the physical layout (Hassan, 2002). This view is also supported by Oxley (1994) who highlight that the warehouse design should be centered on the storage and handling requirements and that the building should then be designed around these (Baker & Canessa, 2009).

Regardless of which factors to include in the decision process, designing a warehouse from scratch is a huge undertaking only performed on rare occasions. It would always be ideal to start from a clean slate, but large improvements can be gained only reviewing current processes and the methods used. This might hold potential due to changed external conditions such as demand variations, and can be done through focusing on redesigning the most costly operations. In warehousing these are, as mentioned, related to the manual order picking, a widely recognized fact among researchers. Improved order picking is closely interrelated to storage allocation methods, and decisions on storage will have a major influence on the performance of the order picking. The decisions regarding where to locate the SKUs, assignment of items to pickers and routing combined hold a large potential for cost savings (Theys, et al., 2010). These areas and how they are related will be examined further in the following two chapters.

3.2 Storage Allocation Methods

Storage refers to the physical preserving of products while awaiting a demand (Frazelle, 2002). It is a major warehouse function that primarily deals with decisions regarding the amount of inventory to keep of each SKU, the replenishment pattern and where the SKUs should be stored in the warehouse. Inventory levels and replenishment relates to the areas of lot sizing and staggering problems and are not to be further examined in this report. The storage allocation of SKUs however is closely related to the order picking routes, and will have a great influence on the warehouse efficiency (Gu, et al., 2007). It has been showed that choosing the right product allocation method allows the current picking distance to be reduced by more than 10 percent. And post-optimization procedures can further reduce picking distances with up to 20 percent of the current distances. While order picking has received much attention in the research over the years due to its high costs, product location strategies have received considerably less, although the main objective when locating products is to facilitate the order picking (Renaud & Ruiz, 2008).

Much of the research results that do exist are in line with industry practice, where there is a unanimous agreement that the fastest moving SKUs should be put in the most convenient locations, according to Bartholdi and Hackman (2010). In this context, the term convenient refers to a location that will result in short total travel distance, from a product's point of entry in receiving, to final exit in shipping. In bin-shelving storage the convenient locations can be further narrowed down by utilizing the concept of the "golden zone" i.e. that highly slotted SKUs should be stored between a picker's waist and shoulders to reduce total fulfillment time, although the travel distance might increase (Petersen, et al., 2005). By storing the SKUs carefully, the most frequently visited locations are those of greatest convenience thereby minimizing the annual labor cost connected to put-away and picking. Consequently, the layout of the warehouse determines the cost associated with each storage location (Bartholdi III & Hackman, 2010).

Furthermore, the layout in terms of docks locations, aisle orientation, length, width and number of aisles is determined by the material flow pattern. There are several different product flow configurations to choose from when designing the warehouse layout. Each type is characterized by the placement of the dock locations for reception and shipment, the I/O points, and the convenience of the storage locations. Two common SKU layouts are U-shaped (cross-docking) and flow-through. Characteristic for the U-shaped layout is that the docks are located on the same side of the warehouse, see Figure 7. This way the more convenient positions get even better, at the expense of the less convenient locations getting worse. With this in mind, the U-shaped layout is most appropriate for warehouses where a small share of the SKUs account for the largest activity within the warehouse (Huertas, et al., 2007). This layout however requires that the docks are flexible and when needed can be used both for receiving and shipping (Bartholdi III & Hackman, 2010).

The flow-through layout refers to when the docks for reception and shipping are located on opposite sides of the warehouse, see Figure 8. This way, only a few locations can be considered very convenient. Instead, a larger share of the locations is fairly good and equally convenient. The flow-through layout is appropriate when handling very large volumes, or when the warehouse dimension is long and narrow. Another feature is that this layout reduces congestion and risk of errors in picking. In general, it is an advantage to orient the aisles so that they run parallel with the material flow. However, this is not always the case. In situations when movements between storage locations are necessary, cross aisles can be implemented to increase the efficiency, see Figure 9 (Bartholdi III & Hackman, 2010). Other aisle configurations to consider when improving the warehouse operations are for example that narrow aisles allow picking from both sides of an aisle at each stop in a picking tour, whereas wide aisles allow pickers to meet or overpass each other. Further, long aisles might increase space utilization while shorter aisles might reduce the risk of congestion (Hassan, 2002).

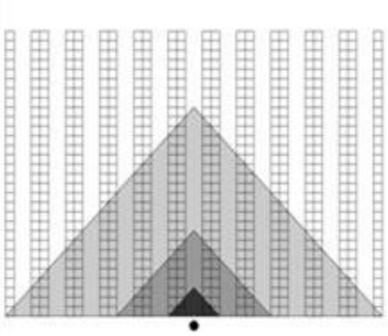


Figure 7 U-shaped layout (Bartholdi III & Hackman, 2010).

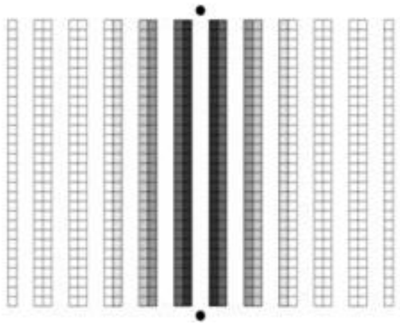


Figure 8 Flow-through layout (Bartholdi III & Hackman, 2010).

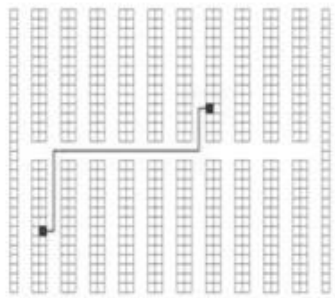


Figure 9 Usage of cross aisle (Bartholdi III & Hackman, 2010).

Storage is also often sectionalized in order to facilitate operations and reduce movement and congestion. This can be done based on the overall material flow, demand, pick frequency, or type of unit loads. The most common partition, which can be further divided into different sub-areas, is in reserve and forward areas (Hassan, 2002). The reserve area, also called bulk area, is where SKUs are stored in the most economical way i.e. in bulk or full pallets, while the forward or picking area is where SKUs are stored for easy retrieval by an order picker (Rouwenhorst, et al., 2000). The forward area can be described as a “warehouse within a warehouse” and is commonly used in high-volume distribution in order to minimize unproductive travel between far-distant locations (Walter, et al., 2013). The area usually refers to a limited area for fast-moving SKUs, located close to the I/O points. It contains smaller amounts of SKUs that stay there for a shorter period of time, and is replenished from the reserve. This way, the order picking cost is reduced, at the expense of additional material handling and increased travelling due to the replenishment (Gu, et al., 2007).

The approach raises the question of which SKUs it should store, how much space should be allocated to each SKU and its overall size. Methods proposed try to optimize the good of the area through balancing the expected labor-time related to order picking and replenishing during busy days (Gu, et al., 2007). The main tradeoff is thus reduced picking effort versus resources spent on replenishment. That is, a compact forward area increase picking efficiency through shorter direct distance travelled related to the SKUs it holds. On the other hand, it requires additional effort in terms of double handling and additional travelling related to the on replenishment. The two aspects must be well balanced in order to result in overall improvements. Walter et al. (2013) present three formulas for calculating the optimal choice, one for each main problem. The first allocate storage space among a given set of SKUs, the second select the products to be stored in the area, and the last addresses the storage allocation problem for the overall size of the area. One drawback is the complexity of the real problem and thus also the formulas that aim to solve it. For example, it is difficult to include limitations such as odd shapes of certain SKUs and thereby requirements on the shelving.

The placement of products within the storage area, whether in forward or reserve, can be determined in numerous ways. Three common storage allocation methods are random, dedicated and class-based storage (CBS), see evaluation in Table 2 at the end of this chapter. Random storage is when SKUs are randomly assigned to each location which mean their placement constantly change and that a SKU might have several storage locations spread out in the warehouse, as opposed to dedicated storage where each SKU belongs to one location only (Le-Duc & De Koster, 2005). Dedicated storage has the advantage over random storage that fast-moving SKUs can be located close to the I/O points and therefore get a more efficient material handling. On the other hand, this requires more storage space, since storage area must be reserved for the maximum inventory of each product. The random storage is suitable when the pick density is high. Pick density is calculated as:

Pick density (Chan & Chan, 2011) = $\frac{Number\ of\ SKUs\ in\ an\ order}{Total\ number\ of\ SKUs\ in\ a\ warehouse}$

In words, the concept is defined as the variety of items in a customer order that affects the performance of picking (Chan & Chan, 2011).

The third policy, CBS, has the benefits of both dedicated and random storage (Gu, et al., 2007). Here, the warehouse is divided into a number of zones and the SKUs are divided into the same number of classes, usually based on pick frequency. Then each class is assigned to one of the identified zones in the warehouse, so that each class of SKUs is dedicated to a zone. This way the total distance from picking the most frequent SKUs results in short travel, while keeping down the required storage space. Expressed in terms of CBS, the random storage would have one class only while the dedicated would have a number of classes equal to the total number of SKUs in the warehouse. Both random and dedicated storage can be applied within each zone in CBS (Gu, et al., 2007).

The three most frequently used criteria used when ranking SKUs or classes and linking them to storage locations are, according to Gu et al. (2007):

- *Popularity*, defined as the number of storage/retrieval operations per unit of time and puts the most popular SKUs in the most desired locations.
- *Maximum inventory*, which ranks products according to their maximum inventory. The classes with the lowest maximum inventory are assigned the most desirable locations.

- *Cube-Per-Order Index* (COI), defined as the ratio of the maximum allocated storage space to the number of storage/retrieval operations per unit time. The SKUs with the lowest COI are stored in the most desirable locations. Using COI, both popularity and space requirements are taken into account.

COI has gained the most attention among researchers, and has been proved to optimally minimize the material handling costs in dedicated storage, given certain premises. For example, the objective must be to minimize the long-term average order picking cost. Another premise is that the travel cost depends only on locations and therefore exclude e.g. cases when travel cost is item dependent (Gu, et al., 2007). According to Le-Duc and De Koster (2005) COI is suitable when there are very stable assortments with limited changes in order frequency and limited changes in the stored volume, which is rather uncommon in reality. Similarly, Ang et al. (2012) conclude that a large number of papers on the issue of storage allocation assume that the demand for each product is stationary over the planning horizon, and that this is rarely representative due to seasonality or the life cycle of products.

Petersen et al. (2005) state that the three best performing criteria, or slotting measures as they call it, in regards to reducing travelling are: popularity, COI and turnover, defined as the total quantity of SKU shipped during a given time period. All of the mentioned criteria are fairly easy to use and flexible enough to be practiced in many different types of warehouses. However, popularity is the most widely used since it is both performing well in terms of travelling and fulfillment time, as well as being easier to understand and implement than COI (Petersen, et al., 2005). Popularity is also the base of the classification made in rest of the research about CBS presented in this chapter.

In CBS the SKU ranking is followed by dividing the list in to classes from a chosen criterion. The procedure often uses the classic ABC analysis (Petersen, et al., 2004). The ABC analysis is a tool based on the Pareto principle or 80/20 rule, a concept stating that a small number of objects account for a large share of the total effect, which means a company might profit from differentiating its treatment of the objects according to their share. In this case it means a ranking the SKUs according to a specific criterion. It is very common to use the product of popularity and value or popularity in relation to total demand as criteria, but other factors can also be used. Next step is analyzing the list and its distribution of SKUs before specifying a suitable number of intervals, each representing a class: A, B, C etc. Each SKU is then classified according to the interval it belongs to. A common outcome is that about 20 percent of the SKUs turn out to represent 80 percent of the total demand (Jonsson & Mattsson, 2005).

CBS is stated to be the most popular storage method since it generally outperforms complete random storage in terms of picking distance (Le-Duc & De Koster, 2005), a view that is supported by Petersen et al. (2004). They show that CBS perform far better than random storage in a number of situations, see Figure 10, and Appendix B for similar comparison with regard to different routing methods. Their conclusion, which clearly shows in the figure, is that the savings increase along with the number of classes used, while savings decreases as the number of SKUs on the pick list increase. This is a rather intuitive as many SKUs on a pick list means increased likelihood of including also less popular SKUs, which in turn results in more travel to storage locations farther from the I/O. If however the pick list consists of one item only, the choices of zone configurations and storage policies are statistically insignificant (Petersen, 2002).

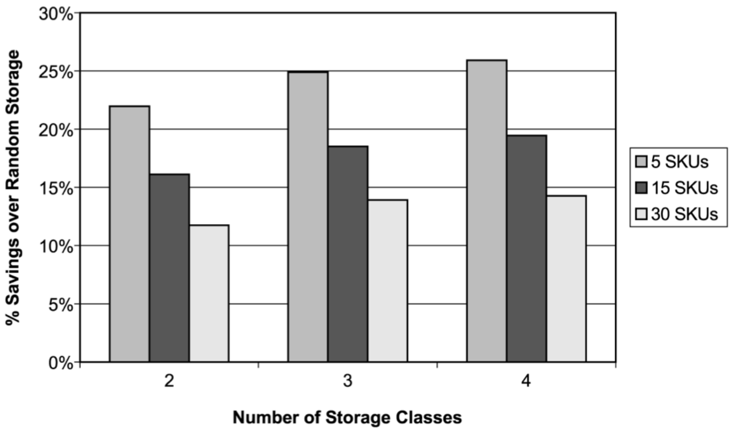


Figure 10 Comparison of CBS and random storage (Petersen, et al., 2004).

The likelihood of picking unpopular SKUs is closely related to the overall demand pattern. The demand pattern has a strong impact on the location of the SKUs in the warehouse and a reasonable assumption in most cases is that this is not the same for all SKUs. In Petersen's study from 2000 he uses the Pareto principle to investigate how the demand pattern affects the performance of different storage allocation methods. The study differs between three levels of skewness: high, medium and low, see Figure 11. High skewness means that the top 20 percent of the SKUs by demand account for 80 percent of the total demand, while medium and low account for 60 percent and 40 percent respectively (Petersen II, 2000).

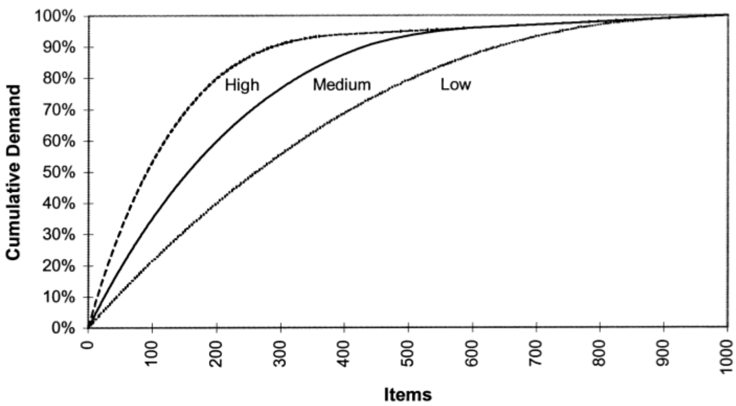
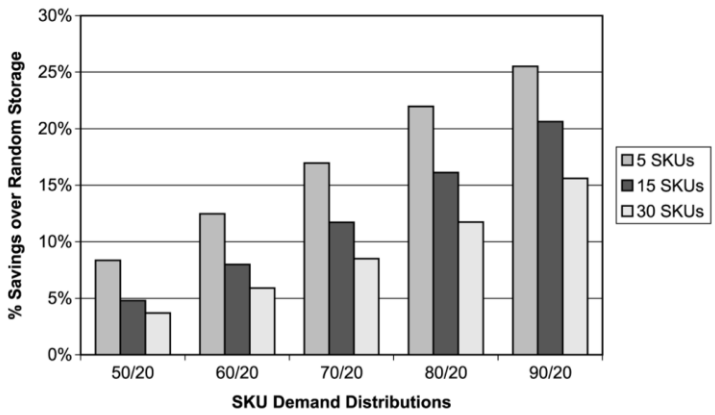


Figure 11 Demand skewness patterns (Petersen II, 2000).

In opposite to general belief, the long-term skewness is usually less than a theoretical 80/20 pattern. This is of great relevance since the performance of CBS over random storage has been shown to increase along with skewness, see Figure 12 (Petersen, et al., 2004). Once again, it can be observed that the savings decrease as size of pick list increase.

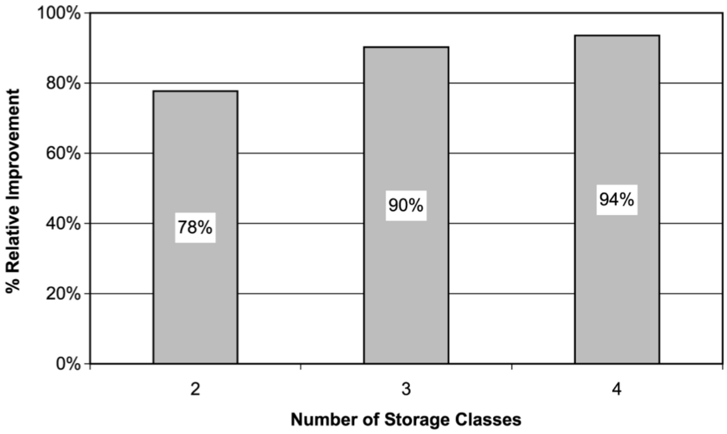


Note: 50/20 indicates that 20 percent of the SKUs account for 50 percent of the demand

Figure 12 Savings of CBS over random storage, depending on SKU demand distribution and size of pick list (Petersen, et al., 2004).

The observed pattern of increased savings along with increased number of classes, calls for the introduction of a version of the dedicated method, volume-based storage (VBS). Just like when using CBS, the SKUs are here assigned to storage locations based on their expected demand. The SKUs with the highest expected demand are assigned locations near the I/O point. The main difference is that the SKUs are not separated or categorized into classes; each SKU has its specific storage location (Petersen, et al., 2004).

With previous sections in mind, it might be easy to believe that using VBS should always be preferred over CBS. However, this is not the case. One major drawback with using VBS is that it requires a complete list of SKUs ranked by volume, and thus is more difficult to administer and require more information than when implementing CBS. In warehouses where seasonality of SKUs is distinct, usage of VBS may require periodic and costly reassignment of the SKU storage locations. Further, it has been shown that a large share of the potential benefits from using VBS can be achieved by introducing only two classes, and that additional classes bring successively decreasing marginal improvements, see Figure 13 (Petersen, et al., 2004).



Note: Percentage relative improvement is ratio of the savings of CBS over random storage to the savings of VBS over random storage

Figure 13 Performance of CBS compared to VBS when the number of storage classes is varied (Petersen, et al., 2004).

Despite CBS being the most popular storage method, there are few articles on storage planning for this purpose. Gray et al. (1992) presented a framework for designing warehouses with zone picking to determine number of zones, pickers, zone size, storage within as well as between zones and order batch size. Their main basis for determining the storage space required for each SKU was the replenishment quantity and cost, together with demand and SKU size. Similarly, Sarker et al. (1994) recommend that the area assigned to an entire class/zone should be proportional to its demand and percentage of inventory i.e. the Pareto principle might proof useful also in this matter. Petersen (2002) investigated the effects of zone shape on operational cost with simulation. The conclusion was that the shape of the zone has a great impact on the operational cost. Other researches propose further approaches to assigning SKUs to zones and to balance the workloads of the pickers between zones (Gu, et al., 2007). The zone formation is also connected to what is considered convenient locations and how the workers will move within the warehouse to avoid congestion and waiting time. Two common configurations when using CBS or fully dedicated storage (e.g. VBS) are within-aisle and across-aisle. The concepts refer to if the SKUs with the same ranking should be stored across several aisles with the same distance from depot/I/O, or within/along the aisles, see Figure 14 (Petersen, 2002).

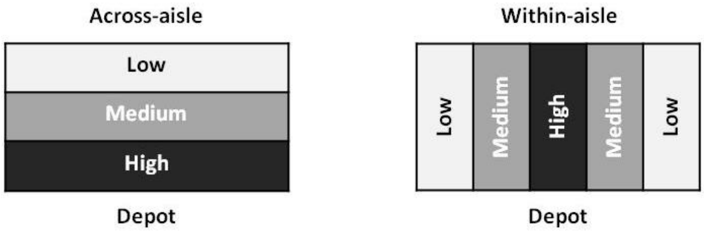


Figure 14 Two common storage configurations. High, medium and low refer to the ranking in of the SKUs stored in each area (Petersen, 2002).

In a subsequent article, Petersen et al. (2004) describe that the within-aisle storage usually performs best when using VBS. However, they also present three other storage allocation strategies, visualized in Figure 15. Rectangular storage is shown to perform almost as well as within-aisle when using two, three or four storage classes, while diagonal storage is outperformed by its alternatives. The performance of diagonal and rectangular storage relative within-aisle is presented in Appendix B.

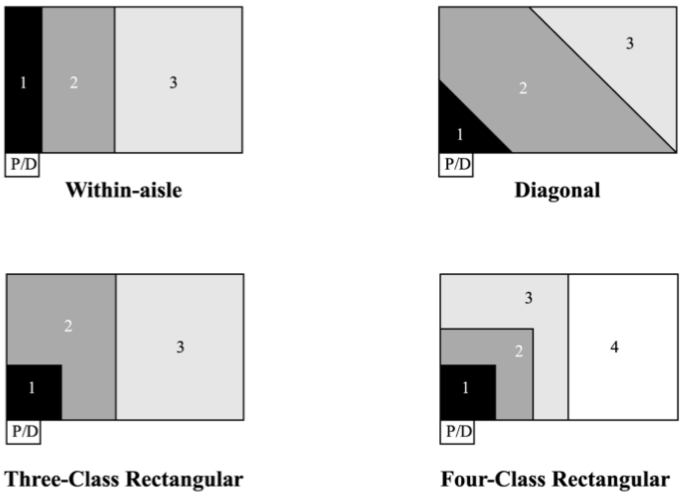


Figure 15 Variants of allocation of storage classes where the darkest shade represents the most popular SKUs, and P/D the I/O (Petersen, et al., 2004).

A summary of the qualities, advantages and disadvantages for all the storage allocation methods reviewed in this chapter is provided in Table 2.

Table 2 Evaluation of storage allocation methods. The sources to each statement are as follows: [1] Petersen (2002); [2] Chan & Chan (2010); [3] Bartoholdi III & Hackman (2010); [4] Petersen & Aase (2004); [5] Petersen, et al. (2004); [6] Petersen et al. (2005); [7] Hassan (2002); [8] Le-Duc & De Koster (2005).

Storage type	When	Pros	Cons
Random	• High number of items on pick list (gap to VBS policies decreases) [1]. • High pick density [2] • In reserve storage areas with a computerized inventory system [2]. • In reserve storage areas, where SKUS are held on pallets [3].	• High storage space utilization [2], [3]. • Easy to use [2], [4]. • Flexible [2]. • Requires less space [4]. • Leveled utilization of aisles [4]. • Reduces risk for congestion [4]. • Easy to administer [5].	• Increased travel distance [2], [3], [4]. • Requires use of WMS, workers cannot learn locations [3]. • Put-away might be more time-consuming if same SKU is stored in several places [3]. • Pickers might be tempted to pick the SKU from a more convenient location if stored in several places, thus creating discrepancies between records and physical inventory [3]. • Complicated to manage because it introduces many possible tradeoffs, especially between space and time (labor) [3].
Class-based storage, CBS	• A distinction between products can be made [2]. • Vertical CBS in multi-level rack warehouse to reduce order retrieval time [2]. • Horizontal CBS in single-level rack warehouse and to reduce total travel distance [2]. • Within-aisle together with turnover based classing [6]. • Across aisle with COI and popularity [6].	• Combines advantages of random and dedicated storage (reduced travel while staying flexible and with high storage space utilization) [2]. • Reduce travel [2], [7]. • Shorter travel than random [4], [5], [8]. • Easier to use than VBS [4]. • Easier to implement than VBS [5]. • Less administrative overhead than VBS [5]. • 2-class system attained nearly 80% of benefits of VBS [5]. • Widely used in practice [8]. • Convenient to implement and maintain [8]. • Easily handle assortment changes [8]. • Easily handle changes in pick frequency [8].	• Might increase congestion within aisles containing popular SKUs, thus limiting productivity [4], [5]. • Might require periodic movement of SKUs to reflect seasonality in demand [4], [5]. • Benefits might disappear if additional sorting is required [4]. • Can reduce congestion, particularly if popular SKUs not are allocated to one class [7].

Volume-based storage, VBS (dedicated)	• In the most active picking areas [3].	• Helps to maximize throughput [2]. • Shorter travel than random [3]. • Popular SKUs in convenient locations [3]. • Workers can learn the layout [3]. • Generally most effective at improving performance [5].	• Does not utilize space efficiently [3]. • Requires more time and effort to administer - more difficult [4]. • Might require periodic and costly movement of SKUs to reflect seasonality in demand [4]. • Information intense, requires more administration [4]. • Might increase congestion within aisles containing popular SKUs [4]. • Additional saving only 1% compared to CBS with 4 classes [4].
Within-aisle, VBS (dedicated)	• Smaller zones [1]. • Wider zone than depth [1].	• Shorter travel than random [1], [4]. • Pick lists >1 item: significantly less picker travel than alternatives [1]. • Reduces travel time [4]	• Increases congestion [4].
Across-aisle, VBS (dedicated)	• Within a picking zone (not entire warehouse) [1]. • Deeper zone than width [1]. • Pick lists =1 item, about as good as within-aisle [1].	• Shorter travel than random [1].	• Not as effective as other VBS policies [1].

3.3 Order Picking Methods

One purpose with determining the best storage locations for different SKUs is to increase the utilization the warehouse, another to be able to perform the order picking in the most efficient way. These resource intensive processes where SKUs are manually retrieved from their locations to fulfill customer orders can be further broken into sub-activities. Exactly how to divide the sub-activities, as well as the specific time distribution differ between researchers, one example is shown in Table 3. Travelling is however, the activity that generally requires the most time in order picking. Therefore, much of the picking design should focus on reducing this unproductive time. In the words of Bartholdi and Hackman (2010, p. 143): “travel time is waste. It costs labor hours but does not add value”.

Table 3 Average distribution of order picker time (Bartholdi III & Hackman, 2010).

Activity	% of order picking time
Travelling	55%
Paperwork and other activities	20%
Searching	15%
Extracting	10%

The procedure of deciding on efficient order picking methods needs to balance several aspects: time, resources available, picking accuracy and damages. Balance is the keyword. A too high focus on time reduction, might postpone associated costs through e.g. a negative impact on accuracy or damages.

There are many order-picking methods, all consisting of some or all of the following fundamental steps: batching, routing and sequencing, and sorting (Gu, et al., 2007). Four basic procedures for picking orders are single, batch, zone, and wave. Single picking means that one person picks one order, one line at the time; this can also be referred to as strict or discrete order picking. The opposite is batch picking, where one person picks multiple orders at the time. In zone picking the warehouse is divided into zones, as described in 3.2 Storage Allocation Methods.

Each zone has a limited subset of SKUs, and the pickers are assigned to a certain zone where they perform the required picking. Zone picking can be further divided into sub-categories: Sequential zone picking is when an order is assembled progressively from zone to zone, while batch zoning is a combination of batching and zoning; orders are batched, but pickers have their own picking zones, and all items in a batch must be picked before the next batch is begun (Petersen II, 2000). And finally in wave picking, orders are picked to meet the required shipping schedule (Renaud & Ruiz , 2008). That means batch zoning with very large batches that are picked based on a certain time frame, usually between 0.5 and 2 hours, rather than based on volume or order (Petersen II, 2000). These procedures can be combined depending on e.g. if they are performed in a zoned warehouse or not, or at what point in the picking process the batched articles will be sorted (Gu, et al., 2007).

Batching is a suitable option if the number of orders is large but the order size is small (Hassan, 2002). More thoroughly, the batching problem reads as follows: Given a set of orders, the problem is to partition this set into batches. Each batch will then be picked and accumulated for packing and shipping during a limited time frame, a pick wave. If this is employed in a warehouse with zones, it is necessary to balance the picking efforts between the zones to get high picker utilization, while minimizing pick time so that the total number of pickers can be minimized (Gu, et al., 2007). The disadvantage with this method is that it requires the items to be sorted at some point downstream, which require additional time and is a labor consuming process. Also, it is likely to increase the number of errors. It is generally economically beneficial to batch single-line orders since they require no additional sorting. The same is usually true for very large orders containing SKUs small enough to be picked in one trip. Following this reasoning, the medium sized orders provide the greatest challenge (Bartholdi III & Hackman, 2010). A comparison of the different order picking methods and when they are suitable can be viewed in Table 4.

Table 4 Evaluation of order picking methods. The sources to each statement are as follows: [1] Chan & Chan (2011); [2] Petersen II (2000); [3] Bartholdi III & Hackman (2010); [4] Hassan (2002); [5] Petersen & Aase (2004); [6] Cormier & Gunn (1992); [7] Petersen II (1997); [8] Gu et al. (2007).

Order picking type	When	Pros	Cons
Single picking (1 order/picking tour)	• Fairly large orders [1].	• Easy to implement [2]. • Maintains order integrity [2], [3]. • Avoids double handling [2]. • Direct error checking [2]. • Direct responsibility to single worker [2]. • Fast service [2]. • No consolidation needed [3]. • No coordination of pickers needed [3].	• Require much travelling [1], [2], [3]. • Does not allow for speed picking of large quantities of a single item [2].
Batching (>1 order/picking tour, 1 picker/order)	• Small orders [1]. • For most operating conditions [2]. • Requires a balance of travel savings and the cost of sorting and errors [2]. • If large number of orders but small order sizes [4]. • Not suitable if average order size approaches the maximum batch size [5].	• Less travel time per item [2]. • Fairly easy to implement [2]. • No adverse effects of demand skewness and order volume [2]. • Reduce travel [5].	• Order integrity is lost if not using special cart with compartments for each order and doing sort-by-picking, else increased risk of errors, additional consolidation space might be required for sorting [1], [2]. • Congestion can affect performance [2]. • Order assigned to the same batch must be picked within the same time window [6].
Zone picking (storage area is divided into zones, pickers are assigned to each zone)	• If workload must be shared due to large orders, orders that span over distant regions of the warehouse, or time constraints (parallel picking) [3]. • In large warehouses (benefits increase with size) [5]. • In wider warehouses with more aisles, so that each picking zone contains only one aisle [7].	• Limits congestion [2]. • Pickers can take advantage of the learning curve [3]. • Travel savings [8]. • Increases picker's item familiarity [8]. • Reduces congestion [8]. • Reduced order picking time span (parallel picking) [3], [8].	• Requires secondary consolidation operations [5]. • Additional costs due to sorting operations (parallel picking) or queuing (sequential picking) [8]. • Planning of storage assignment and zone shape required in order to minimize cost and balance workloads [8].

Sequential zone (an order is assembled progressively from zone to zone)	• Not if order volume increase [2]. • For warehouses that move a lot of small SKUs for each of many customers [3].	• Maintains order integrity (no sorting required) [2], [3]. • Travel savings [2]. • Increases picker's item familiarity [2]. • Reduces congestion [2]. • Increases accountability for productivity and housekeeping within a zone [2]. • Pickers can take advantage of the learning curve [3]. • Orders can emerge in the same order as they are released: ease truck-loading [3].	• Requires a conveyer to move an order from zone to zone [2]. • Delays due to workload imbalances can cause blocking and starving in previous and succeeding zones [2]. • Requires work balancing similarly to in an assembly line conducted by e.g. an industrial engineer [3].
Batch zone (orders are batched, but pickers have their own picking zones)	• Not if order volume increase [8]	• Volume picking of items is possible [2]. • Travel savings [2]. • Increases picker's item familiarity [2]. • Reduces congestion [2]. • Increases accountability for productivity and housekeeping within a zone [2]. • Pickers can take advantage of the learning curve [3].	• No order integrity requires sorting and consolidation after picking, including space and equipment for this. This also causes double handling and increased risk of errors [2]. • Workloads might vary between zones, causing idle time [2].
Wave (batch zone with very large batches based on time, 0.5-2h)	• For most operating conditions [2]. • If workload must be shared due to large orders, orders that span over distant regions of the warehouse, or time constraints [3]. • In large warehouses (benefits increase with size) [5].	• Even greater volume picking than in batch zone (any item is only picked once per wave) [2]. • Very efficient in pick, travel and unloading [2]. • Travel savings [2]. • Increases picker's item familiarity [2]. • Reduces congestion [2]. • Increases accountability for productivity and housekeeping within a zone [2]. • Pickers can take advantage of the learning curve [3]. • Reduce total picking time [5].	• No order integrity requires sorting and consolidation after picking, including space and equipment for this. This also causes double handling and increased risk of errors [2]. • Require more time and space for order consolidation than batch zone, since waves contain more orders than batches [2]. • Require more coordination and planning [2]. • Workloads might vary between zones, causing idle time [2]. • No order integrity, requires sorting and consolidation of order after picking [5].

3.4 Routing Methods

The routing method is a concept specifying the sequence in which SKUs are to be picked by the picker. It results in routes appropriate for the given order pattern (Petersen, 2002). The main objective is to minimize the distance travelled by the picker. The routing method describes how to travel each aisle during the picking. Six different routing methods that determine this where described and evaluated by Petersen II in 1997, herein referred to as transversal, return, composite, midpoint, and largest gap heuristics, and optimal procedures. The transversal method, also known as traversal, serpentine or S-shape heuristic, state that a picker must travel the entire aisle once entered, while the picker enters and leaves the aisle from the same side when using the return method. The composite heuristic is a combination of the transversal and return methods, meaning that an aisle is either entirely traversed or entered and left on same side, sometimes it is also referred to as the combined heuristic. In the midpoint method, the warehouse is divided in two sections across the aisles and pickers can only access an aisle as far as this midpoint. That means return routes are constantly used, sometimes both from front and back aisle. The largest gap method has a similar procedure, but an aisle is only entered as far as the largest gap: between two adjacent picks, first pick and front aisle, or last pick and back aisle. Return routes from one or both sides are used; hence the largest gap is the portion of the aisle the picker does not traverse. All these heuristics state that an aisle without pick is not entered, and examples of these strategies can be viewed in Figure 16 (Petersen II, 1997).

The optimal procedures are routes determined by using an optimization algorithm in a computer model, calculating the “best” pick paths. The result might appear counterintuitive and illogical, which is why the procedure is not visualized in Figure 16. A well-known solution to determine the minimum distance picker route is the Travelling Salesman Problem (TSP). In short, the TSP determines a minimum distance cycle that passes through each vertex (here referring to each product to be picked) only once. The general TSP problem connected to warehouse routing is NP-hard, there are nevertheless several efficient TSP algorithms for optimizing picker routes that works in certain warehouse configurations. However, since many warehouses do not fit these preconditions and it rarely is an option to constantly update the routes, most warehouses use predetermined routes in order to simplify for the pickers (Renaud & Ruiz , 2008). Such general but efficient routes where the sequence of visiting the storage locations is respected by all travel is sometimes referred to as global paths. The goal is to create a path outline that will induce a short pick path for most orders and still be so simple in structure so that order-pickers can understand it, which means it is usually based on one or several of the heuristics mentioned above. An effective path outline will account for the physical layout of rack, where the most popular items are stored, and what a typical order looks like, while helping the picker visualize the next location and how to travel there most directly. In addition, management may devise simple rules by which the path outline can be adapted for the particular customer orders. By providing the order-pickers with a set of rules to adapt the path, they leverage the intelligence of the work force, rather than embedding the decision-making in the WMS software (Bartholdi III & Hackman, 2010).

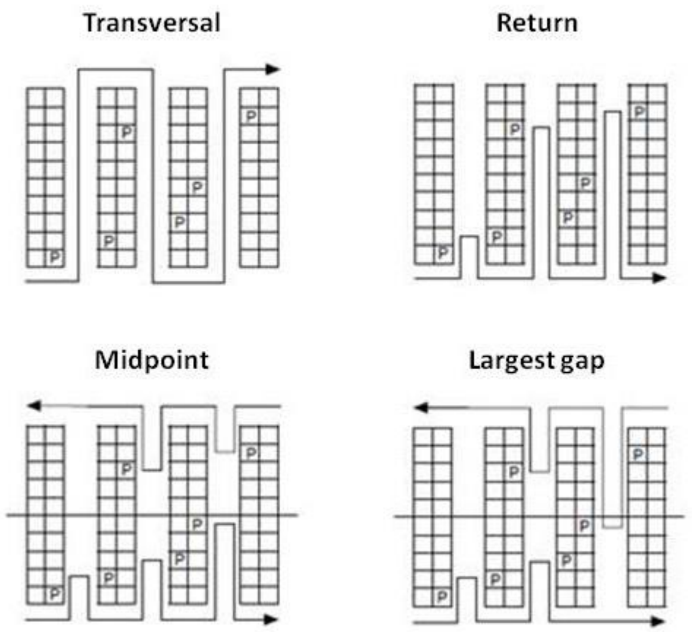


Figure 16 Examples of routing methods where P symbolizes storage positions of the SKUs to pick in this route (Petersen II, 1997).

Petersen (1997) conducted an extensive experimental study and evaluation of different order picking routings mentioned above. He compared their mean route length when picking the same randomly generated pick lists as other constraints changed. The graphs of how the methods perform as number of aisles, and pick list size change can be viewed in Figure 17 and 18.

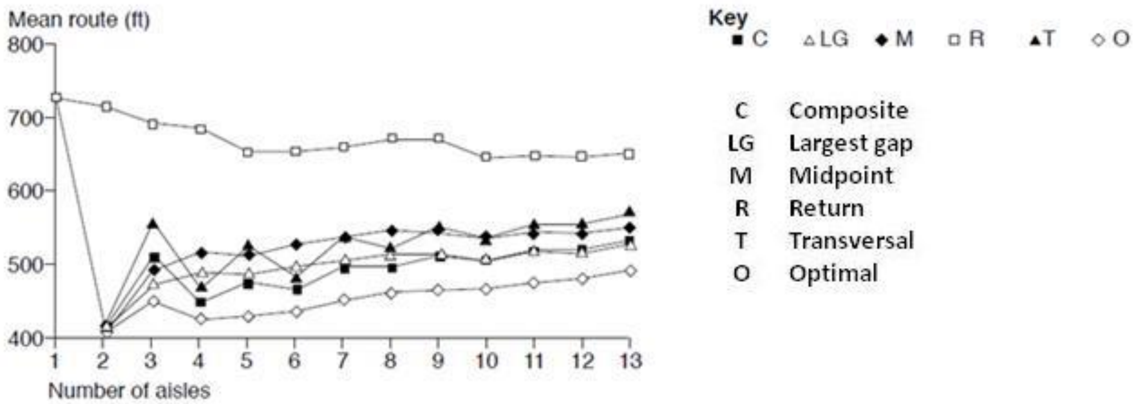


Figure 17 Impact of number of aisles in a warehouse on the performance of routing methods (Petersen II, 1997).

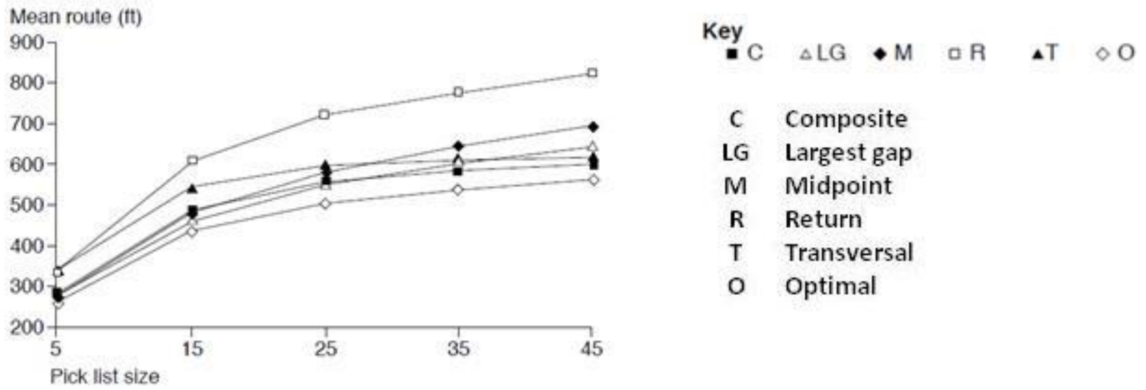


Figure 18 Interaction of routing methods by pick list size (Petersen II, 1997).

These graphs show that the return method usually has the poorest performance, while the optimal procedure performs best. The difference in mean route length between the different routing methods are however sometimes not so significant with heuristics performing near-optimal. An evaluation of the different routing methods that also consider other researchers' results can be viewed in Table 5. Some table cells are left blank since the information and research regarding some heuristics was incomplete.

Table 5 Evaluation of routing methods. The sources to each statement are as follows: [1] Chan & Chan (2011); [2] Petersen II (1997); [3] Petersen & Aase (2004); [4] Petersen et al. (2004); [5] Bartholdi III & Hackman (2010); [6] Le-Duc & De Koster (2005).

Routing type	When	Pros	Cons
Transversal heuristic (pickers must travel entire aisle once entered)	• Pick density is high [1]. • Large pick lists [2]. • High pick density per picking aisle [3]. • Large order sizes (result in high pick density i.e. optimal and combined routes tend to become traversal) [3]. • In combination with CBS [4].	• Simple [2]. • Easy to use [3]. • Considered more acceptable because it usually form more consistent routes compared to routes generated by optimal procedures, complex routes might cause confusion, increasing picker time and errors [3].	• Can result in wasted travel [5].
Return heuristic (pickers enter and leave aisle from the same side)	• In CBS with low pick density [1]. • Not in random storage [1].	• Simple [2]. • Easy to use [3]. • Considered more acceptable because it usually form more consistent routes compared to routes generated by optimal procedures, complex routes might cause confusion, increasing picker time and errors [3].	• Duplicate travels of aisles with picks [1]. • Worse than combined and transversal [1]. • Most inefficient routing method [2].
Composite heuristic (aisle is either entirely traversed or entered and left on the same side)	• In vertical CBS storage [1]. • Large pick lists [2].	• Shortest travel and order retrieval time due to flexibility. Minimizes the travel distance between the farthest picks in two adjacent aisles [1].	

		• Better than transversal and return [1]. • Near-optimal solution [2], [3]. • Top 2 heuristic [2]. Most efficient routing heuristic [6].	
Midpoint heuristic (pickers can only access an aisle as far as the midpoint)	• Small pick lists [2].		
Largest gap heuristic (pickers enter an aisle only as far as the largest gap between two adjacent picks)	• Small pick lists [2].	• Near-optimal solution [2]. • Top 2 heuristic [2].	
Optimal procedures (computer solution with optimal algorithm, e.g. TSP)	• Distance savings are more important than ease of use [2].	• Best routing method [2]. • Fast [2]. • Can be conducted on PC [2]. • Provides best solution [3].	• Requires use of optimization model (rather than heuristic) [2]. • Can give confusing routes; follow no discernible pattern and often backtrack [2]. • Complex routes can cause confusion, which will increase picker time and errors [3]. • Requires detailed information about layout and distances. Most WMS do not maintain this level of information; hence they do not support more complicated pick-path optimization [5].

3.5 Demand Pattern; Seasonality

One concept that influences both the design of the physical warehouse and its operations is seasonality. Seasonality can refer to the total overall variations in demand, or the shift in variation among different SKUs. Both implications need to be considered since fluctuation in order volume is common in real order pick systems. It has been shown that workload equalization between peak and slack periods is crucial to the system efficiency (Jane, 2000). Despite this, many research articles assume stability in demand over a specific time period (Ang, et al., 2012). Seasonality affect the storage requirements of the warehouse, hence both the outer dimensions and the sizing of different storage areas inside. One of the most difficult decisions to make when dimensioning a warehouse is how large share of the demand peak to accommodate in storage capacity. Figure 19 illustrates the deviation from average in storage requirement during a peak period. Frazelle (2002) suggests that a temporary space, e.g. trailer storage or an area outside the warehouse should be considered if a peak is short lived and the ratio of peak to average is high. At what point the ratio is considered high is not defined.

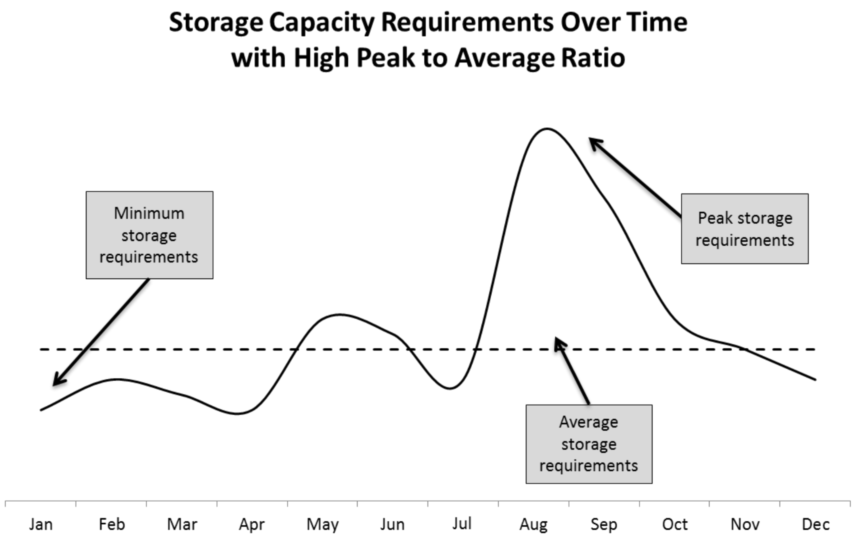


Figure 19 Storage capacity requirements over time with high peak to average ratio, inspired by Frazelle (2002).

Another way to handle this issue on a more operational level is to relocate some pallets closer to the I/O point for the heaviest workload period. In short, this means expanding the number or picking zones when demand is high, and reducing the number of picking zones when demand is low (Jane, 2000).

4 Developing the Decision Support Tool

This chapter will start with presenting two existing decision support models for redesigning warehouses in order to create a basis for developing the decision support tool. It continues by combining them and the aspects identified in the evaluations in chapter 3 in to a conceptual model for how to make the right choices when updating and improving the storage allocation, picking and routing methods in a warehouse, which is then explained in the succeeding chapters step by step.

In order to create a decision support tool for managers that want to update their existing warehouse operations procedures, the research presented in the previous chapter is used as a theoretical foundation. Warehouse design frameworks by Rouwenhorst et al. (2000) and Hassan (2002) and similar attempts are reviewed and used for structural inspiration. That way, two levels of research are combined: specific and general. The actual tool should thereby represent and reflect all reviewed research combined. The result is first visualized in a conceptual model, followed by a stepwise description of input data, procedure and output. The goal is to provide decision support for the choices to make when changing the methods used in a warehouse' picking operations where many of the physical parameters can be considered fixed.

4.1 Existing Decision Support Models for Redesigning Warehouses

Attempts to fill the lack of methods for redesigning warehouse operations have been made, although the focus has been on the overall design rather than merely performing continuous updates. Most researchers emphasize decisions excluded from this study or factors assumed fixed and are therefore not applicable. Two fairly comprehensive approaches to solving the warehouse design problems that partly fit the situation at hand have been concluded by Rouwenhorst et al. (2000), and Hassan (2002). Both aim to get an overview of all steps to include in a design process, as well as consider the interrelation between the decisions. They also bring up that some design decisions probably will have to be reviewed or updated in subsequent steps or in the future. The consideration of both interrelated decisions and the need for updates made them suitable inspiration when creating a decision support tool for reviewing the choices of storage allocation, order picking, and routing methods.

Rouwenhorst et al. (2000) try to structure all the interrelated decisions in a hierarchical framework. They look at warehouses' processes, resources and organization and try to determine what design issues to consider and how to solve them under different time horizons. This means that decisions made at a higher level will have a long-term impact and involve higher investments than decisions made at lower levels. These choices will also provide the constraints for lower level design problems. By using a top-down approach, a rough first design get more and more refined at the subsequent stages. The idea is to cluster related problems at the same design level and simultaneously optimize the various sub problems in order to reach a global optimum. On the strategic level decisions often concern system type selection based on technical feasibility and design objectives, while the tactical level decisions deal with dimensioning the different warehouse areas and the equipment.

Decisions made on an operational level are e.g. task assignment to personnel, batch formation, and routing. Rouwenhorst et al. (2000) also discuss different performance criteria for evaluating a particular warehouse design such as: investment and operational costs, volume and mix flexibility, throughput, storage capacity, response time, and order fulfillment quality (accuracy).

Hassan (2002) on the other hand created a framework for major design requirements needed in order for a warehouse layout to support its operations. Just as Rouwenhorst et al., he stresses the complexity of the interrelated decisions but instead of basing the framework on the time horizons of the decisions, he focuses on the physical layout. The goal is to give it characteristics such as modularity, adaptability, flexibility, compactness, and accessibility by making design decisions according to certain consecutive steps, see Table 6 (Hassan, 2002):

Table 6 Framework for the design of warehouse layout (Hassan, 2002).

Framework for warehouse decision making	
Step 1:	Specifying the type and purpose of the warehouse
Step 2:	**Forecasting and analysis of expected demand**
Step 3:	Establishing operating policies
Step 4:	**Determining inventory levels**
Step 5:	**Class formation**
Step 6:	Departmentalization and the general layout
Step 7:	Storage partition
Step 8:	Design of material handling, storage, and sortation systems
Step 9:	Design of aisles
Step 10:	Determining space requirements
Step 11:	Determining the number and location of I/O points
Step 12:	Determining the number and location of docks
Step 13:	**Arrangement of storage**
Step 14:	**Zone formation**

The possibilities for the decisions to make in each step rely on the previous steps. However, some of them might not be possible to finalize until subsequent decisions are made. Hassan also state that many of the steps can be performed more frequently i.e. revisited during the operations of a warehouse, or during a design update, which is in line with what this study tries to accomplish. The bold steps are of particular interest in such updates due to varying conditions such as the “dynamic nature of the demand” (Hassan, 2002, p. 438). Furthermore, Hassan points out that step 13 *Arrangement of storage* might require physical modifications of the warehouse, and in such cases the simplicity of the flow pattern should be kept intact in order to maintain streamlined warehouse operations.

4.2 Theoretical Result; Decision Support Tool

By using the decision frameworks by Rouwenhorst et al. (2000) and Hassan (2002) for structure and inspiration, a tool for decision support when updating the storage and picking operations of a warehouse was created, see illustrative overview in Figure 20. The first three steps determine the company specific situation. They create the framework that limits the possibilities of the following three steps; the preconditions when deciding on warehouse operation methods. The different steps and each linked decision indications were concluded by consulting the theory from chapters 3.1 to 3.5, and the evaluations of the different methods presented in Tables 2, 4, and 5. The steps are to be followed in sequential order to ease the updating process, where the knowledge attained in the previous step is used or at least considered. Divisions of data might lead to that steps 4, 5, and 6 must be repeated separately for each data portion. A more thorough description of each step is presented in the following chapters.

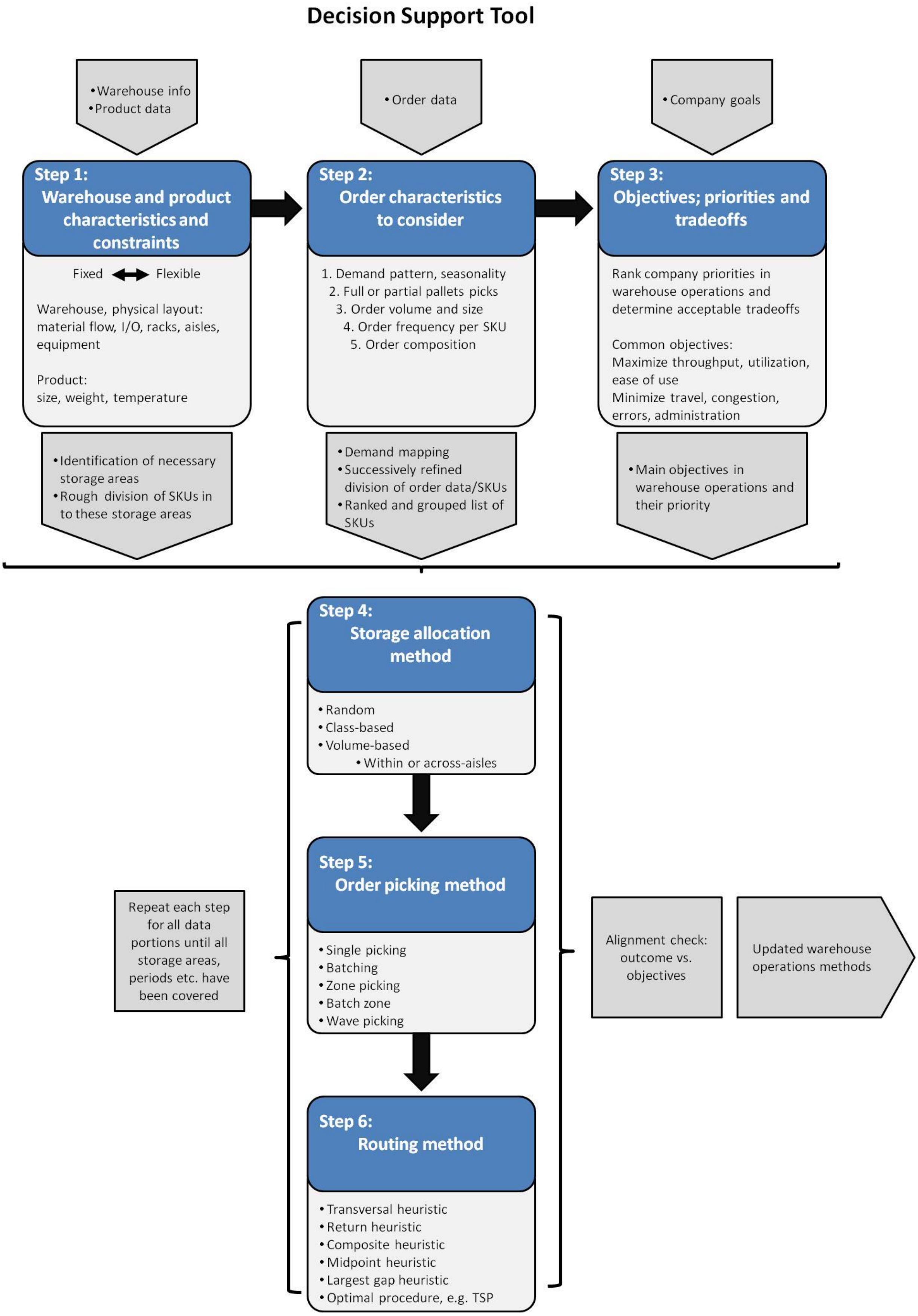


Figure 20 Overview of the created decision support tool (Gildebrand & Josefsson, 2014).

4.2.1 Step 1 Physical Warehouse and Product Characteristics and Constraints

Input: Information about the warehouse and product data.

Conclude the physical constraints of the warehouse, such as layout and equipment: material flow, pick locations, I/O docks, aisle configuration, storage systems, material handling equipment etc. Also identify product characteristics that put constraints on storage and picking options: shape, volume, weight, heterogeneity (Frazelle, 2002), and storage requirements (Hassan, 2002). Conclude which of these characteristics that should be considered fixed and which that are flexible and can be altered. Then convert this in to a rough storage area layout where certain SKUs need to be placed in certain areas, e.g. heavy items on stronger racks, or perishable items in refrigerated rooms.

Output: Identification of constraints related to storage areas and a rough division of SKUs accordingly.

4.2.2 Step 2 Analyzing the Order Characteristics

Input: Order data.

Determine order characteristics by examining order data for the period to be updated, either by actual orders or by using forecasts. Conclude the following features (Hassan, 2002):

1) Demand pattern and mix. Identify seasonality if any.
2) Percentage of items to be ordered and picked in full vs. partial loads/pallets.
3) Order volume and order size; average number of pallets and SKUs per order, respectively, and corresponding pick density.
4) High and low demand SKUs and level of demand skewness; order frequency in average number of picks per time period.
5) Order composition; identify products frequently ordered together.

Each of these order characteristics might divide the order data and its included SKUs in to smaller portions such as different time periods, or full or partial pallet picks. Previously lifted theory point out that one way of determining the time periods are to split the order data when the ratio of peak demand to average is high. The interpretation of this statement is rather arbitrary, and where the exact breaking point should be is left to the user to identify. If seasons are difficult to detect, this might not be a relevant step to perform.

There is no set hierarchical order to the characteristics above; the main idea is that each division made should be kept in the sequential partition. Hence, this step might lead to order data divided in to several time periods, and within these periods further be divided in to full pallets picks and partial pallet picks. Each part would then get its own order data analyzed and the SKUs ranked and grouped based on order frequency and composition.

Output: Demand mapping, successive division of order data and SKUs in to time periods and storage groups based on demand pattern, pick size, and order volume, size, frequency, and composition. A list of all the SKUs in each part, ranked and grouped based on the main criterion for its partition.

4.2.3 Step 3 Objectives; Priorities and Tradeoffs

Input: Internal company goals and competitive strategy.

Determine how company goals and competitive strategy should manifest in terms of its warehouse operations. Main objectives according to research concern minimizing travel, congestion, errors and administrative work, as well as maximizing throughput, utilization and ease of use. Conclude the objectives' importance and the company preferences and priorities, as well as which tradeoffs to find acceptable when deciding on priorities. When for example adopting VBS in order to minimize the travelled distance, the tradeoffs of increased risk for congestion and a more complex system to implement and uphold must be acknowledged and accepted. Or if implementing random storage in order to maximize the warehouse utilization, the main tradeoff of significantly longer travel distances has to be recognized, see Tables 2, 4, 5 in chapter 3.

Output: Main objectives for warehouse operations and their priority.

4.2.4 Step 4 Storage Allocation Method

Input: Rough storage area division from step 1. Order data divided into suitable portions and listed and ranked SKUs for each portion from step 2. Company priorities in warehouse operations from step 3.

Examine each storage area and each order data portion separately. Based on order, SKU and warehouse information together with the main objectives and acceptable tradeoffs, determine the suitable storage allocation method:

- Random storage
- CBS
- VBS

The radar chart in Figure 21 is one aid in making the decision. It illustrates the different pros and cons of the storage alternatives in correlation with company priorities, where a high score indicates a strong correspondence between the method and the statement or variable at the end of the spoke, a low score indicates the opposite. No score at all means that no research has been found connecting this particular method with that variable. Note that the relative position of the axis is uninformative as well as the relative magnitude of the indicators, their importance depends on the company's objectives. The scores connected to a certain variable are arbitrary but related in size, e.g.: Random storage is stated to give a very high warehouse utilization so its score is significantly higher than CBS', although the exact difference is not graded due to the context specificity of their performance.

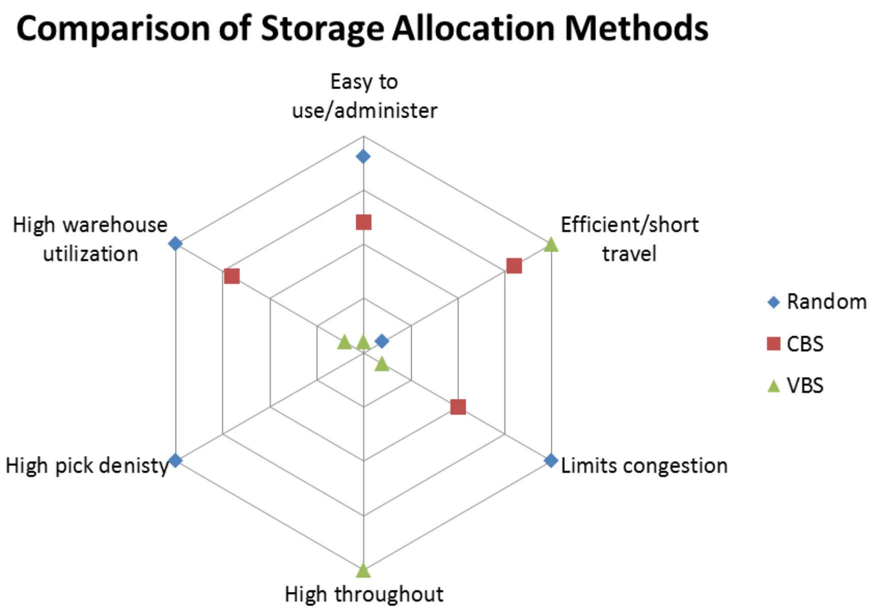


Figure 21 Radar chart comparing the different storage allocation methods' performance, based on the research presented in Table 2 (Gildebrand & Josefsson, 2014).

If using CBS or VBS, then refine the storage area division by determining storage configuration and conclude the most convenient locations in each storage area. If using CBS, then also determine suitable classes; number, size, and separating characteristic for the products stored in each e.g. popularity or COI. Then conduct the storage area formation for each class. Perhaps this process includes testing several options and adding different modification in order to make a final decision. Finally allocate the SKUs.

Output: Storage allocation methods for all parts of the warehouse under the studied time period as well as a complete map with the resulting storage locations.

4.2.5 Step 5: Order Picking Method

Input: Demand pattern as mapped in step 2, company priorities in warehouse operations from step 3 and storage allocation method from step 4.

Examine each storage area and each order data portion separately. Look at each SKU and its pick location in correlation with the demand pattern, especially order size and composition. Based on this, together with the main objectives and acceptable tradeoffs, determine the suitable order picking method:

- Single picking
- Batching
- Zone picking
- Sequential zone picking
- Batch zone picking
- Wave picking

The radar chart in Figure 22 is one aid in these decisions. It illustrates the different strengths and weaknesses of the order picking alternatives in correlation with company priorities. A high score on the axis indicates a strong correspondence between the method and the statement or variable at the end of the spoke, a low score indicates the opposite. No score at all means that no research has been found connecting this particular method with that variable. Note that the relative position of the axis is uninformative as well as the relative magnitude of the indicators, their importance depends on the company's objectives. The scores connected to a certain variable are arbitrary but related in size. If choosing a batch or zone based method, also conclude how to batch, suitable zone formations, time frames etc.

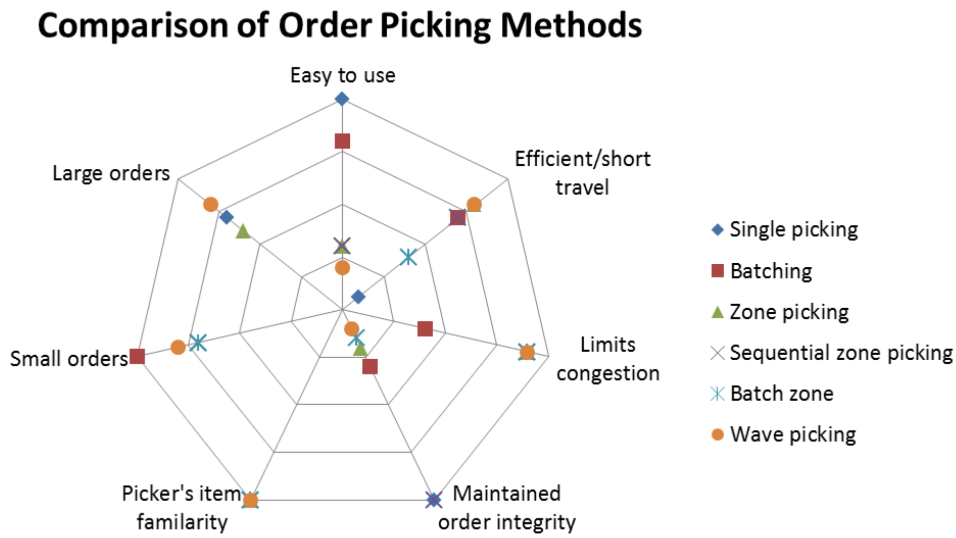


Figure 22 Radar chart comparing the different order picking methods' performance, based on the research presented in Table 4.

Output: Order picking methods for all parts of the warehouse under the studied time period.

4.2.6 Step 6: Routing Method

Input: Company priorities in warehouse operations from step 3 along with storage allocation and order picking methods from step 4 and 5.

Examine each storage area and each order data portion separately, but also consider the overall picking in each time period. Based on order information together with the main objectives and acceptable tradeoffs, determine the suitable routing method:

- Transversal heuristic
- Return heuristic
- Composite heuristic
- Midpoint heuristic
- Largest gap heuristic
- Optimal procedure

The radar chart in Figure 23 is one aid in these decisions. It illustrates the different strengths and weaknesses of the routing alternatives in correlation with company priorities. A high score on the axis indicates a strong correspondence between the method and the statement or variable at the end of the spoke, a low score indicates the opposite. No score at all means that no research has been found connecting this particular method with that variable. Note that the relative position of the axis is uninformative as well as the relative magnitude of the indicators, their importance depends on the company's objectives. The scores connected to a certain variable are arbitrary but related in size.

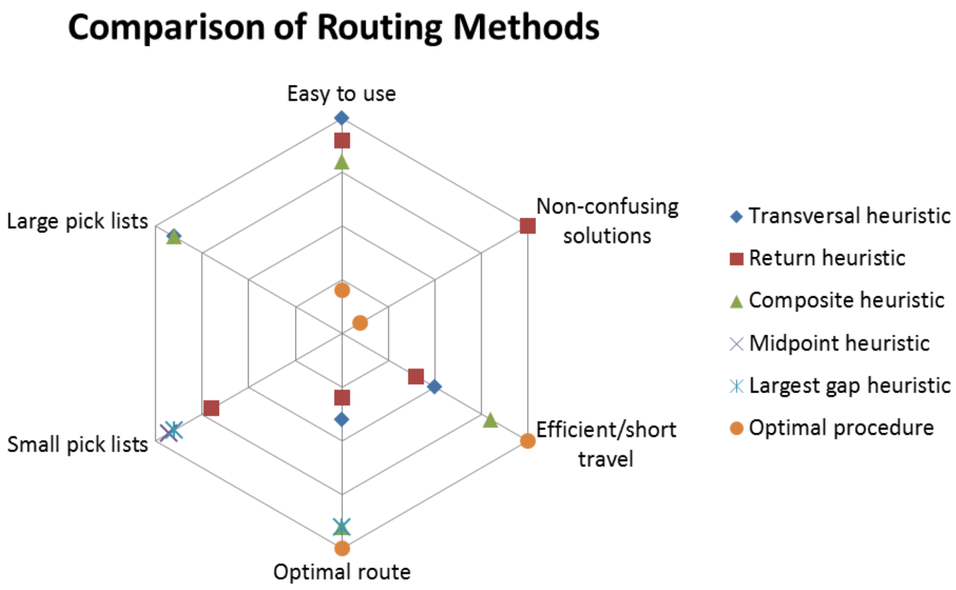


Figure 23 Radar chart comparing the different routing methods' performance, based on the research presented in Table 5 (Gildebrand & Josefsson, 2014).

Output: Routing methods for all parts of the warehouse during the studied time period.

The six steps presented above should now have provided enough support to finalize the decisions regarding which methods to use in storage allocation, order picking and routing for the studied time period. Hence, the final output should be guidance for what to apply in the warehouse operations, e.g. in the WMS settings. However, before implementing the update, make sure to check that the combined outcome really is in line with the internal company objectives concluded in step 3 so that no contradicting choices have been made.

5 Illustrative Example; Empirical Data

This chapter will present the information about the Thule Group needed in order to provide an illustrative example of how to use the decision support tool presented in chapter 4.2. The empirical data includes all information needed to update the warehouse operations for the Huta DC: physical warehouse constraints, product characteristics, and order characteristics.

An illustrative example was used in this master thesis in order to show and test the usability of the decision support tool presented in chapter 4.2. This part of the study was performed together with the company Thule Group. The purpose was to get the empirical data required as input to the tool by using historical demand from the company along with the planned dimensions and conditions in one of its warehouses as an example. Information concerning warehouse layout and warehouse operations issues, product range, and order history was collected to get a deeper understanding of the setting, and to be able to use the tool. The chapter is structured according to the first three steps in the tool, but starts with some general information about the Thule Group and its new DC.

5.1 The Thule Group and Its New DC

The Thule Group was founded in Sweden in 1942 and has its headquarters in Malmö. The company has over 3 400 employees at more than 50 production and sales locations all over the world. The business idea is to help "transport anything you care for safely, easily, and in style so you are free to live your active life" (The Thule Group, 2013). Hence, the product portfolio consists of all from roof racks, bike carriers and winter sport carriers, to daypacks, camera cases and multifunctional child carriers (The Thule Group, 2013). Thule has a number of buffer storages in connection to its production sites. Even though the storages were only supposed to fill the purpose of buffering, they have to an increasing extent been used for tasks that usually are assigned to, and better performed by a DC (Janas-Kaszuba, 2014). A DC is a type of warehouse used for accumulating and consolidating products from various points of manufacture for combined shipment to common customers (Frazelle, 2002). In Thule's case this means combining items both from the production on site and from its other plants. Unintentionally operating multiple smaller buffering storages as DC's was not optimal, and raised the need for a larger consolidating European DC that could unite production flows and distribution channels. As a result Thule decided to build a DC in connection to its largest production site, which makes bike carriers, in Huta, Poland. It will start to operate in December 2014 (Risholm, 2013).

Beside the buffer storages, Thule has a 3PL carrier in Duisburg, Germany, managing parts of its product flow. The new DC will mainly support the larger customers in Europe, and thereby both unburden and complement the current 3PL carrier with regard to geographical markets served and customer size (Andersson, 2014b). The arrangement follows the common setup in logistics of having a small number of large DCs with an extensive distribution network, often serving an entire continent (van den Berg & Zijm, 1999). Similarly, De Koster et al. (2007) recognize a current trend within warehousing to replace many smaller warehouses with few larger ones in order to benefit from economies of scale. For the typical warehouse this means that larger volumes are to be handled in a given time frame (De Koster, et al., 2007).

The Huta DC will be built to handle the expected demand in 2017-2018, including about 4 500 SKUs. Performing this type of warehouse operations in-house is a new experience for Thule, at least for the staff in Poland. Still, knowledge and expertise can be gained both from the more advanced operations in Thule's warehouse in Haverhill, England, and from the set up in the current 3PL DC. In line with most warehouses, the order picking is presumed to be the most resource intensive part of the warehouse operations, and needs to be designed carefully (Janas-Kaszuba, 2014). Consequently, the decision support tool described in chapter 4.2 will be a useful tool in this process. The tool mainly regards situations with known order and product characteristics, as well as preset conditions regarding physical layout etc. This case concerns a new, non-operating DC so some facts or constraints might be unknown. However, data about the SKUs to be handled at the DC and about previous order history is available through the company's ERP system, and the general physical layout is already determined. The company's main internal wishes and priorities are also already established. That means there is enough information to be able to apply the tool. The key aspects will be further described in chapters 5.2 to 5.5.

5.2 Physical Warehouse Constraints at the Huta DC

Warehouse layout is an essential part when designing new warehouse processes, as discussed in chapter 3.1 Physical Design of the Warehouse. However, the decision support tool established in chapter 4.2 regards the layout and available equipment as relatively fixed, e.g. it might be possible to alter some rack dimensions and thus the storage locations, but the general design and flow are already determined. These features set the physical constraints for the update of storage and picking operations. The overall layout of Thule's new DC in Huta, along with available resources, was thus considered given factors in this case, although the construction of the building and its interior are not finalized before the end of this project. There was also a more detailed layout suggestion with exact dimensions of the pallet racks, and number of pallet positions. This suggestion was, however, not considered fixed apart from the existence and size of the VLM and flow racks. The planned layout design and equipment for the Huta DC can be viewed in Table 7 and Figure 24.

Table 7 Planned physical constraints to Thule's Huta DC (Andersson, 2014b).

Physical parameter	Constraint
Building dimensions	
Length x width x height (meter)	112 x 85 x 12
Row length (meter)	60
Number of trucks	6
Pick truck	3
Reach forkliftStand on stacker	2
Number of I/O docks	10

Number of pallet positions	(color Figure 24)	Pick locations	Height pick locations
Fixed			
VLM	bright green	1 900	
Flow racks, 2.8 meter deep	pink	469	0.3 - 0.4 meter
Flexible			
Pallet racks, 1.1 - 1.5 meter deep	dark green, blue, red, black, orange	1 527	1.6 - 2.5 meter
Upper levels pallet racks	not showing	10 168	1.6 - 2.5 meter

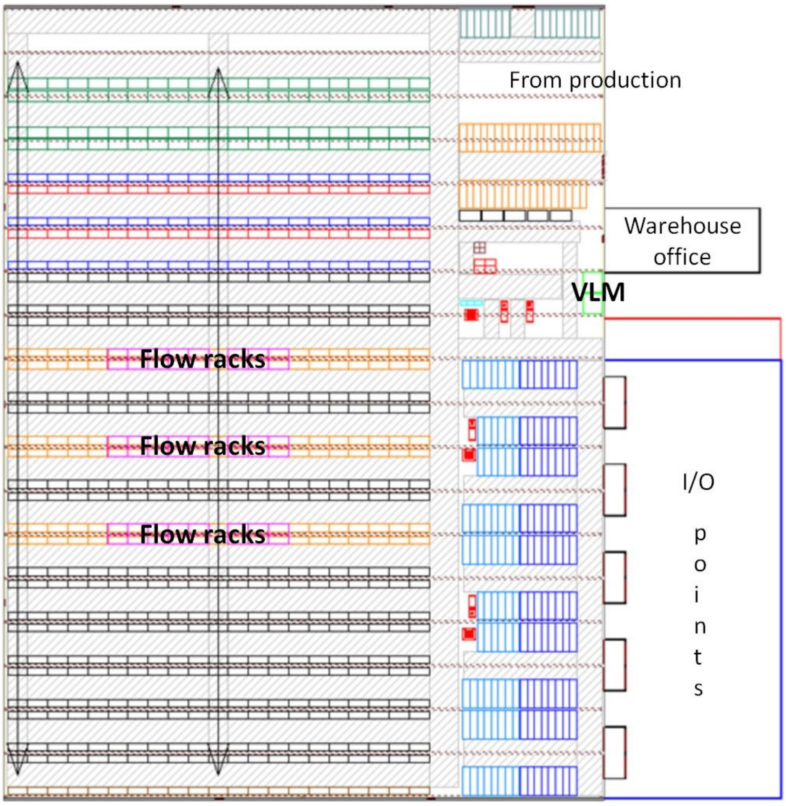


Figure 24 Detailed layout suggestion for the Huta DC provided by the Thule Group in January 2014. The two vertical arrows indicate pathways (Andersson, 2014b).

5.3 Product Characteristics

Information about the SKUs to be stored in the Huta DC was compiled in an Excel file provided by Risholm (2014). It contained necessary information about the characteristics of the SKUs. Item number and name, production site/manufacturer, package and pallet sizes and weight, items per package, and per pallet as well as pallet type and volume. A sample of the product information can be found in Table 8.

Table 8 Sample of the product information provided by Thule in the Excel sheet *SKU dimensions* (Risholm, 2014).

Item No	Name	Produced in Huta	Pallet length	Pallet width	Pallet height	Pallet weight	Pallet type	Items per pallet
100015	Sport rack – full rack	No	1.20	0.80	1.15	12	C1	96
561000	Bike carrier 561 Out Ride	Yes	1.20	0.80	1.15	73	C1	27
562000	Ski carrier 562	No	1.00	0.80	1.15	93	B1	300

Product characteristics that typically constrain the storage possibilities are connected the SKU and pallet dimensions, especially length and height, and how they fit the storage equipment. The SKUs to be stored in the Huta DC vary greatly in size, and thus has to be located accordingly. Table 9 presents the suggested categorization of the SKUs by size, i.e. each height or length restricted category corresponds to a suggested rack size in Figure 24. Other product characteristics that could have a high impact on warehouse operations methods not considered in this study are weight; disregarded due to lack of information about rack constraints, and production site; the inflow and put-away operations were excluded from the project scope.

Table 9 Product characteristics of the SKUs to be stored in Thule's Huta DC (Risholm, 2014).

Product characteristics	Number of SKUs
Number of SKUs	
Total	4 500
Included in study	2 306
Pallet height restrictions	
SKUs > 1.6 meter	60
SKUs < 1.6 meter	2 151
Pallet length restrictions	
SKUs ≤ 1.3 meter	1 972
1.2 < SKUs < 1.8 meter	195
SKUs ≥ 1.8 meter	44
Flow rack restrictions	
All SKU dimensions < 0.4 meter	395
VLM restrictions	
One SKU dimension < 0.4 meter	1 193

5.4 Order Characteristics in the Huta DC

The customer order data for the Huta DC was compiled in the same Excel file provided by Risholm (2014) but in another sheet: *Order data 12-13*. It contained one year of historical order data, from July 2012 to June 2013 and concerned orders of the SKUs the new DC will contain. Which SKUs that was delivered to which customer and in which shipment on which date, as well as number of items and corresponding number of pallets. Of special interest was the information concerning delivery number and order line, but since none of them was unique for a certain SKU and pick, an additional column was added named *Unique pick line* which gave each row in the order data a unique number. It should correspond to each individual pick made in the warehouse, but it was found that these unique pick lines might contain several full pallets, which obviously represent more than one pick.

Another adjustment was adding an extra column extracting year and date from the delivery date in order to simplify the visualization of the demand per month. A sample of the information the file contained is presented in Table 10, and an extended version can be found in Appendix C.

Table 10 Sample of the order information provided by Thule in the Excel sheet *Order data 12-13* (Risholm, 2014).

Delivery no	Unique pick line	Order number-line	Year-month	Item no	Item name	Quantity	#Pallets
2493856	2493856-1	3100096705-300	2012-07	970003	Xpress 970	48	0.75
2493856	2493856-2	3100096705-300	2012-07	970003	Xpress 970	64	1
2942265	2942265-1	3500216324-1200	2013-05	100001	Tote- Black	15	0.31

The SKUs already allocated to the VLM, as well as the spare parts, were excluded prior to the sorting and filtering the order data according to parameters in Table 11 and Figure 25.

Table 11 Summary of order characteristics representative for the Huta DC in yearly averages (Risholm, 2014).

Order characteristics, yearly averages	
Number of orders per day	61
Number of picks per day, in unique pick lines	641
Order volume, number of pallets per order	2.95
Order size, number of SKUs per order	11

The demand pattern for the SKUs in the Huta DC in terms of number of unique pick lines per month can be seen in Figure 26. The graphs in Figure 27 compare this pattern with the quantity of ordered items per month for the same time period. Figure 28 illustrates the demand skewness for all SKUs to be stored in the Huta DC; an area chart of the SKUs', sorted after popularity, accumulated share of all unique picks. The SKUs popularity skewness is then further examined in Figure 28 where the average number of unique picks per day for all SKUs picked at least every other week is shown (about 38 percent of all SKUs, representing about 94 percent of all unique picks).

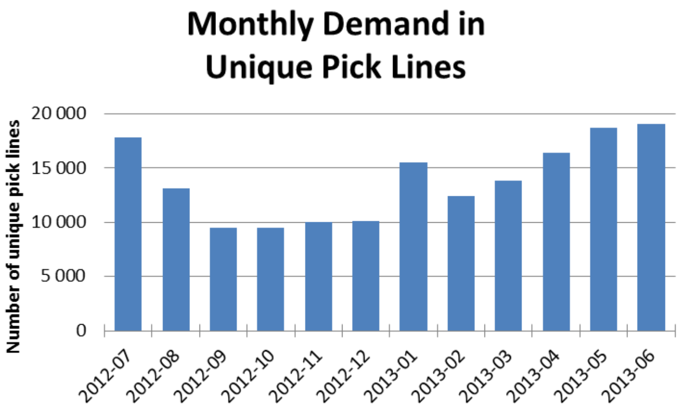


Figure 25 Demand distribution in number of unique pick lines per month of SKUs to be stored in the Huta DC, data from July 2012 to June 2013 (Risholm, 2014).

Figure 26 Comparison of the demand patterns of number of unique pick lines and order quantity per month of SKUs to be stored in the Huta DC, data from July 2012 to June 2013 (Risholm, 2014).

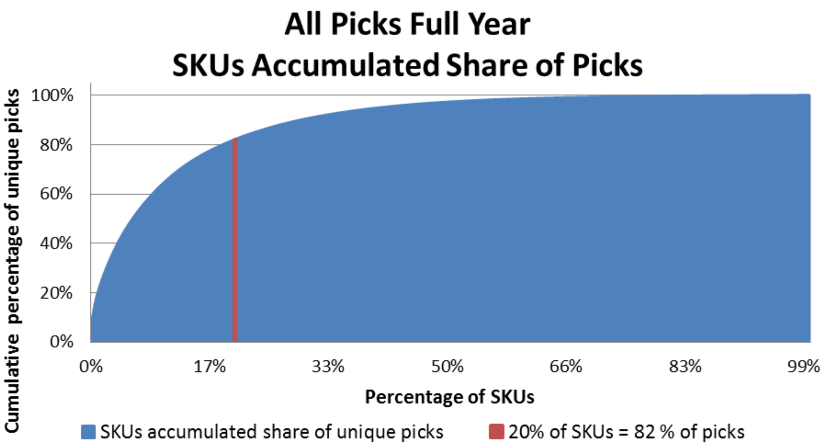


Figure 27 The cumulative percentage of the SKUs to be stored in the Huta DC picked from July 2012 to June 2013 and the accumulated share of all unique pick lines they represent (Risholm, 2014). The red line indicate that the level of demand skewness is high; 20 percent of the SKUs represent 82 percent of all unique pick lines.

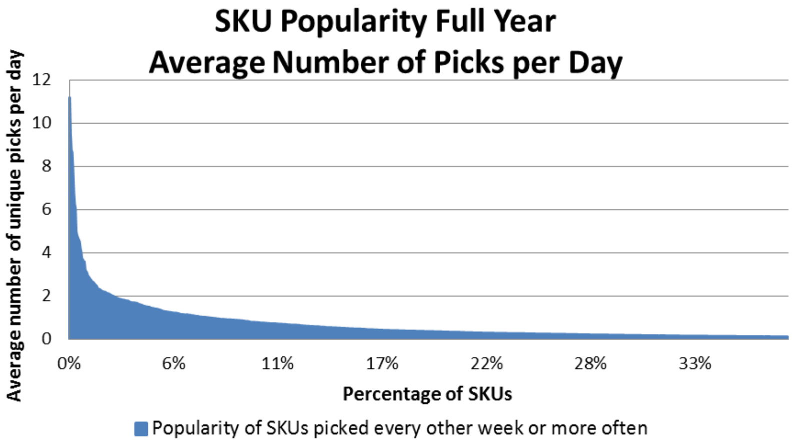


Figure 28 The average number of picks per day for the most popular SKUs to be stored at the Huta DC, calculations based on data from July 2012 to June 2013 (Risholm, 2014).

5.5 The Thule Group's Warehousing Objectives; Priorities and Tradeoffs

Situations where tradeoff decisions must be made are inescapable. When faced, it is central to know which state to target, and to make sure that the whole business is heading in the same direction. The objectives and goals of Thule's warehouse operations were identified by interviewing three of its warehouse managers, the complete interview guide can be found in Appendix A. The purpose was to determine what the company considered to be the prioritized issues in its warehouses and to map previous and expected challenges. Critical tradeoffs in the warehouse operations are likely to affect which method choices to make. Based on the possible goals of warehouse operations described in chapter 3 Frame of Reference the managers were asked to conclude and rank their five main priorities. The prioritized objectives turned out to concern service level, minimized travel, and ensuring high warehouse utilization, the exact result can be found in Table 12. These factors are also in line with the company's overall goals of delivering on time in full to end customers, being cost efficient, and having lean solutions in administration (Janas-Kaszuba, 2014).

Table 12 Thule's main objectives regarding its warehouse operations, ranked according to priority (Janas-Kaszuba, 2014; Hunt, 2014).

Rank of objectives	Huta DC (Janas-Kaszuba)	UK warehouse (Hunt)
1	Guarantee a certain service level	Guarantee a certain service level
2	Decrease travel in picking	Health and safety
3	High warehouse utilization	Decrease the overall labor
4	Lower the risk of congestion	Reduce picking errors
5	Build up competence	System simplicity, ease of use

The Thule Group was also asked about the greatest challenges connected to its warehouse operations. Historically the largest challenges have concerned guaranteeing a high service level, picking accuracy, securing the availability of products and handle seasonality. The same areas are considered to be the main challenges for the new DC, along with building up competence through training and implementing the new processes in their new ERP and WMS systems. The main solution to these issues is to try to make warehouse activities and processes as standardized and simple as possible (Persson, 1995). This will simplify the daily work and hopefully impact the performance positively through improved learning and thereby less mix-ups, damages and picking errors. It will also make the training of new personnel easier, which is an important and reoccurring event in the warehouse.

The usage of temporary contracts is one of Thule's main strategies when dealing with demand seasonality; together with modulating the number of shifts, and using banked work hours of the ordinary staff i.e. full time employees work extra hours in peak periods, and in return get days off in the low season. The temporary employees need to be trained in advance of the peak periods, which mean a successive ramping up the work force. However, simplified working procedures facilitate the training and steepen the learning curve. Ultimately the work force would deliver a higher quality, work more efficient and be sourced within shorter lead-times as a result of standardized and simplified warehouse operations (Janas-Kaszuba, 2014).

6 Applying Decision Support Tool on the Huta DC

This chapter will start with providing an illustrative example of how the decision support tool can be used in practice by applying it on the Thule Group. The indications of each step will be analyzed and concluded before summarizing the recommendations for the Huta DC in the final section.

In order to provide an illustrative example of how the created decision support tool should be used, the empirical data achieved through the study of the Thule Group and its Huta DC will in this chapter be used to test the tool and generate recommendations regarding what processes to adopt in order to increase the efficiency in its picking processes. Each step in the tool will be performed based on the situation in Huta. The output is recommendations regarding the warehouse operations methods to use at the DC. Since the tool successively divides the studied data into several storage areas, SKU groups and time periods, some of the steps will be conducted multiple times and the results will be presented according to these divisions. Each group will follow the same logic, why step 1 to 3 only will be thoroughly described once. Finally, the output from the steps will be concluded in a chapter presenting final recommendations regarding storage allocation method, order picking method and routing method for the Huta DC.

6.1 Step 1: Warehouse and Product Characteristics and Constraints

The first step in the decision support tool is to examine the warehouse and product characteristics and determine which factors that should be considered fixed and constraining, and which that are flexible enough not to limit the solution. In this case the warehouse outer dimensions, the I/O points and corresponding U-shaped material flow, cross-aisle configuration, the presence of reserve and picking areas, and total number of pallet and picking locations where considered fixed. This also meant that each pick location's level of convenience was fixed with the best pick locations close to the I/O points. However, the exact size of each location i.e. the height and length of the racks was thought to be changeable. This was because the warehouse is under construction and do not have any racks at all yet; hence their size should be flexible. It was also decided in order to create a more general recommendation, and a complement and possible antipole to Thule's internal solution. Product characteristics such as size and weight were therefore ignored for the most part, i.e. not considered constraining even if they are not flexible per se.

Figure 29 Input and output in illustrative example, step 1 (Gildebrand & Josefsson, 2014).

A rough division of SKUs in to some storage areas was conducted. The warehouse characteristics that were considered constraining was the use of VLM and flow rack storage, along with the products to be stored there. This was predetermined by Thule based on the criteria of small product size, low yearly demand and low average stock April to June. The output of this step was therefore three storage areas and corresponding groups of SKUs: flow racks, VLM and the general pallet area i.e. the combined reserve and partial picking areas with pallet storage, both on floor and upper levels. An overview of the input and output in this step is provided in Figure 29, and a schematic illustration and the exact division in number of SKUs and pick locations in each storage area can be found in Figure 30 and Table 13. Note that the SKUs stored in the VLM are hereafter completely disregarded since they are not included in the project scope, see chapter 1.6 Delimitations.

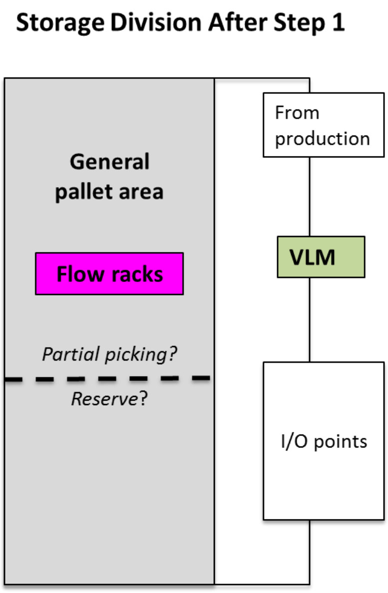


Figure 30 Schematic layout of storage areas on floor level after step 1, the exact division can be found in Table 13.

Table 13 Storage division and number of SKUs and pick locations in each area after step 1 (Andersson, 2014a).

Storage area	Number of SKUs	Number of pick locations, floor level	Number of storage locations, upper levels
General pallet area (reserve + partial picking)	1 953	1 527	10 168
Flow racks	353	469	-
VLM	1 193	1 900	-

6.2 Step 2: Order Characteristics

By stepwise examining the order data according to the five order characteristics presented in the tool's step 2, the orders and the SKUs where successively further divided into smaller portions. See input and output to the step in Figure 31.

6.2.1 Demand Pattern

First, the general demand pattern was determined. Figure 32 shows the trends identified by looking at the fluctuating demand size per month in terms of unique pick lines for the two different groups of SKUs, those to put in flow racks and those stored in the general pallet area. It was evident that there was a strong increase in sales during the spring-summer months for both groups. Moreover, according to the company's warehouse managers this pattern is repeated every year and is thereby cyclic (Janas-Kaszuba, 2014; Risholm, 2014). Hence, these fluctuations appeared to be a significant characteristic that justifies dividing the order data further in to two time

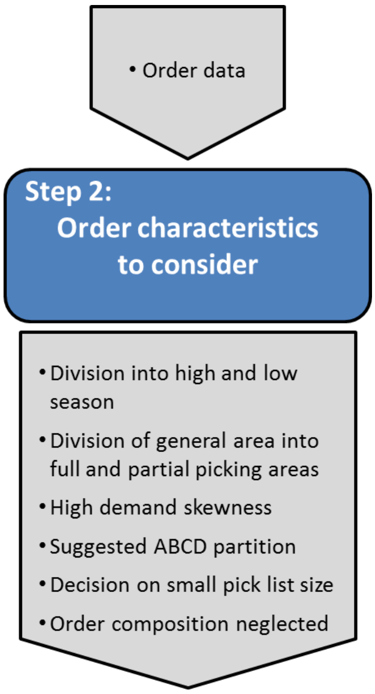


Figure 31 Input and output in illustrative example, step 2. (Gildebrand & Josefsson, 2014).

periods based on the seasonality of demand.

Theory states that the division should be done when the ratio of peak to average is high. In Thule's case the high season with peaking demand was identified to last four months ranging from April to July, and the low season with significantly less orders the eight months stretching from August to March. The average number of orders per day during these time periods is 83 in high season and 53 in low season. These seasons will henceforth be described and analyzed separately where their result differs.

The division is further supported by the fact that several of Thule's products are season specific. The most frequent SKUs have their peak in the summer, e.g. kayak and canoe carriers, and the products for winter activities have a peak in corresponding period, although their demand is not of comparable size. This is one of the reasons why the peak in January was ignored. A further reason is that customers to Thule might be lowering its inventory prior to stocktaking before entering a new year in order to keep the costs down for this resource demanding process. Consequently, they then have to increase levels of stock in order to meet the peak in winter demand (Andersson, 2014a). It might thus be an idea to treat the month of January or at least its high runners separately, e.g. by including a third season; this is however not performed in this study.

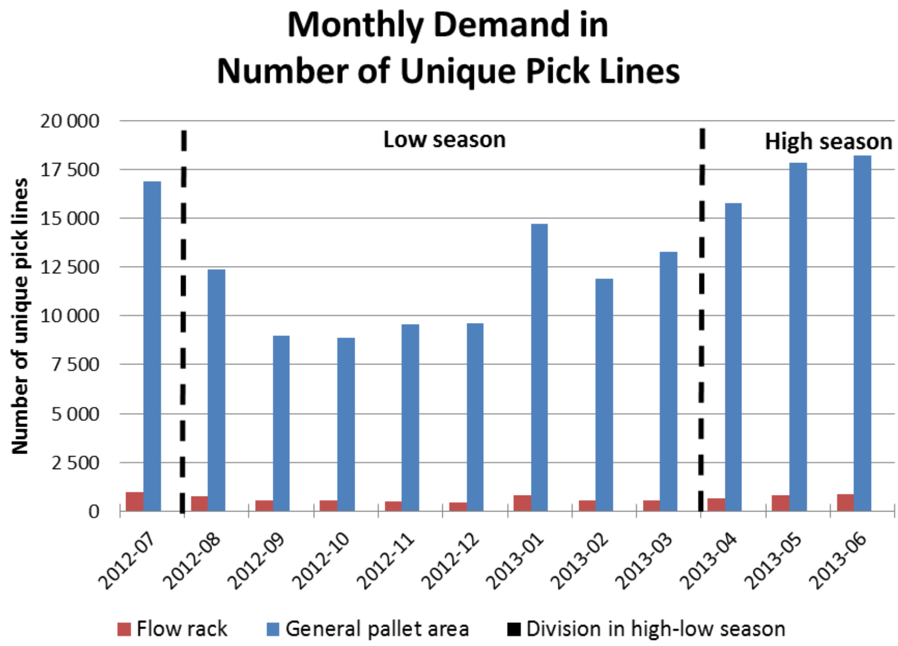


Figure 32 Distribution of the demand in number of pick lines per month from July 2012 to June 2013 (Risholm, 2014).

6.2.2 Full and Partial Pallet Picks

Next, the percentage of SKUs to be ordered and picked in full respectively partial pallets, as well as the individual partition of each SKU were determined by looking at demand and order volume in number of pallets for each time period. It was assumed that all orders of one or more pallets are to be picked in as many full pallets as possible, consequently a unique pick line of 7.44 pallets are considered to consist of 7 full pallet picks and one partial pick of 0.44 pallets. This specific situation of unique pick lines with multiple pallets ordered in an uneven number however turned out to be very rare, representing only about 1 percent of all unique pick lines. It is therefore mostly ignored in the following sections. Due to the structure of the order information available it was also assumed that a unique pick line including more than one pallet still can be considered as one unique pick in terms of demand and popularity.

Since a clear distinction could be made, a further division of the orders concerning full pallet picks, and the orders of partial pallets was performed. Hence, when applicable the order data examined in the following division steps distinguish between order lines containing full pallets which can be picked directly from the reserve area, and partial pallet picks to be conducted in the picking area with case or piece picking. The size of these two areas was determined based on demand in terms of picks and volume. Researchers such as Walter et al. (2013) suggest more exact methods for forward and reserve area sizing that involve replenishment costs and quantities, but since they were excluded from the scope of the study that was not possible. Instead the general pallet area was divided by constructing a combined weight of both outbound volume and number of unique pick lines. The percentage of outbound volume multiplied by the percentage of unique pick lines for full and partial pallets, respectively, was concluded and then the ratio between these figures determined the ratio between the two storage areas. Although a very rough instrument, it follows Sarker et al. (1994)'s recommendation of creating storage areas proportional to the demand to some extent by taking both number of pallets and number of picks for each SKU into account. The result was that 71 percent of the pick locations on floor level should be for partial picks in high season, while the corresponding number in low season increases to 80 percent. Using this difference to adjust the sizes of the reserve and picking areas accordingly for the two time periods is in line with Jane (2000)'s suggestions of how to handle seasonality. The SKUs stored in the flow racks were not included in this division since they are partial pallet picks by definition.

The result in terms of percentage of SKUs only ordered and picked in full versus partial pallets, or in both can be found in Table 14. It also contains statistics of the percentage of the outbound volume to be ordered in full or partial pallets, as well as the percentage of all unique pick lines per time period that contains even full pallets, only a partial pallet i.e. less than a full, or an uneven number of more than one pallet. It is worth noting that most of the SKUs picked in each of the two time periods are only picked in partial loads, 77 versus 79 percent respectively, excluding the SKUs stored in flow racks. At the same time, 17 to 18 percent of the SKUs are always picked in full pallets. This means that they can be treated differently in terms of storage areas; the first group only uses the reserve area for replenishment, which means they do not need very convenient storage locations there. The other group however can be completely excluded from the case/piece picking area, and thus claim the convenient locations in the reserve area. The number of SKUs to be picked both in full and partial pallets is very small, only 4 to 5 percent, and are the only to be picked from both areas and consequently will be included in both order data portions. It should be noticed that a large share of the SKUs, about 10 percent of all SKUs ordered during a year, are not included in the high season data at all since they are not ordered during this time period.

Another interesting fact is that the outbound flow of full pallet orders is substantial. About 75 percent of the total order volume per year can be picked directly from the reserve area, or 62 and 64 percent respectively when looking at even full pallet orders for high and low season.

This is in line with the numbers provided by Janas-Kaszuba (2014), stating that about 140 out of 240 pallets a day go out full which is more than 58 percent. At the same time these picks only correspond to 10 and 7 percent respectively of all unique pick lines per year. Hence, most of the unique pick lines are for a relatively small item volume in terms of pallets, which also is confirmed by a Thule manager who claims that "a large proportion (around 45 to 50 percent) of their order lines are for single items" (Janas-Kaszuba, 2014).

It is evident that the demand peak in high season consists of a larger share of full pallet orders than during low season, although the number of unique SKUs to be ordered in each category stays more or less the same. This means the peak does not result in partial pallet orders changing to full pallet orders for SKUs that usually are ordered in partial loads. For more statistics regarding full and partial pallets, see Appendix D.

Table 14 Number of SKUs, number of unique pick lines, and order volume in number of pallets when dividing the order data based on SKUs being picked in full or partial pallets, or in both, excluding all flow rack SKUs and their orders.

Season	Pick category, items picked as… (excluding flow racks)	Ratio of SKUs in each pick category	Unique pick lines		Outbound volume		Weighted share of area on floor level
			Ratio	Pick lines per day	Ratio	Pallets per day	
High	**Full pallets**	**18%**	**10%**	77	**62%**	164	**29%**
	Partial pallet	**77%**	89%	686	22%	58	**71%**
	Both partial and full pallets	**5%**	1%	10	16%	43	**-**
Low	**Full pallets**	**17%**	**7%**	37	64%	85	**20%**
	Partial pallet	**79%**	92%	485	**24%**	32	**80%**
	Both partial and full pallets	**4%**	1%	3	12%	15	-

6.2.3 Order Volume and Order Size

The next order characteristics to be examined were the average order volume and order size. They were determined for the two mutually exclusive groups of full pallet orders and partial pallet orders, as well as their combined data; all orders. Order volume was measured in number of pallets per order, while order size was calculated as average number of different SKUs per order. The pick density is the average number of SKUs per order out of all the SKUs ever included in that pick category i.e. SKUs only picked in full pallets are not included when calculating the pick density for the partial pallet picks etc. The result for the different divisions can be found in Table 15 and 16. Overall it can be concluded that the standard deviations for all parameters are large; bigger than its corresponding mean and some are even two or three times that size. Such strong variances indicate that there are orders with values very far from the mean, in this case with much larger order volume or size. A full pallet is however always considered a single pick no matter how many that makes up an order, why the partial pallet picks are more interesting to investigate further when improving storage and picking methods. Hence, their median values were calculated as well. The result shows that the order volume in pallets per order for partial pallet picks usually is less than a full pallet and with a relatively large standard deviation. The median is less than a tenth of a full pallet both in high and low season. This indicates batching opportunities i.e. more than one order can be picked and fit on a forklift's pallet. The average order size is about 10 SKUs per order for all orders as well as partial pallet orders both during high and low season, which results in a very low pick density of less than 1 percent for all types of picks, although the partial pallet picks are the most extreme since that group of SKUs is so much larger. The median order size for all types of orders is 2 SKUs per order, which means that the majority of all orders have an even lower pick density of barely 0.1 percent.

Table 15 Compilation of the calculated means and standard deviations of order volume as pallet per order, and order quantity in items per order during high and low season (Risholm, 2014).

Season	Order volume				Orders per day
	All orders	Full pallets	Partial pallets	Median, partial pallets	
High	3.19 ± **8.94**	2.44 ± **8.39**	**0.75 ± 1.86**	**0.09**	124 ± 370
Low	2.52 ± **6.70**	1.89 ± **6.36**	**0.63 ± 1.48**	**0.08**	115 ± 331

Table 16 Compilation of the calculated means and standard deviations of order size and pick quantity for high and low season (Risholm, 2014). The pick density is the average number of SKUs per order out of all the SKUs ever included in that pick category.

Season	Order size			Pick density		
	All orders	Full pallets	Partial pallets	All picks	Full pallet picks	Partial pallet picks
High	**9.70** ± **22.37**	3.48 ± **4.24**	10.13 ± **22.61**	**0.42%**	**0.99%**	**0.60%**
Low	**10.48** ± **22.38**	2.87 ± **3.54**	11.36 ± **23.20**	**0.45%**	**0.78%**	**0.58%**

6.2.4 Order Frequency per SKU and Order Composition

The result of examining the two last order characteristics in the tool is from now on not storage area and order data divisions, but rather grouping and ranking the SKUs within each division and to map statistics useful in steps 4, 5 and 6. The order data for the three storage areas: reserve, picking, and flow rack, for each of the two time periods were examined in order to identify high and low demand items. The sorting was done based on popularity since it is one of the best performing criteria for reducing travel which is the ultimate goal of the research, as well as fulfillment time according to Petersen et al. (2005). Popularity is easy to use and suitable for Thule's warehouse type. Popularity is also the criteria used in most of the research the decision support tool is built upon, which means such SKU ranking should fit better with its recommendations. For the Huta DC, the term popularity was translated into how often each SKU appeared in an order line per day, which roughly corresponds to the number of individual picks of a SKU per day.

Once the ranking and the accumulated share of total order lines were concluded, the skewness of demand could be determined; a key feature when deciding on storage allocation method. The cumulative percentage of SKUs picked in each storage area responsible for the accumulated number of unique picks of full pallet, partial pallet and flow rack picks during high season can be viewed in Figure 33 to 35. It is evident that the level of demand skewness for the SKUs in the Huta DC is overall high according to Petersen II (2000)'s classification, averaging around the classic Pareto distribution where 20 percent of all SKUs represent 80 percent of all unique picks. The full pallet picks to be stored in the reserve area however have an even more extreme distribution: Figure 33 clearly shows that the graph is even steeper for the most popular SKUs; the top 10 percent alone actually stands for about 65 percent of all unique picks. Figure 34 displays a more evenly distributed but still high skewness also for the partial pallet pick area, where 20 percent of the SKUs represent 76 percent of the picks. The SKUs stored in flow racks on the other hand has a more leveled demand pattern where the top 20 percent of the SKUs only represent about 60 percent of all unique picks, which would classify it as a medium skewness level, see Figure 35. The corresponding statistics for low season are similar, although a bit less skewed in full pallet and flow rack picks (20 percent of the SKUs represent 75 and 57 percent of picks, respectively), and can be found in Appendix E.

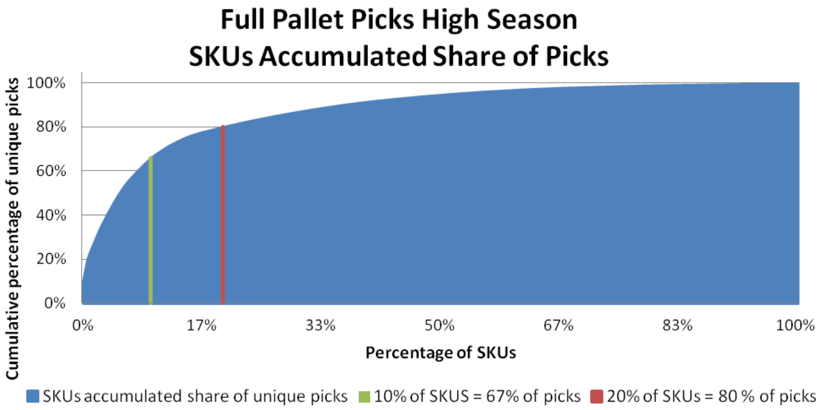


Figure 33 The cumulative percentage of SKUs picked in full pallets during high season that represent a certain accumulated share of all unique pick lines. The red and green lines indicate the level of skewness: very high.

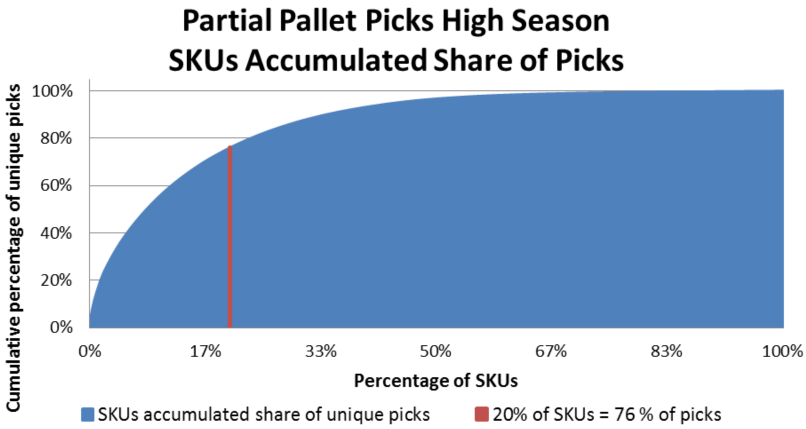


Figure 34 The cumulative percentage of SKUs picked in partial loads during high season that represent a certain accumulated share of all unique pick lines. The red line indicates the level of skewness: high.

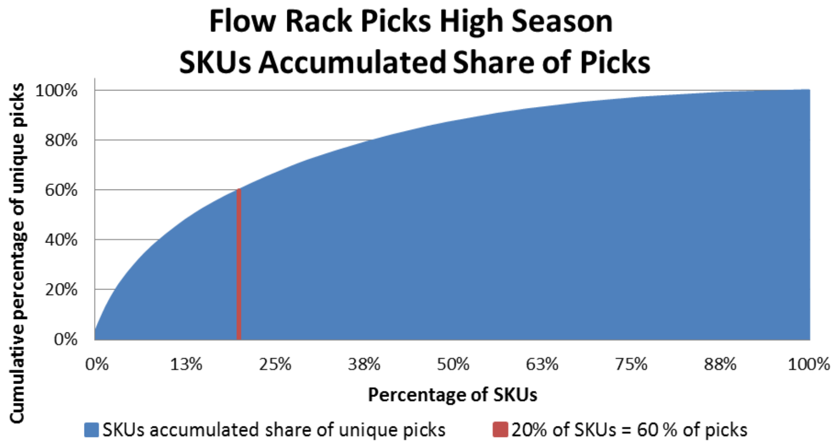


Figure 35 The cumulative percentage of SKUs picked from flow racks during high season that represent a certain accumulated share of all unique pick lines. The red line indicates the level of skewness: medium.

In connection to this ranking, a classification of the SKUs was conducted accordingly. Such classes are not always used in the final outcome of the decision support tool, but initially making a division can be helpful when analyzing the order data further so see order relations and patterns. How many classes to use and the exact partition are different in each unique situation. Petersen et al. (2004)'s recommendation is to create four classes when using CBS, which was done in this step. The general rule of thumb when dividing the SKUs is to make suitable choices, and commonly the Pareto principle is used. In Thule's case the Pareto distribution turned out to be rather distinct and it was used as a baseline, although the exact classification was conducted based on the number of picks per day to have a more precise and accessible measurement. The classification suggestion turned out as follows: A-class SKUs were those picked at least twice a day, B-classed SKUs every other day up to two times a day, C-classed SKUs between twice a month and every other day, while all SKUs picked less often than that received the classification D. This division might not be suitable to all conditions in Huta, especially number of pick locations and replenishment patterns, and using the same criteria and intervals for all pick categories might not turn out to be the best solution. This means that there is a possibility that the outcome is modified in subsequent steps. Nevertheless, the result of the previously mentioned classification is summarized in Table 17 and an area chart of the classification for the SKUs picked in partial loads during high season is provided as an illustrative example in Figure 36. It is worth noting that no flow rack SKUs got an A-classification.

Table 17 Suggested ABCD classifications of the SKUs picked in full pallets, partial loads or from flow racks during high and low season, respectively.

Season	Class (x picks/day)	Full pallet picks: Ratio of SKUs in each class	Full pallet picks: Share of unique picks	Partial pallet picks: Ratio of SKUs in each class	Partial pallet picks: Share of unique picks	Flow rack picks: Ratio of SKUs in each class	Flow rack picks: Share of unique picks
High	**A** ($x \geq 2$)	1.1%	22.6%	5.8%	41.6%	-	-
	B ($0.5 \leq x < 2$)	10.6%	48.0%	21.6%	43.0%	5%	26.0%
	C ($0.08 \leq x < 0.5$)	29.4%	21.5%	26.9%	12.9%	42%	59.0%
	D ($x < 0.08$)	58.9%	7.9%	45.7%	2.4%	53%	14.8%

Low	**A** ($x \geq 2$)	0.3%	6.5%	1.9%	22.3%	-	-
	B ($0.5 \leq x < 2$)	6.8%	43.5%	16.9%	51.0%	0.9%	6.3%
	C ($0.09 \leq x < 0.5$)	19.3%	31.5%	27.7%	22.9%	29.8%	64.4%
	D ($x < 0.09$)	73.6%	18.5%	53.6%	3.8%	69.3%	29.3%

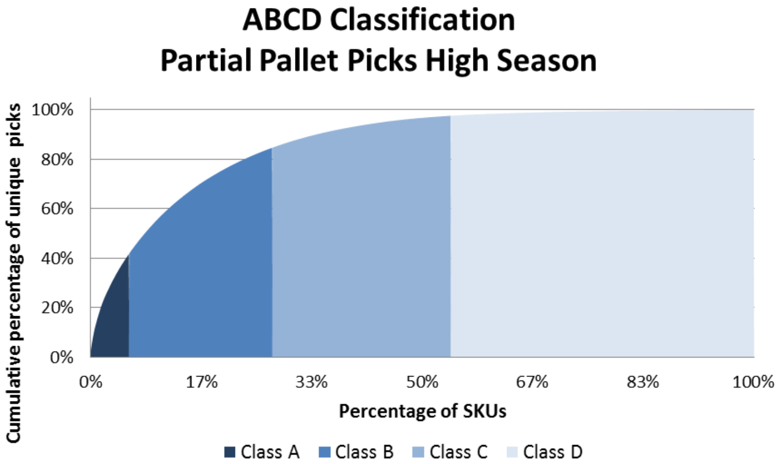


Figure 36 Suggested ABCD classification of the SKUs picked in partial loads during high season.

An important finding when conducting the rankings that the classification helped identify was that different SKUs are among the most popular in the two time periods. 54 percent of all SKUs ever picked in partial pallets have different classes in high and low season or are only picked in one of them. Sometimes the difference is as vast as being classified an A-SKU in high season, and not being picked at all in low season. A sample of SKUs picked in partial pallets, their average number of picks per day and corresponding classification for high and low season can be found in Appendix F. The outcome with different popularity rankings are consistent with the motivations presented when initially introducing the high and low season division of data i.e. that some of Thule’s products are for winter or summer use only. It also strengthens the reasons for continuously updating the storage allocation in a warehouse since the SKU ranking and possibly also the ABC classification can be input in step 4 by helping deciding where each SKU should be placed.

The last order characteristic presented in the tool, order composition, will not be investigated in this study. It was considered too complex and time-consuming to be a relevant part of this illustrative example. In addition, there is not sufficient research to support a solution where order composition is included. The purpose of such an investigation would be to add an extra dimension to a possible classification and zone division by identifying SKUs frequently ordered together, and other patterns that would provide greater detail to the input for steps 4 to 6.

6.3 Step 3: Objectives; Priorities and Tradeoffs

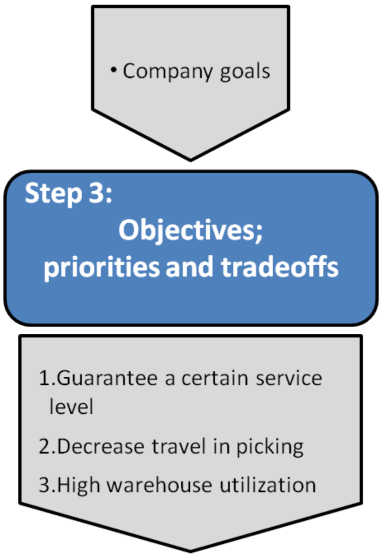


Figure 37 Input and output in illustrative example, step 3 (Gildebrand & Josefsson, 2014).

The Thule Group's main company objectives connected to its warehousing operations are presented in chapter 5.5. An overview of the input and output in this step is provided in Figure 37. The rankings received from Janas-Kaszuba (2014) along with input from Andersson (2014a) are the most relevant for the method decisions for the Huta DC, since they are the ones with the most knowledge about that warehouse. Rankings received from Hunt (2014) were mainly used for comparison. Hunt manages a smaller Thule warehouse in another country with other customers, and the response he gave corresponds to those characteristics rather than those for the new Huta DC. It would be desired to include additional respondents in the study, and to make sure that they reach an aligned answer. In an already operating warehouse this should be fairly easy to do, but the limitations to the DC studied in this illustrative example, connected to it being under construction, prevent such possibilities. Instead, this is left as a suggestion for future usage of the tool, when there are additional people with knowledge about the Huta DC to include.

Both interviewees share the primary priority, guaranteeing a high service level. It displays a unified view of the purpose with why they operate and what they want to achieve. The objective is closely related to decreasing picking time, since fast deliveries is a common requirement in order to meet the service level. It is however also related to the number of deliveries damaged, mixed up, or returned for any reason that could have been avoided by operating the warehouse in a different way. These objectives are not indicated to be a priority, and therefore the interpretation of guaranteeing a certain service level will focus on the aspect of time.

The priority ranked as second most important, decrease travel in picking, share objective with most research on order picking. The travelling in itself does not add any value; on the contrary it is resource draining and is therefore desired to be as low as possible in most warehouses. In connection to time, this is the step with the most potential for reduction. Since decrease travel time when picking is the most targeted objective, there are also a lot of suggested solutions for the purpose. If considering travel only, this priority would bring us straight to VBS. This is however not the case, and future steps where choices is made will have to weigh the benefits and downsides in order to reach the globally best solution. For example, the thirdly ranked objective to increase warehouse utilization would suggest a random storage method everything else ignored. From this perspective, VBS is the worst choice, while random storage methods perform the worst with regard to travel distance. This is a good example implying that all priorities have to be put in a context and then be evaluated together. Tradeoffs are inevitable, which is the reason the interviewed warehouse managers were asked to rank a limited number of chosen objectives, rather than get the chance to indicate an unlimited number of equally important objectives. This way, when a decision is to be made, the main priorities are weighted and easier to use.

Step 3 is finalized by connecting the objectives with suitable choices from theory, see Table 18. One feature, repeatedly brought up in theory that affects all three method-decisions is size of pick list. It is mainly related to order composition, order picking, and routing. Research gives different advice on suitable methods depending on if the pick lists are large or small. However, assuming that Thule does not have to accommodate a certain pick list size but rather choose it, the suggestion is to use fairly small pick lists. The reason is that overall, larger pick lists decrease the amount of potential savings when applying most of the studied methods. It is thus recommended in this step to review the size of the pick lists, and if possible, lower it.

Table 18 Objectives ranked by Janas-Kaszuba (2014) paired with suitable choices of storage allocation, order picking method and routing methods (Gildebrand & Josefsson, 2014).

Rank	Objective	Related suggested choices from literature
1	Guarantee a certain service level	VBS, CBS; batching, zone picking; transversal heuristic
2	Decrease travel in picking	VBS, CBS with 4 classes, within-aisle; batching, zone picking; composite heuristic, largest gap heuristic, optimal procedures
3	High warehouse utilization	Random storage or CBS with few classes
4	Lower the risk of congestion	Random storage, across aisle; zone picking; transversal heuristic, composite heuristic
5	Build up competence	VBS or CBS; zone picking; transversal heuristic, return heuristic

6.4 Step 4: Storage Allocation Method

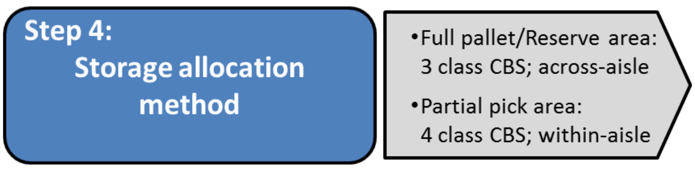


Figure 38 Output in illustrative example, step 4 (Gildebrand & Josefsson, 2014).

This is the most extensive step in the decision support tool. It includes deciding on storage allocation methods for the different storage areas and time periods that suits the priorities as well as characteristics concluded in the previous steps. An overview of the output is shown in Figure 38. The reviewed theory shows that VBS outperform CBS in terms of picking distance travelled. On the other hand, it also shows that CBS almost reaches the performance of VBS when implementing four classes. Keeping in mind that VBS is more complicated to implement than CBS, and that it also lower the warehouse utilization and increases the risk for congestion, this alternative is not considered suitable for the Huta DC.

If instead reviewing the method of random storage, it has the primary benefit of delivering the highest warehouse utilization out of all the methods presented. This corresponds to the priority ranked three by Janas-Kaszuba, but does not fulfill either the first or second priority.

In fact it even thwarts the premier two choices. Further, the Huta DC is built to hold the forecasted demand for 2017-2018, and will thereby not reach its targeted level of utilization until then. The point when the warehouse reaches a critical level of utilization can thereby be estimated to occur first several years after opening. This period is likely to include a lot of changes, internal as well as external. Thule is recommended to review its processes during this period and consider random storage only if the warehouse utilization develops into a critical factor to the extent that time for travel in picking can be disregarded.

Having deselected VBS and random storage, the adequateness of CBS remains to be investigated. Knowing that VBS performs the best with regard to travel time, but that implementing three or four classes in CBS performs almost as good, the latter is a choice close at hand. This would also decrease the risk of congestion, depending on the design of the storage configurations. Out of the options presented on this matter, the within-aisle storage configuration is claimed to reduce travel time significantly more than its alternatives when using VBS. It is also the best configuration when using CBS, although the three- and four class rectangular configurations perform almost as well with only slightly increased fulfillment times. Having a small pick list also minimizes the performance difference between the within- and across-aisle configurations. Since travel time is the most critical aspect for the Huta DC, CBS with four classes stored in a within-aisle configuration is considered the most suitable choice. The main downside with this storage allocation method would be an increased risk of congestion, so if this turns out to cause problems the rectangular configuration would be the next option. Another limitation to this general recommendation is that each of the storage areas within the warehouse has different preconditions that influence the choice of storage allocation method for its particular SKUs. Hence, each area will be receive individual guidelines and all of the reasoning behind the decisions for each of them will be thoroughly discussed below, before summarizing the outcome in Table 19 and illustrating the high season version in Figure 39 and Table 20 at the end of chapter 6.4. Note that the same assumptions about unique picks etc. presented in chapter 5.4 are used here, and that the storage recommendations aim to fill all pick locations in the warehouse with SKUs only picked in the observed time period; an simplified scenario still believed to be close enough to reality for it to reasonable.

6.4.1 Full Pallet Storage Allocation

The storage area for all full pallets is both a certain part of the floor level, and all upper level storage locations. Most of these upper levels should however be consider a reserve area only for replenishment storage. Hence, it is the floor level area, sized according to the weighted share of picks and order volume that the full pallet picks represent (see step 2), that should be the main focus when choosing storage allocation method for full pallet picks. When examining the order characteristics of the full pallet picks concluded in step 2 the main conclusion is that there is a very high skewness of demand, both in terms of unique pick lines and order volume. A small number of SKUs stand for a large share of the outbound flow, especially since many orders are for more than one full pallet of a certain SKU. Each SKU also corresponds to a unique pick since one full pallet is the max capacity of the forklifts. This state indicates a high traffic flow of pickers moving in the full pallet area and to/from the loading area for further transportation. Thule is therefore recommended, in line with its own layout suggestion, to place the full pallet pick area close to the I/O points.

This demand pattern is a strong indication that CBS would be the best option for the full pallet floor area, rather than random storage. However, the number of SKUs picked in full pallets during low season is greater than the total number of pick locations for full pallet picks on floor level, in addition the high level of skewness mean that many of the SKUs very rarely are picked. In order to resolve this matter, it was decided that the D-class SKUs concluded in step 2 only should be stored in the upper levels; or rather the D-classed full pallet picked SKUs should form a new class together with all replenishment pallets. This would also help increasing the pick density on floor level and make the pick movements there more economical. The SKUs in the very large upper level class would of course be stored randomly within it, since that is the design of CBS, which is in line with both Chan and Chan (2011) and Bartholdi and Hackman (2010)'s recommendations that random storage is suitable for reserve areas. This alternative could be slightly adjusted by dividing the upper levels in to two zones, one of them only consisting of purely partial pallet picked SKUs to store on the levels above the picking area, and the other of D-classed SKUs as well as the extra stock for all other SKUs ever picked in full pallets. Such a solution would help reduce congestion since most picks from the upper levels are directly above the picking area, i.e. replenishment actions, could be scheduled to less busy time periods.

Using CBS in the full pallet pick area on floor level will, as mentioned above, help meeting several of Thule's warehousing objectives. Theory recommends three or four classes, but each added class adds administration and since each pick location is emptied after every pick in the full pallet storage, it is better to ease the overall material flow by not limiting the storage possibilities too much. Hence, three classes are recommended for the full pallet area since each pick consists of one SKU only. Further, the across-aisle storage configuration is chosen since it performs just as well as within-aisle under given conditions. The across-aisle configuration fits in picking zones that are more deep than wide, and has the advantage of limiting congestion by spreading out popular SKUs over several aisles; which is especially important since full pallet picks means single picking and that no special routing method is of use.

The sizing of the storage zones on floor level was done according to demand. Initially each A-, B-, and C-SKU was entitled one pick location; the additional spots in the full pallet floor area were then allocated based on order volume. The SKUs were already ranked and classified according to number of unique pick lines, by adding share of total volume of all orders picked in full pallets as a second sorting dimension it was possible to distribute the extra slots. The volume share admitted all SKUs to the equivalent share of the extra slots, rounded to full pallets. By successively moving down the popularity ranking and giving the top SKUs their additional pick locations all slots were filled. The total number of pick locations allocated to each class then determined the overall size of each class zone.

6.4.2 Partial Pallet Storage Allocation

When examining the SKU and order characteristics connected to the area for partial pallet picks, it was evident that this group also showed a high level of demand skewness. It was also clear that it is a very large group in terms of number of SKUs that represent the vast majority of all picks in the warehouse, often in small volumes. Hence, it was believed that great savings could be made in travel and fulfillment time by choosing the most fitting storage allocation method described above: CBS with four classes stored in a within-aisle configuration. Under these circumstances the lower prioritized and somewhat conflicting objective of limiting congestions was disregarded. The overall size of the picking area was determined according to the weighted share of picks and order volume that the partial pallet picks represent concluded in step 2. The exact sizing of the class-zones in this picking area was done in a similar way as described for full pallet picks: Initially each A-, B-, C-, and D-SKU was entitled one pick location, but since there was not enough slots all SKUs picked less than every second month was excluded i.e. they should only be stored in the upper level reserve area. Next the additional spots that now existed were allocated among the most popular SKUs based on share of order volume, rounded to full pallets. By successively moving down the ABC-ranking and giving the top SKUs their additional pick locations all extra slots were filled. The total number of pick locations allocated to each class then determined the overall size of each class zone.

6.4.3 Flow Rack Storage Allocation

Three aspects are central when determining the most suitable storage allocation method for the flow rack area. First of all, the medium skewed demand means that the savings of CBS compared to random storage are not as great as for the full and partial picks. Secondly, the comparatively low demand means none of the SKUs qualified to class A of more than 2 unique picks per day in the classification made in step 2. Thirdly, each rack consists of three levels of which the upper one is considered to offer the most convenient pick locations in the so-called golden zone. Together these factors indicate that a SKU division into two classes allocated to two zones would be both suitable and sufficient, especially since a two-class system attains nearly 80 percent of all the benefits of VBS, but without as much administration.

The first class consists of the most popular SKUs, roughly corresponding to class B and parts of class C from step 2, and be allocated to the golden zone. The rest of the SKUs would be randomly allocated within the other zone i.e. the two lower levels of the flow racks. Using the golden zone does however create a tradeoff situation. It helps meeting the company objectives of reducing picking time and limiting congestion, but at the same time it will increase travel distance. Since Thule reported guaranteeing a high service level i.e. reducing fulfillment time the highest priority, it will rule the decision. The first two aspects also indicate that the flow racks should be positioned among SKUs with similar level of demand i.e. the C- and D-zones of the picking area. The exact partition of the SKUs was done by first giving one pick location to each SKU picked that time period. Then the additional pick locations were divided among the most popular SKUs by successively filling the extra slots according to their relative share of demand volume, rounded up to full pick locations. For SKUs with the same popularity, priority was given to those with higher volume. Finally the golden zone class was created by successively filling up the golden zone slots (GZ in Figure 39) with as many of the top SKUs as possible, each allocated its total number of pick locations. However, the overall low popularity level of the flow rack SKUs also indicate that the central placement of the flow racks in Thule's layout suggestion in Figure 24 would occupy convenient pick locations better utilized by more popular SKUs. Hence, the recommendation to Thule is to place the flow racks further away from the I/O points.

Table 19 Recommended storage allocation methods during high and low season.

Season	Storage allocation methods		
	Full pallet picking (reserve)	**Partial pallet picking**	**Flow rack**
High	CBS with 3 classes based on popularity; across-aisle	CBS with 4 classes based on popularity; within-aisle	CBS with 2 classes based on popularity; golden zone
Low	CBS with 3 classes based on popularity; across-aisle	CBS with 4 classes based on popularity; within-aisle	CBS with 2 classes based on popularity; golden zone

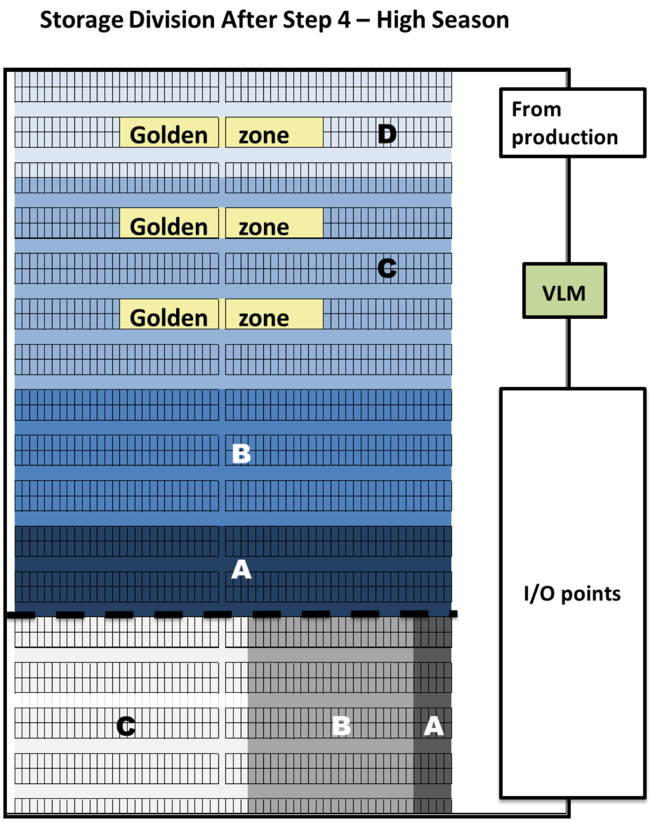


Figure 39 Schematic layout for high season of storage areas on floor level after step 4, upper levels i.e. reserve area, and lower shelves in flow racks are not shown. More information about the areas can be found in Table 20 (Gildebrand & Josefsson, 2014).

Table 20 Storage division and percentage of pick locations, SKUs and unique pick lines during high season for each area after step 4.

Pick area	Class	Share of floor level pick locations	Share of all SKUs	Share of unique pick lines
Full pallet	A	2.4%	0.2%	2.4%
	B	10.3%	2.1%	5.0%
	C	13.9%	5.8%	2.3%
Partial pallet	A	12.6%	4.3%	35.3%
	B	18.1%	16.1%	36.5%
	C	21.4%	20.0%	11.0%
	D	13.0%	12.2%	1.3%
Flow rack	GZ	8.3%	2.0%	2.2%
	B	-	13.8%	2.4%
Reserve		-		1.6%

6.4.4 Seasonal Storage Allocation Changes

The choice of storage allocation method is also affected by the seasonality in the Huta DC. As Table 19 shows, the chosen methods are identical for the two periods. However, identical methods do not necessarily mean identical layouts. Although the use of CBS and its number of classes should be kept constant, the SKUs included in each class and their individual number of pick locations should not. If for example the A and B ranked SKUs during low season are related to winter activities, they are unlikely to be part of these top classes during summer. Hence, the SKUs will get different classifications in the two time periods and should thereby be allocated accordingly in order to maintain a low travel distance. Failing to perform this update might result in unnecessary travels to remote locations storing the popular SKUs. Further, the size of the partial pallet picking and full pallet/reserve areas should be revised. Since its size is decided from the share of full versus partial pallet picks, changed proportions would call for adjustments in storage allocation and number of pick locations in each class zone.

Apart from changing the sizes of the two storage areas, another promising storage strategy to implement especially during high season with its fast material flow is to set up a smaller forward area within the main picking area to accommodate the orders concerning the top most popular SKUs. The research regarding this option is scarce. No clear recommendations regarding what SKUs to include, in what volumes or how the area should be dimensioned are encountered in the literature study. Neither are the benefits of implementing a forward area weighted against its main tradeoff double handling. Despite this, it is considered an interesting solution with potential for large improvements. While waiting for further research, this alternative either could be set up, performed and measured in an experimental fashion, or ignored.

6.5 Step 5: Order Picking Method

There are no clear recommendations for when to use what order picking method. Some guidelines in the decision making can be found by first determining whether the warehouse in question is large, small or wide, whether number of orders is large or small, and whether order size if to be classified as large or small. Hence, tradeoff priorities have to be very distinct in order to choose picking method. An overview of the output is shown in Figure 40.

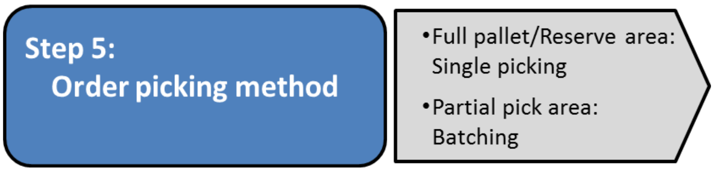


Figure 40 Output in illustrative example, step 5 (Gildebrand & Josefsson, 2014).

For Thule, single picking is the obvious choice for the reserve area since it concerns full pallet picks, while the partial picking area including the flow racks is tougher to decide on. The Huta DC will, according to previous order data, have a large number of orders but a small median order size in both high and low season. Despite vague recommendations, it is safe to say that based on these characteristics batching is a better-qualified method than single line picking for the partial pick area. The volume of most unique pick lines for partial pallet is also small which indicate that several orders would fit on one truck during picking operations. The disadvantages of batching such as an increased risk for errors in picking and the need for additional sorting are not identified as prioritized issues by the Thule managers. On the other hand, the benefits of the method are. Reduced travel distance is pointed out as the second most important objective by Janas-Kaszuba (2014).

The use of batch zoning answers to several desired objectives for Thule, as well as the already chosen method regarding storage allocation. Batch zoning is stated to result in increased benefits as warehouse size increases. Huta DC is large, and is thus likely to benefit from applying batch zoning. Further benefits are increased picker familiarity, reduced congestion and that it results in savings in travel distance; factors that are all pointed out as priorities for Thule. The main tradeoff to be aware of for this choice is that it might lead to poorly utilized workforce due to uneven workload and this aspect should therefore be continuously monitored by Thule in order to maintain balance. To conclude, the order picking choice for the reserve area is single picking while batch zoning is opted for the partial pick area (see Table 21).

The remaining methods are not chosen due to several reasons. Sequential zoning requires a link between the zones, which usually means additional investments, and a redesign of the warehouse layout to make room for a conveyor belt. Further it requires large pick lists, which is also true for wave picking. Although the methods benefit from economies of scale and are claimed to result in savings in travel distance, they counteract the benefits that can be achieved from the CBS chosen in the previous step. CBS builds on the fact that it will generate large savings when used in combination with small pick lists. Applying wave zoning where one wave can last for up to two hours would entirely eliminate the benefits from a carefully designed CBS.

The choice of order picking method also concerns the logistics of picking in terms of where and how the pickers and orders should move. Should zones be created for pickers and if so, how should the partition be made and allocated to pickers? Should the batches travel between zones or is it better for them to be entirely independent? These are subsequent decisions not explicitly brought up in the tool, but left for Thule to decide once the methods are fully set.

Table 21 Recommended order picking methods during high and low season.

Season	Order picking methods		
	Full pallet picking (reserve)	Partial pallet picking	Flow rack
High	Single picking	Batching; batch zoning	Batching
Low	Single picking	Batching; batch zoning	Batching

6.6 Step 6: Routing Method

The pick routes in the Huta DC can be divided in two parts; the full pallet and the partial pallet picks, and the recommendation for each of them can be viewed in Figure 41.

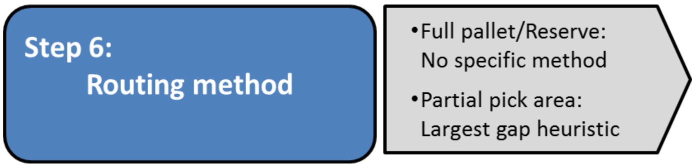


Figure 41 Output in illustrative example, step 6 (Gildebrand & Josefsson, 2014).

For the full pallet picks in the reserve area using a particular routing method is believed to be unnecessary since all picks will be for one SKU only –the only reason to adapt a specific heuristic would be if congestion prohibits the obvious route to and from the I/O depot. On the other hand the partial pick area, which also includes the flow rack picks, has a lot to gain from using a suitable routing method. The key features when determining suitable routing methods for a warehouse are pick list size and pick density which both are closely linked to order size. The order size derived from the historical order data is relatively low and the pick density is very low due to the vast range of SKUs to be stored in the Huta DC. In the previous steps it was decided to use small pick lists to accommodate for CBS and batch zoning. The implementation of CBS would however increase the pick density within each class zone, especially the A-class zone. This means that Thule has the possibility to examine the order characteristics for each class zone in the next method update to get a second dimension when reevaluating its method choices.

As for the current situation, transversal routing often fit CBS storage but preferably with large order sizes and high pick density. It is thus not a good option. The return heuristic can seem suitable for the priorities and conditions at the Huta DC. The method is easy to use and suits warehouses with CBS and low pick density. However, it is stated to be the most inefficient routing method, which is strongly supported by the graphs presented in theory. Thereby it contradicts the two top priorities of high service level and decreased travel and is not a suitable option for the Huta DC. According to research presented in the literature review, the optimal procedure is the method outperforming all the other options regardless of number of aisles and pick list size. This is however not the method chosen for the Huta DC either, due to its heavy reliance on computer software and the confusing routes it often results in, which lower the buy in and acceptance among the pickers. Instead the largest gap method is selected, which is the procedure performing second best under the named conditions. The reason is that this method is especially pointed out as suitable for small pick lists, which is an overall priority in step 4-6. Further, it responds to priorities set by Thule, and also ensures that the already chosen methods remain aligned. The largest gap heuristic would also suit the Huta DC layout since it has been showed to perform well in warehouses with many aisles.

Similar to most other routing methods, the largest gap method has to be managed by a system. It is difficult or even impossible for the picker to figure out the route without directions from a system generating the sequence and route. It is assumed that the systems to be used in the Huta DC can be programmed according to the chosen method. Finally, the choice in this step is not at all related to seasonality, why the choices in Table 22 are identical for the two periods.

Table 22 Recommended routing methods during high and low season.

Season	Routing methods		
	Full pallet picking (reserve)	**Partial pallet picking**	**Flow rack**
High	**Not applicable**	**Largest gap heuristic**	
Low	**Not applicable**	**Largest gap heuristic**	

6.7 Final Recommendations to the Huta DC

To begin with it should be emphasized that the high skewness identified for the demand data from Thule is a strong indicator that putting effort into making suitable decisions in the finalizing steps will pay off. Combined with a short pick list, this is strengthened even further. The output from the steps generating the final recommendations is presented in Figure 42 below, and summarized in subsequent sections.

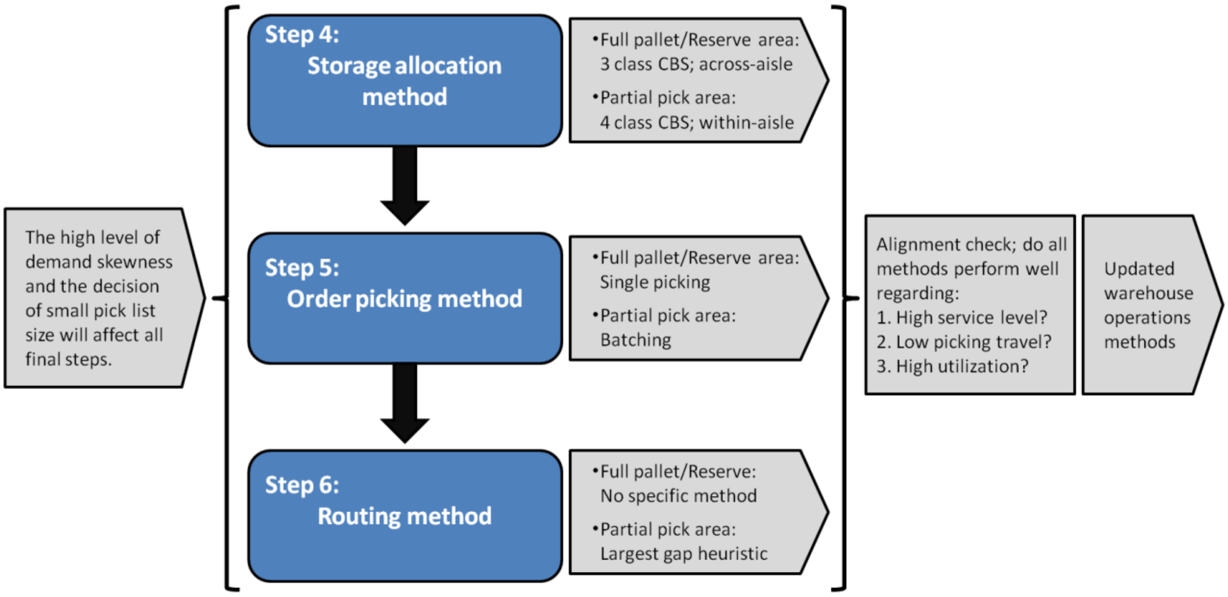


Figure 42 Final recommendations to the Huta DC visualized in the decision support tool (Gildebrand & Josefsson, 2014).

The most profound recommendation for the Huta DC is that the strong variations in demand throughout the year indicate that the warehouse operations should be revised and altered for the high and low season to accommodate the different order conditions. One central part of this is the division of the pick locations on floor level. It is recommended to split the area into one full pallet pick area and one partial pick area; also including the flow racks. The dimensions of these two areas should be based on the demand in number of picks, which means it would change for the two seasons. The upper level storage locations are to be used for replenishment and storage of the least frequently picked products i.e. some of the D-classed SKUs.

CBS based on popularity ranking is the recommended storage allocation method for both the full and the partial pallet pick areas, and both in high and low season. The difference is the number of classes and configuration: the SKUs in the full pallet area should be divided into three classes, while the SKUs picked in partial pallets should have four classes. The SKUs stored in flow racks should be split in two groups, where the most frequently picked group is allocated in the pick location in the so called golden zone, described in the literature review. The emphasis is the partition into classes and design of picking zones. The division into A-, B-, C-, and D-classified SKUs was based on popularity; the number of times a certain SKU was picked in each season. For example, all SKUs picked on average more than twice a day was categorized A. The zone dimensioning was roughly performed by giving each SKU the share of pick locations equivalent to its share of demand in number of picks, some adjustments was made to ensure all SKUs at least one pallet position and to accommodate large order volumes. The storage configurations of across-aisle in the full pallet area and within-aisle in the partial pallet picking area were chosen due to their characteristics. Their respective advantages made the best fit for the conditions at the Huta DC especially concerning material flow, pick density and pick list size. A review of the current location of the flow racks resulted in the suggestion of moving them to a less convenient location that better suits the frequency of the SKUs it holds. The result for the two seasons is visualized in Figure 43.

The figure illustrate that the output from step 4 differ between high and low season. The main difference is the size of the full and partial picking areas, but also the change in size for each class is noticeable. Does this mean that Thule should change the zone size twice a year? Unfortunately, there is no good answer or support for doing this. The advice is to evaluate the differences in size between the class zones. Unless differences are very high, it might not pay off to relocate the SKUs. The heat maps should therefore merely be considered to visualize the changes in demand that do happen over time. It is thus left to the warehouse managers to interpret the implication for the warehouse in question, and if aligning zones according to demand would bring any improvements.

One aspect of seasonality where the recommendation is more straightforward regards changes in relative demand among SKUs. The demand at the Huta DC displays great varieties among the different SKUs depending on season. The implication is that some of the SKUs located in an A zone during high season, might be better located in a C or D zone during low season. If no storage allocation change takes place, the benefits that can be expected from using class-based storage will be diminished. In worst case, benefits may even be counteracted. To conclude, it is highly recommended to make seasonal updates of the SKUs stored in the most popular classes, but optional to review the zone dimensions.

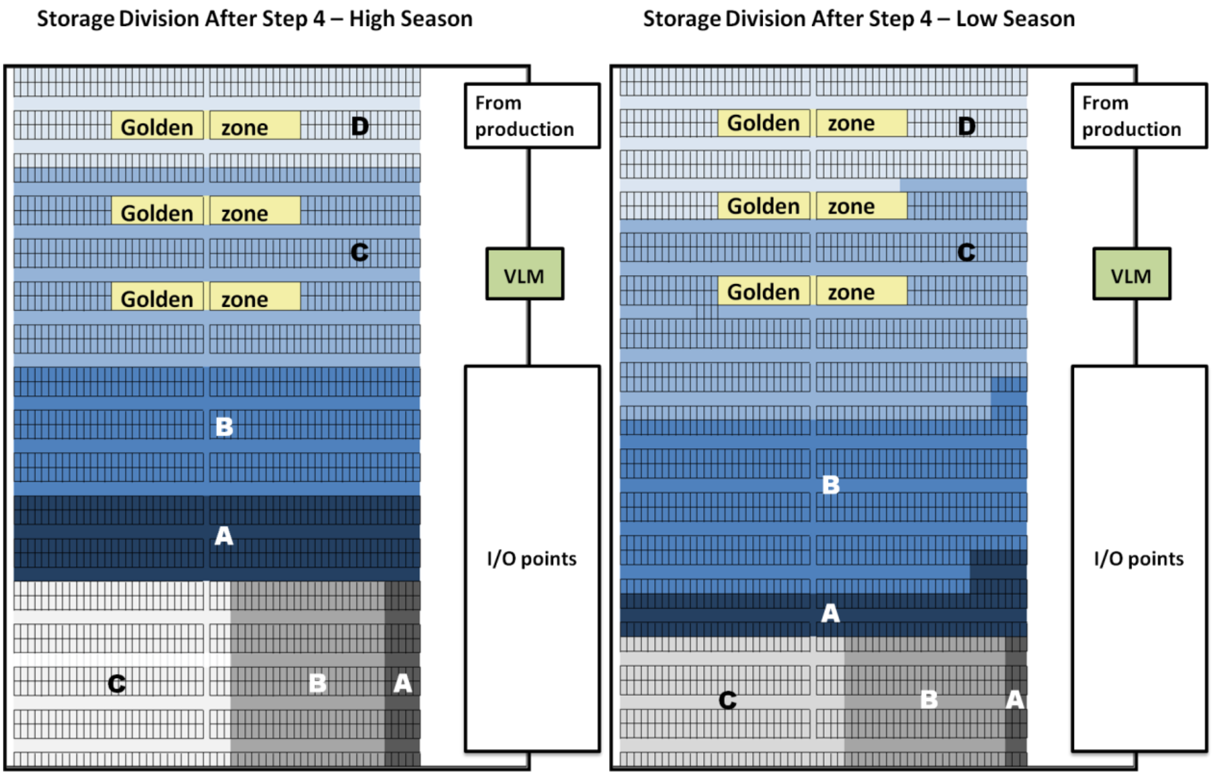


Figure 43 Recommended SKU allocation in high versus low season (Gildebrand & Josefsson, 2014).

The order picking method to use in the full pallet picking area is per definition single picking, while the partial pallet picking area including the flow racks will be best utilized by using batching and batch zoning. Routing methods are of interest when multiple SKUs are to be picked at the same time. For those areas in the Huta DC, the largest gap method was chosen. The performance of the methods chosen in these two final steps is not affected by seasonality, which thereby can be disregarded in this respect.

7 Analysis of Decision Support Tool

This section will provide a thorough analysis of the created decision support tool from multiple perspectives. First, the existing theory will be analyzed, followed by the tools' performance and usability and finally, gaps between the theoretical decision support and what reality requires, along with weaknesses with the decision support tool will be examined.

The appliance of the decision support tool in the previous chapter lead to several realizations regarding its performance and also the complexity of the decisions to make. It also revealed some of the limitations and ambiguousness of the theoretical framework, especially regarding which features to consider when choosing warehouse operations methods. Thus, this chapter will first analyze the existing theory in terms of interpretation possibilities and consensus before moving on to analyzing the structure of the decision support tool. Its performance and usability will be evaluated, in order to finally identify its gaps and weaknesses.

7.1 Analysis of Existing Theory

The decision support tool strives to provide a framework based on existing research in order to increase the understanding of available options when improving warehouse-picking operations. The summarized theory provides valuable results for many central decision parameters, although some are hardly covered at all (see chapter 8.3 Suggestions for Further Studies). Several authors point out that the area is very complex and contextualized, which might be a reason for the absence of clear recommendations. When analyzing the research in order picking, it appears to be a common view that picking cannot be improved without also reviewing connected warehousing areas, e.g. storage allocation and layout. That was therefore the approach in this master thesis, although the physical design of the warehouse was seen as pre-determined.

7.1.1 Analyzing Storage Allocation Theory

The existing research regarding storage allocation is partially detailed and relatively easy to interpret. Large focus lies on the choices between random storage, CBS or VBS based on performance. The main features that influence which method that is considered most suitable i.e. perform best in a given situation are level of demand pattern skewness and pick density. The higher level of skewness of demand distribution, the larger the possible gains from reviewing the SKU allocation method and implementing one of the more advanced alternatives of CBS or VBS, rather than random. The opposite goes for pick density; the higher percentage of all SKUs represented in an order, the more advantageous is random storage. The meaning of high, low or medium is somewhat arbitrary which can cause interpretation issues. Petersen II (2000) classifies according to the Pareto principle: high skewness is when 20 percent of all SKUs represent 80 percent of demand. This 80/20 distribution phenomenon is commonly found in SCM, which strengthen the reasonableness of using it as a baseline when categorizing skewness of demand.

Further, research suggests how to create classes when using CBS and alternative partition factors for the use of VBS. Usually the partition is made based on SKU popularity, which is interlinked with demand skewness, since many researchers consider it the criteria that bring the best results. It is also a very intuitive and accessible measurement, which can increase the acceptance among the pickers. Other criteria for classification are also suggested, but there is a lack of ranking methods proposed by researchers that includes both popularity and value of the product. Such a combined criteria can be very useful in a warehouse where the differences in value are large and the benefit from prioritizing these products exceed the loss due to potentially not meeting the service level for the products of less value. The exact grouping of the ranked SKUs in to classes is however not very clear in research, neither is the allocation of pick locations to each group and each individual SKU. The partitions should be made where *suitable* and sometimes the Pareto principle is used in this context as well, but overall the hands-on decision support for creating the ABC-classes is insufficient.

Research is more thorough when describing the advantages and disadvantages with each storage allocation method regarding e.g. warehouse utilization level, travel time and ease of use, and the researchers generally agree on these matters. However, the intended interpretation is sometimes ambiguous also in this area. For example when the random storage allocation method is described as *easy to use* it presumably refers solely to the undirected insertion of the SKUs anywhere available in the warehouse. The step when the SKU is picked from its location will instead be more difficult if taking the view of the picker, who never gets the chance to learn where to find the SKUs, but instead must rely on the location advised on the pick list. When, on the other hand, a fully dedicated method is described as *easy to use*, it most likely refers to the retrieval of the SKUs. While the insertion is governed by the allocation system, the retrieval will be simpler for the picker, who gradually will learn where to find certain SKUs, which might increase the picker's efficiency and reduce picking errors. The relative importance of each strength identified for all the recommended methods is rarely quantified in the reviewed research, and thereby not possible to weight against its weaknesses. For example, using a complete random storage allocation method brings the highest utilization level but at the same time the longest picking distances; in what situations does the benefit of a high utilization outperform the downside of a longer total picking distance? Or in the case of using VBS, with the benefit of short picking distances but the downside of an increased risk for congestion; at what point will the congestion neutralize the benefits of short picking distances through an increase in picking time?

The same reasoning is highly relevant in the theory about the storage layout or configurations for both VBS and CBS. Within-aisle storage is unanimously seen as the most efficient storage configuration that minimizes travel, but its superiority diminishes as the pick list size is reduced or number of classes increase. This means that the increased risk for congestion it brings can be a crucial characteristic in a tradeoff situation. Consequently, the recommendations are rather fuzzy when concerning warehouses with varying pick list sizes or many storage classes. Moreover, most of the case studies in research have been conducted in specific settings with a certain number of aisles or a specific position of the I/O points. Hence results treated as general in this study might actually be situation specific.

Overall the link between the material flow and the warehouse layout i.e. the position of the most convenient locations, and the optimal storage configuration could be more evident. However, the difference in performance of many configurations is insignificant when the pick list size approaches one which means that other objectives and priorities will rule the storage configuration decisions; something not as well-covered in research as the distance aspect. Luckily, pick list size is a feature possible to design in order to fit the circumstances. In short, a long pick list is only preferable if a complete random allocation method is adopted along with a simple routing method that passes through most aisles in the warehouse anyway. Once again the meaning of long and short is up to the user to define. The main take away is to understand that as the number of SKUs on a pick list increases, it simultaneously blunt possible savings.

One possible storage variant that can be thought of as an extreme A-class zone within-aisle configuration is the forward area. It is acknowledged as a suitable solution for very frequently picked SKUs, since the total picking distance will be significantly reduced. At the same time, the solution requires replenishment and thus double handling. The existing research is not sufficient to provide support for decisions on this matter. For example, what factors determine when the benefits of a forward area outweigh the resource-demanding disadvantage of double handling? How should a suitable size of the forward area be determined? And how much more frequent should the selected SKUs be in relation to the remaining SKUs in order to lower the total pickings distances and time? Thus, setting up a forward area at periods when demand is especially skewed might be a solution holding great potential for savings, but in order to provide decision support the method needs to be studied further.

To summarize: many research articles highlight certain storage allocation methods and the effect of using them, but without weighing the advantages against the disadvantages. Naturally, this is due to the complexity of the area and differences in conditions among warehouses. Evaluating the alternative storage allocation methods beyond picking distance, including also costs and time, would make them more comparable and strengthen the recommendations of the tool. This would however require very detailed knowledge and be rather complicated to perform. At the current stage of the research, the recommendations should therefore be considered to alert and raise an awareness regarding tradeoffs rather than deliver solid answers.

7.1.2 Analyzing Order Picking Theory

The research area of order picking methods is less extensive but more straightforward than storage allocation's counterpart. Emphasis lies on travel time and distance, as opposed to the other order picking activities: searching, extracting and paperwork. Commonly, the latter three represent smaller parts of the order picking process and thereby hold less potential for improvement. The recommendations for when a method is suitable are fairly easy to interpret; order size, order volume and warehouse size seem to be the most crucial features to consider. However, the recommendations would be more applicable if they were more extensive and used less vague phrasing. The following wordings are common; use in *large* warehouses, use for *fairly large* orders, use in *wide* warehouses, suitable for *small* orders, and so on, which means there is a shortfall of directions for warehouses and companies finding themselves in the middle. It is up to each warehouse manager to conclude the meaning of these recommendations and compare them with their own conditions.

There is an abundance of stated pros and cons with all the different order picking methods, as the evaluation in Table 4 clearly shows, which means the tradeoff decisions when choosing will be crucial. Hence, the company priorities have to be very distinct and preferably include opinions about the most frequently mentioned terms when reviewing the methods such as ease of use, travel savings, administrative requirements, congestion, order integrity, double handling, picker's familiarity with SKUs and storage locations, and work balance. Once again, the lack of weighted comparisons between the advantages and disadvantages of all the order picking variants prevents unequivocal decision support in this method choice. In addition, the reviewed research does not provide clear, detailed guidance regarding how to apply the methods i.e. how to set up the batching or wave picking. Consequently, this is also left to each warehouse manager to figure out.

7.1.3 Analyzing Routing Theory

The choice of routing methods is the decision area with the most direct linkage to the actual distance travelled, and for which the outcome of the previous steps aims to facilitate. The theory on routing derives only from a handful of researchers, but it is comprehensible and provides clear guidelines. Routing methods are easier to measure and compare than the storage allocation and order picking methods, since it is fairly simple to construct computer simulations based on known distances and travel time where the same orders are picked but with different routing. There are fewer parameters involved than in the other method choices, and the outcome is therefore more straightforward and general. First of all, choice of suitable routing method highly depends on which storage allocation method is used, since some match up better than others. Secondly, pick list size and pick density are important features, just as when deciding on storage allocation method. Research comes to an intuitive but nevertheless important conclusion; the longer the pick list for an average route, the fewer benefits can be obtained from improving classification, allocation and routing. The reason is that longer pick lists are more likely to include SKUs of a lower frequency, and will therefore be more likely to result in a long route through the warehouse. Shorter pick lists however are more likely to only include the most popular SKUs, and therefore have the potential to lower the average picking length when these SKUs are conveniently located in the warehouse. For warehouses in general, this means that the value of improving storage allocation and routing decreases as the size of the pick list increases. This does not mean that routing should be neglected when pick lists are long, but that a too vast work with decreasing the picking distances is unlikely to pay off the way it would if the average size of a pick list was short.

One researcher studied how six different routing methods performed as number of aisles and pick list size varied. The result clearly showed that the optimal routing procedure performs outstandingly well, while the return heuristic results in the longest mean pick routes. The other heuristics gave more mixed indications as the variables changed, why their adequacy more depends on how well their properties fits with the company conditions and objectives; especially regarding pick efficiency and ease of use.

7.1.4 Analyzing the View on Demand Pattern Effects on Picking Efficiency

The chapter reviewing demand patterns and seasonality connected to warehouse operations is short, reflecting the amount of research available in the area. The authors found this surprising, since some degree of seasonality is an influential reality in many operating warehouses today, both in total volume and among the products. The price of neglecting these variations can be high. For example, responding to change with a firefighting approach instead of anticipating it probably will result in a lowered service level through mixed up orders, temporary storage solutions not designed for the products in question, increased risk for damages due to increased double handling, and so on. One of the few solutions discussed in research is increasing the number of picking zones during high season and similarly decreasing the number of picking zones during low season. This recommendation is adopted and reviewed in the decision support tool with the ambition to result in a solution that can increase performance in the picking and travelled distances in high as well as low season. A warehouse operating only daytime, five days a week, can make many adjustments beyond storage allocation in order to increase productivity. Expanding the work time, to include weekends and adding operating shifts is likely to achieve this without making any other adjustments, but comes with the drawback of being costly due to overtime and or weekend pay.

7.2 Analysis of Tool Structure

The main structure of the decision support tool is similar to the frameworks presented by Rouwenhorst et al. (2000) and Hassan (2002). By focusing on the same areas, or at least the ones they claim should be reviewed after the initial warehouse design phase, the content of the tool's steps was thought to be valid. The order of the steps was inspired by the frameworks. The overall idea was to start with steps that process internal and external company specific input, and continue with the decision areas that use the processed information to make well-considered choices. The exact order, especially on a more detailed level is however not that explicitly described in research. Hence, one problem with the recommendations provided for storage allocation methods, order picking methods and routing methods, is that performance only is evaluated *within* each area. In this thesis, storage allocation method is the area with most available research and where the largest emphasize lies. It is therefore put first in the decision support tool, and although the process should be iterative to ensure aligned decisions, the chosen storage allocation method is meant to rule the choice of order picking to a greater extent than the other way around. If the choice of order picking method had positioned prior to storage allocation method in the tool, recommendations would have guided the choice for the Huta DC towards wave picking instead of batching and zone batching. The reason is that wave picking is stated to provide the largest benefits if only considering Huta's situation in regard to the particular decision area of order picking. However, wave picking is a poor match to the choice of CBS in the previous step due to the large size of pick list it requires to be beneficial. This is also the reason why it is not compatible with recommendations provided for routing methods, which strongly suggest that a pick list size of five will result in the shortest average route length regardless of method chosen. The described problem illustrates the difficulty of interpreting recommendations that build on research from isolated areas only, since reality seldom is that simple.

Two central parts when creating the decision support tool was to ensure its ease of use and repeatability. The stepwise procedure in the tool aims to respond to the easiness, despite the fact that the actual process is likely to turn out more complex than simply linear step-by-step. It is important to emphasize the iterative nature of the process, and also encourage a holistic view. The repeatability is ensured by the detailed guidance of what data to include and how to use it. There is however still a risk of interpretation errors connected to the collection of the soft data (e.g. interviews regarding priorities) and the analysis of the hard order data due to the vague wording in the supporting recommendations that nothing but thoroughness and more explicit new research can aid. The resulting tool therefore shed light on suitable options, rather than provide conclusive recommendations.

The horizontal steps of the tool visualized in Figure 20 illustrate the input elements that are necessary in order to perform the succeeding steps. It contains both hard and soft information entirely derived from the company in question. The hard historical data is most likely easier to collect than the soft data regarding company objectives and opinions, since it is usually registered automatically in companies' ERP systems and ready to retrieve as opposed to being concluded from more time consuming interviews with the selected company representatives. The quantitative nature of the former also means it is relatively undistorted and that its outcome can be calculated and easily formed into statistics etc., while the latter consists of the collected opinions of multiple individuals that might not perceive or know the actual state. The qualitative aspects of step 3; opinions, views and priorities are likely to differ somewhat between the participants in the study. This means that the process of aligning views and priorities can be extensive. Nevertheless it is an essential step where an insufficient focus will sway the result towards a solution that might not bring the benefits that are actually needed. The features of focus in the three primary steps in the tool were identified as central to review when updating the warehouse picking process since they are all prone to change. Demand pattern and size change over time, as well as product range, customer requirements and company priorities.

The vertical steps of the tool in Figure 20, illustrates the iterative steps that combined use the output from the horizontal steps in order to conclude suitable operating choices for the warehouse in question. Although presented in a specific order, it is beneficial to think ahead and try to foresee the effect a decision in a former step will have on a latter. It should be pointed out that there might be multiple solutions that would improve the picking processes. The performance of the chosen methods should be evaluated once implemented by using appropriate Key Performance Indicators (KPIs).

7.3 Analysis of Tool Performance and Usability

The ultimate performance of the tool cannot be analyzed without implementing the result fully, and then evaluating the performance of the warehouse compared to the original situation in terms of picking efficiency etc. Its performance and usability throughout the step-by-step procedure can however be analyzed based on the theoretical framework and the Huta

DC trial-run. The first two steps concern hard company data, easily accessed and understood if dealing with one's own company and ERP system. The key is to know what, in terms of product and warehouse characteristics and requirements, to consider fixed and what to alter or ignore. It is also crucial to know what part of the order data that represent unique picks i.e. travel and time that can be reduced through increased picking efficiency. The better these figures are understood, the better the base for the decision making. The order data features highly impact the choices in step 4 to 6, especially the conclusions drawn from the demand pattern concerning skewness of demand for the different SKUs and the overall fluctuations and possible seasonality.

Step 3 demands more effort in order to get a thorough and valid output, although these types of objectives should be relatively static i.e. once concluded they should be rather simple to update the next time the tool is used. However, to be able to get the right priorities initially, it is important to interview people with the right positions and insight in the company goals and warehouse operations to be able to translate the competitive strategy in to warehouse objectives. The participants in the Thule case interviews all had key positions with regard to warehousing, although in different countries. An undisputed agreement among them regarding priorities was considered to strengthen the usefulness of the continued steps in the tool. In this case, there were not enough significant persons related to the not yet existing warehouse to ask. The employees interviewed now instead provided their views to the extent of their knowledge, in one case in relation to another warehouse. Since this warehouse is much smaller and operates during different conditions than the planned Huta DC, the views of this interviewee were used for comparison rather than as determining factors.

The format of questions regarding the input to step 3 turned out to be essential in getting answers that fit with research's recommendations. A multiple-choice questionnaire was used were the managers should rank their prioritized warehouse objectives. Such layout gave clear answers but it also can lead to interpretation issues. Hence, oral interviews would be better. It is also believed the questions could be sharpened in order to narrow down the company's opinions to the objectives that proved crucial for which methods to choose in step 4 to 6. Hence, the formulations and the exact questions are something that should be revised every time the tool is used in order to update to current conditions and profit from previous learning's. For example, one option in the questionnaire when ranking prioritized objectives was "Other", and Hunt (2014) used it to indicate a priority not included in the provided list; health and safety. It is a central aspect of any operating business, but without clear connection to which storage allocation, order picking or routing methods to choose. In other words, there are no decision areas that would be affected by this priority and thus no reason to include it as an objective in the questionnaire. This lead to the insight that the open choice "Other" in the tradeoff questionnaire should be excluded. All priorities on the list should have a linkage to research that support, or actively does not support, a certain choice. Disregarding "Other" as a choice, this is true for the remaining options in the ranking list.

During the usage of the tool, it became apparent that step 4 was the one where most decisions were left for the user to figure out without suggestions. How to distinguish A from B SKUs is one example, how to dimension the storage areas and which storage configuration to opt for other. Further issues left to the user were how to treat the levels above floor level and how many locations to assign for each SKU. Naturally, the number of storage locations available per SKU is closely related to replenishment patterns and the safety stock set for each SKU, which should mirror how important a SKU is in terms of cost for stock out, service level and customer importance. These aspects are not included in the project scope and not in the illustrative example either, although they in reality strongly affect number of pick locations allocated to each SKU. Hence, the storage configuration and allocation recommended for the Huta DC base its dimensioning solely on the outbound flow; number of picks and order volume. To get a more realistic result the inbound flow to the warehouse and the replenishment activities should be considered as well.

The aspect of seasonality examined in step 2, turned out to be of little importance for the method choices apart from storage allocation. The other choices are likely to stay the same in unless significant changes in priorities and conditions take place the different time periods. In extreme cases the order picking or routing methods might be revised, e.g. if very large outbound volumes and tight schedules indicate wave picking during peak periods, or of congestion inhibit some of the routing procedures. This was not thought to be the situation for the Huta DC. The demand for Thule both has the characteristics of a strong overall seasonality and seasonality among the different SKUs. The two parts go hand in hand for Thule; summer brings a large increase in total demand as well as certain products related to season, while the low season has a low overall demand, but still a peak for the winter products. However in general these differences have different implications; one concerning the SKU allocation and possibly the order picking methods, and one concerning the dimensioning of and content in the picking and/or class zones. The value of revising classes is a result of products being related to season rather than a total change in demand. Should there not be seasonality for the products, this update is not of relevance.

Overall, the outcome of the last three steps heavily depends on the priorities concluded in step 3, which once again point out how important it is to know what to prioritize in a tradeoff situation. The interpretation of the method descriptions and recommendations is also crucial. The wording is, as already stated, often vague, and warehouses with non-distinct or non-extreme features easily end up in a fuzzy middle area in terms of research’s recommendations, which affect the tools usability negatively. Moreover, the foundation of the recommendations is *compiled* research, which means results from many isolated studies, and subjects are combined in to general guidelines. The possible cocktail effect of these combinations forms the main weakness of the tool’s results in terms of reliability. The quality of the results as well as number of studies performed also varies widely between the decision areas. Together this raises the question of the generalizability of the results, e.g. are results from a study in a narrow-aisle warehouse valid in a warehouse with wide-aisles? The authors believe that if several sources point in the same direction, despite examining slightly different warehouse setups or without stressing the specificity in the studied situation, the conclusion is thought as trustworthy.

For users of the decision support tool, the authors’ recommend to perform internal evaluations in order to determine how the company specific setting affects the outcome. KPIs and evaluations are not included in the resulting tool, but are still suggested to confirm that the adjustments bring improvements, and also to quantify them. It is more likely that a company continuously uses the tool and adopts a reoccurring review process if it has clear incentives to do so, i.e. measures and quantifies successful changes. Companies should also fill the gaps in the tool or adapt its content to measured results as well as company specific conditions, which would increase its performance and fit, as well as ease of use. Once the tool has been applied a couple of times, the six steps should more or less be a quick update.

8 Conclusions

This chapter will discuss the usage and analysis of the decision support tool. The outcome of the master thesis will be concluded and the research questions answered. Finally suggestions for further studies within this research area will be presented, which should be of interest both for researchers and practitioners.

In order to wrap up the frame of reference, the illustrative example of Thule’s Huta DC, and the analysis, they are linked to the purpose of the research in this chapter. By summarizing the outcome concise answers to the research questions are provided. Chapter 8.1 corresponds to the first research question, chapter 8.2 to the second research question, and the third and final section of this chapter, 8.3, is devoted to general discussions and suggestions for future research.

8.1 Resulting Design of the Decision Support Tool

The purpose of the decision support tool created in this master thesis is to provide guidance in companies' decision making regarding which methods to use in their warehouse operations connected to order picking. The idea is that the tool should be used for repetitively reviewing and updating the changeable methods while accepting and adapting to fixed factors. As concluded in the introduction and theoretical chapters, choosing suitable methods that ensure efficient picking is very complex. The performance is affected by the preceding and succeeding activities, why storage allocation and routing methods also should be included when creating a supportive tool for easing decisions regarding order picking methods. The intention was to cover the most essential parts when increasing picking efficiency, but that mean the tool might be considered too general for some companies. In addition, few researchers had taken on this wide approach, so most available research was conducted within each specific area i.e. some of the interrelations between the method choices might be unexplored theory-wise. Nonetheless, a theoretical foundation for a decision support tool was established by summarizing the alternative storage allocation, order picking, and routing methods, when they are suitable, and their strengths and weaknesses according to research. Based on this, a conceptual model with step-by-step procedures evolved which uses order data, warehouse features and product information as input. The structure was inspired by other more fundamental design support models but with focus the decisions possible to update relatively easy and often, i.e. which do not require large investments like physical remodeling. Hence, the tool assumes and uses set conditions regarding especially warehouse layout and resources available in order to simplify the decision-making and updating process. The same logic was used for the order of the last three, horizontal steps; starting with the decisions that lead to more fixed outcome, and ending with method choices that can be altered in an instance. The order also corresponds to the amount of research available so that the initial decision concerns the most well examined area and hence has the most profound theoretical support.

The simple but structured design of the tool is a way of ensuring its ease of use in order to enable continuous updates of the warehouse operations method choices. The factors to consider throughout the steps are specific, and the evaluations and comparisons of the method alternatives detailed; all to provide well-founded support to companies' decision makers. The abundance but also ambiguousness of advantages and disadvantages of the different methods highlighted company objectives especially concerning warehouse operations as particularly important to map and take in to account. Identified priorities help concretize preconditions, vital aspects to consider as well as provide a ranking of their relative importance for the company which can guide in tradeoff situations. Aligned with the company's overall goals, the prioritized objectives carry the potential to rule what methods that are considered the best fit for each individual warehouse setting. A simplified version of the decision support tool, focusing on the overall structure can be found in Figure 44. The horizontal and vertical steps of the tool combined manage to assemble, visualize and suggest adjustments for improved warehouse operations. It builds on theory and research, but also requires careful considerations depending on setting in order to bring improvements. Not all possible factors or combinations are covered due to gaps in research, but the general structure is still enough for supporting the decision making and improving the picking operations. The outcome of the tool are guidelines for which storage allocation, order picking and routing methods that are most suitable in a certain setting, e.g. during different time periods or in different areas of the warehouse.

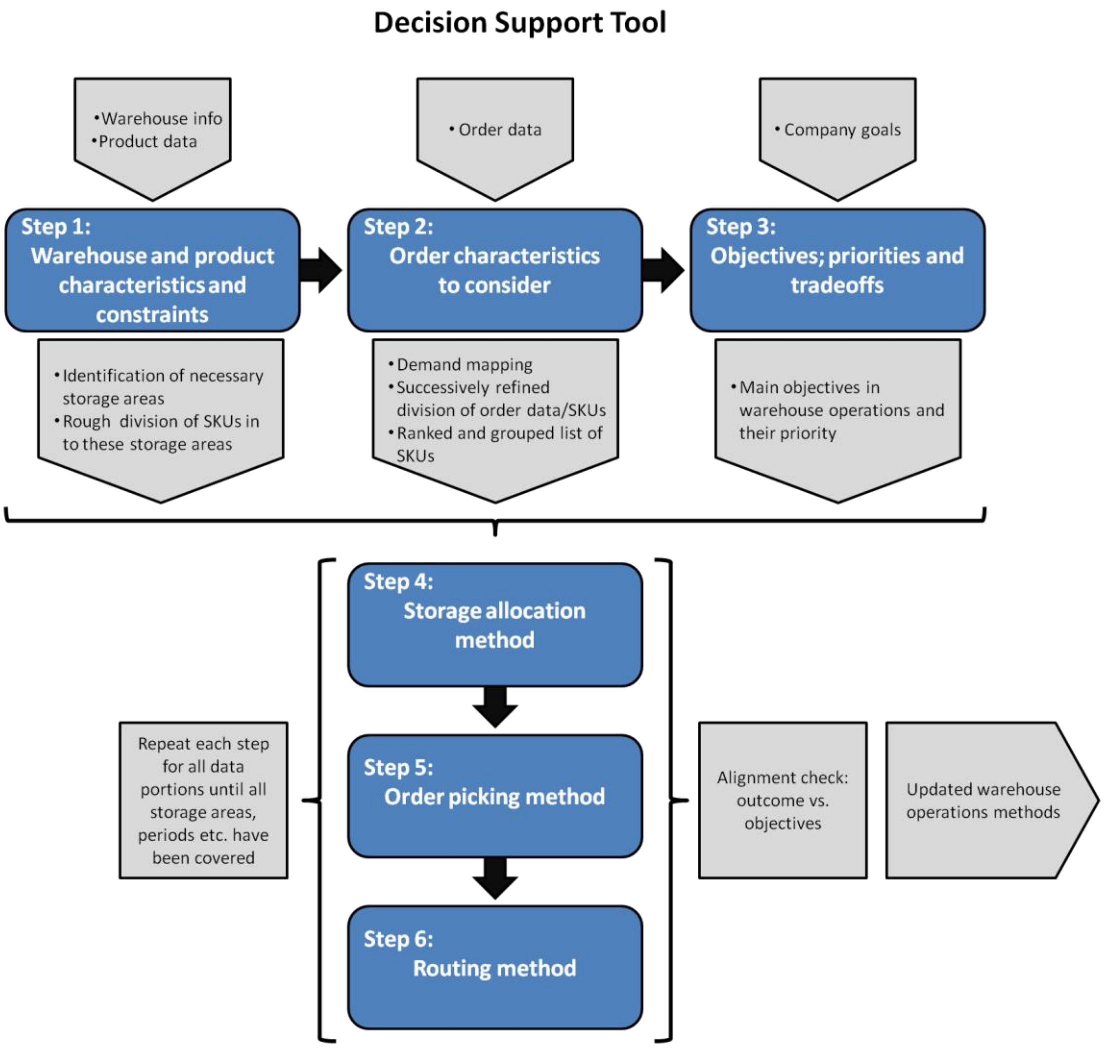


Figure 44 Simplified version of the decision support tool (Gildebrand & Josefsson, 2014).

8.2 Significant Features for Decision Support in Warehouse Operations

There are numerous features to consider in order to choose the most suitable warehouse operations methods. For example, pick density guides the choice between random or dedicated storage while share of full versus partial picks can rule the dimensioning of the SKU allocation. Warehouses with specific characteristics or requirements such as temperature or security restrictions obviously have to make suitable priorities to meet those. However, the reviewed research, the construction of the decision support tool, as well as the field-trial performed by means of the illustrative Huta DC example, lead to that some essential aspects and characteristics for decision support in warehouse operations could be concluded. Three key features to examine when using the tool to be able to make well-supported method choices are described below.

The demand pattern is concluded to be the most important and influential feature to consider. Mapping the prevailing demand pattern will provide valuable information of the overall, as well as the SKU specific variations; seasonality. A high variation in overall seasonality might mean that the most suitable method choices differ between the different seasons. This is also true for variation in frequency on SKU level, even though the total variation might appear stable. Warehouses that experience a high variation between seasons and SKUs are recommended to put extra effort in to choosing SKU allocation method and to do an ABC-classification. If performed on a general level despite strong variation among SKUs, the A-classed SKUs in high season might turn out to be D-classed SKUs in low season, and thus occupy a highly convenient location for no reason. One further feature to emphasize regarding demand pattern is the level of skewness. The higher the skewness, the larger the possible gains from reviewing and improving the current methods.

Company objectives and priorities are the next identified key features. Each company has different products and customers and thereby also different requirements. As a consequence, it has to identify a few, collectively chosen objectives with their warehouse operations that affect which methods to use. This is to ensure a unified direction of the choices at hand, and to raise an awareness of what is not prioritized. Decisions come with both benefits and downsides, and being aware of the downsides is just as important as knowing the benefits. Aiming for all objectives at the same time is an approach that is likely to end up draining potential benefits, which is why the identified objectives also should be ranked according to priority. The ranking will then help ruling in tradeoff situations where several method options are possible, but do not meet the same objectives. To use the existing knowledge among employees and managers about conditions and needs of the warehouse in question is central in all decision-making.

A feature with significant impact on the resulting performance is pick list size. It differs from the previous two features in that it relatively easy can be altered or adjusted, and that it more or less can be decided straight away. Naturally, time constraints as well as order size also affect the pick list size and have to be considered in this decision, but small or large pick lists give different implications for suitable storage allocation, order picking and routing methods why it is an important feature to consider. It has a similar effect as level of skewness i.e.

research shows that the impact of many method choices appears to increase when pick list size decreases.

8.3 Suggestions for Further Studies

The result of this thesis is final only in terms of the project scope. A suggested continuation would be to strengthen the result further by testing the tool in practice and evaluating the outcome after implementation i.e. using multiple real life cases instead of an illustrative example. This should be done in order to increase the validity of the result. The study could also benefit from expanding its scope to include also the areas of replenishment, inventory levels and safety stock to get more thorough recommendations. All three are fairly easy to review and adjust, and all carry the potential of bringing major improvements regarding e.g. warehouse utilization, zone sizes, workload, service level, and to free up capital with only a moderate level of effort. The study has revealed several areas where further research would be needed to provide more comprehensive guidance when choosing the most appropriate method for storage allocation, order picking and routing in a warehouse.

One identified area where additional research would be valuable is ABC-classification: how to divide SKUs in to classes and according to which characteristics. Some suggestions are provided, but reviewing also product value or customer importance and requirements could strengthen the field. For example, using customer segmentation when classifying the SKUs is a criterion not discussed at all in the reviewed research, although it is a commonly proposed strategy for SCM and other business areas (Chopra & Meindl, 2007).

Another, linked research area barely covered in theory is the allocation of classes into corresponding zones when vertical picking area is considered. Vertical ABC-classification is mentioned, but surprisingly few articles discussing ABC-classification and zoning mention the implication from using vertical zoning. Instead, shaping the horizontal zones is a recurring focus. Only assessing the storage locations on floor level appears to be a rather narrow approach, considering that most warehouses have multi-level storage and the total range of SKUs often is larger than the number of floor level pick locations. This means that there is a possibility that the reserve inventory will be stored vertically, and that some low frequent SKUs will have to be stored on less convenient, higher level locations. Another observation is that there seem to be a lack of new research articles within the warehousing field, especially that clearly take advantage of available technological support (e.g. ERP- or WMS systems) by including such solutions to their recommendations.

In general throughout the research studied, more precise recommendations are called for. As of now, the research is abundant with vague, ambiguous wordings that would need to be more detailed in order to be real useful. Further, most research focus on either picking or storage methods, rather than studying them jointly. That means the tool combine results from many isolated studies and subjects, which is the main weakness of the results in terms of reliability. The typical research article treats only one single area in relation to a warehouse with well-defined characteristics. It is a likely scenario that combinations of successful implementations from several studies do not bring the same benefits together as they do alone. It could affect performance in a desired direction through synergies, or in a less preferable way through impairment. This means that there is a need for research that considers combinations of factors and how each method choice affects and interacts with the others. Most previous studies have also been conducted in a very specific setting, e.g. Chan and Chan (2011)'s research on a manual, multi-level rack DC with CBS, which means that it is often difficult to draw any general conclusions from the results. Hence, research that identifies general patterns and try to establish general but specific guidelines for practitioners would be of use. One way of doing this, directly connected to this study, would be to identify the gaps in the tool and then examine in-use warehouses to get travel data to use in a simulation model. Then the model could provide statistics for when each combination of methods would be most appropriate.

As established in chapter 7.1 Analysis of Existing Theory, the research on how to handle variations in demand over time is another scarce area, despite being a very common phenomenon. For example, the research on possible gains from implementing a forward area for frequently picked SKUs during high season is interesting, although not sufficient to provide guidance in the support tool; additional research will be needed in order to evaluate its good. Overall, further research and recommendations of how to meet and adapt to fluctuating demand in terms of warehouse operations methods, as well as indications of the magnitude of improvement would be of use.

Company-wise, recommendations for when to use the tool are needed. Should it be used with a regular interval basis or based on the performance of the warehouse operations? One idea is to use a KPI that continuously is updated. If the KPI crosses a certain level, it indicates that another method might be more suitable, i.e. the choices should be revised through applying the tool. Exactly which KPI and where to set the limits is to be investigated further, but it is suggested to base the KPIs on the identified features that determined the method decisions to begin with. Preferably the KPIs should be in an affectable process-based shape that triggers the warehouse personnel to follow the advice and increase their picking efficiency. It could be worthwhile to transform these demand-based figures into costs since increased costs quickly get attention from managers and it is also easily communicated to the pickers. Cost-based KPIs could also be a convincing measurement to use in the implementation phase to get increased buy-in and commitment from everyone involved. How to successfully implement the method choices the decision support tool recommends is yet another issue left for the companies to deal with on their own; perhaps by using research conducted within the field of change management.

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Appendix A – Interview Guide

Interview Questions for Master Thesis

Background

The new DC in Poland will handle a large number of SKUs. Since the order picking process is the most resource intensive and thus also the most costly part of almost every warehouse, it is of outmost importance that this process is set up in the best possible way.

The purpose of this project is to recommend a storage assignment method and picking process especially designed to suit the characteristics and needs of the new Huta DC. The outcome will be well anchored in the latest research within the field, in order to ensure that the result is aligned with state-of-the-art theories.

Physical constraints of the DC as well as order characteristics will be considered as fixed, since the factors will be used as input when designing our suggestion. Since order pattern is most likely to vary both long and short term, focus will also include how a solution can be updated or continuously revised in order to adapt to new circumstances.

Warehouse Operations

1. What have previously been the *largest challenges* in Thule warehouses?

2. What are the *most time-consuming processes* in a Thule warehouse?

3. What are the *most distinct order characteristics* for Thule?

4. What do you think will be the *largest challenges* for the Huta DC?

5. <u>Indicate the 3 factors you consider to be *main priorities* for the new DC:</u>

- ☐ High warehouse utilization
- ☐ Decrease travelled distance in picking
- ☐ Decrease mix-up when sorting orders
- ☐ Decrease the overall labor
- ☐ Decrease amount of damaged goods
- ☐ Lower computer system dependence
- ☐ Lower the risk of congestion
- ☐ Reduce picking errors
- ☐ Minimize double handling
- ☐ Guarantee a certain service level
- ☐ System simplicity, ease of use
- ☐ Even workload

6. How has the order picking been conducted previously? (Single/batching)

7. How has the pick-path been decided previously?

8. What do you consider to be a suitable method for storing Thule's SKUs?

9. What do you consider to be the best way of dealing with seasonality?

Do you have any further comments of knowledge that you think can be of relevance for our project?

Follow up questions:

10. Rank the top 5 factors you consider to be *main priorities* for the new DC in order of importance, 1 to 5 with 1 being the most important (note that the two last alternatives are added since the previous questionnaire):

- ☐ High warehouse utilization
- ☐ Decrease travelled distance in picking
- ☐ Decrease mix-up when sorting orders
- ☐ Decrease the overall labor
- ☐ Decrease amount of damaged goods
- ☐ Lower computer system dependence
- ☐ Lower the risk of congestion
- ☐ Reduce picking errors
- ☐ Minimize double handling
- ☐ Guarantee a certain service level
- ☐ System simplicity, ease of use
- ☐ Even workload
- ☐ Other:...........................

11. Are your top priorities corresponding to the overall company objectives of the Thule Group? If yes, how? If no, why not?

Appendix B – Comparisons of Different Storage Allocation Methods

A comparison of the percentage increase in average fulfillment time of using diagonal or rectangular storage configurations instead of within-aisle storage when using CBS and 2, 3, and 4 storage classes is found in Figure 45. Comparisons of CBS and random storage allocation methods using optimal routing procedures and transversal routing heuristics, respectively, is found in Figures 46 and 47.

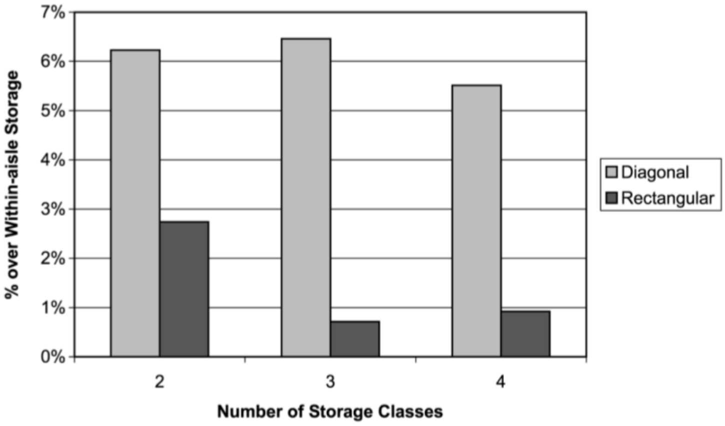

Figure 45 Comparison of storage configuration strategies, the percentage increase in average fulfillment time of diagonal and rectangular storage over within-aisle storage when using 2, 3, and 4 storage classes (Petersen, et al., 2004).

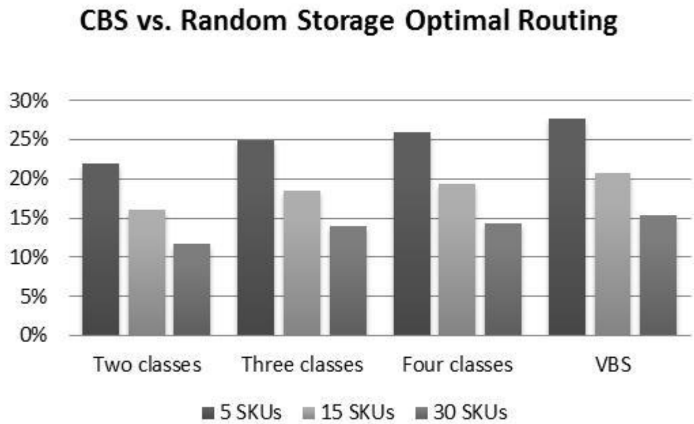

Figure 46 Comparison of CBS and random storage using optimal routing procedures (Petersen, et al., 2004).

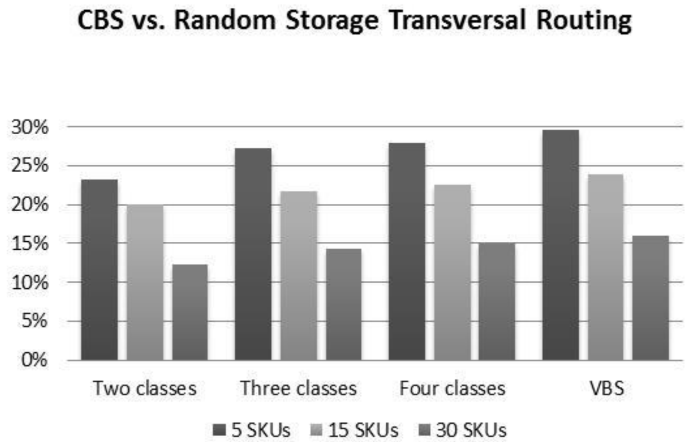

Figure 47 Comparison of CBS and random storage using transversal routing (Petersen, et al., 2004).

Appendix C – Order Data Sample

A larger sample of the order information provided by the Thule Group in the Excel sheet *Order data 12-13* can be found in Figure 48.

Delivery no	Unique pick #	Order number	Order number-Line	Trans ID	Conv. Date	Item type	Item no	Item name	Trans Qty 12-13	# pallets 12-13	Volume / orderline 12-13	Qty / pallet
2647951	2647951-9	3100109329	3100109329-100	Customer Order	2012-07-18	61 - Load carriers	101004	Load carrier Volvo Y286	36	3,00	5,73	12
2647951	2647951-4	3100109329	3100109329-200	Customer Order	2012-07-18	61 - Load carriers	101039	LC VOLVO V40 -04	24	1,00	1,11	24
2648030	2648030-1	3100109338	3100109338-100	Customer Order	2012-07-04	61 - Load carriers	101009	CB AUDI A4 SILVER VOTEX	32	1,00	1,15	32
2648030	2648030-2	3100109338	3100109338-100	Customer Order	2012-07-04	61 - Load carriers	101009	CB AUDI A4 SILVER VOTEX	64	2,00	2,30	32
2650767	2650767-1	3100109524	3100109524-100	Customer Order	2012-07-25	61 - Load carriers	101008	CB AUDI A4 SVART VOTEX	32	1,00	1,15	32
2664546	2664546-1	3100110691	3100110691-200	Customer Order	2012-07-10	61 - Load carriers	101043	LC VAUXHALL CORSA C 01-	50	1,00	1,04	50
2683834	2683834-2	3100112489	3100112489-100	Customer Order	2012-08-01	61 - Load carriers	101038	LC VOLVO S40 -04	24	1,00	1,11	24
2685711	2685711-5	3100112727	3100112727-800	Customer Order	2012-07-13	65 - Bike	101000	BACKPAC RENAULT J81	8	2,00	2,36	4
2689833	2689833-4	3100113136	3100113136-100	Customer Order	2012-08-08	61 - Load carriers	101039	LC VOLVO V40 -04	24	1,00	1,11	24
2689833	2689833-6	3100113136	3100113136-2200	Customer Order	2012-08-08	61 - Load carriers	101063	LC VOLVO V70 00-	32	2,00	2,23	16
2689833	2689833-7	3100113136	3100113136-800	Customer Order	2012-08-08	61 - Load carriers	101063	LC VOLVO V70 00-	32	2,00	2,23	16
2689833	2689833-15	3100115906	3100115906-100	Customer Order	2012-08-08	61 - Load carriers	101063	LC VOLVO V70 00-	32	2,00	2,23	16
2702964	2702964-11	3100114426	3100114426-100	Customer Order	2012-09-12	61 - Load carriers	101004	Load carrier Volvo Y286	36	3,00	5,73	12
2704232	2704232-1	3100114542	3100114542-100	Customer Order	2012-07-24	61 - Load carriers	101042	LC OPEL CORSA C 01-	50	1,00	0,96	50
2704670	2704670-1	3100114167	3100114167-100	Customer Order	2012-07-25	61 - Load carriers	101009	CB AUDI A4 SILVER VOTEX	96	3,00	3,46	32
2705328	2705328-8	6000082100	6000082100	Customer Order	2012-07-26	61 - Load carriers	101044	LC Mazda 626 HB 97-	32	1,00	1,28	32
2705328	2705328-1	6000081454	6000081454	Customer Order	2012-07-26	61 - Load carriers	101066	LC SAAB 9-5 SDN 98-	96	3,00	2,88	32
2709350	2709350-1	3100115057	3100115057-100	Customer Order	2012-09-06	61 - Load carriers	101009	CB AUDI A4 SILVER VOTEX	64	2,00	2,30	32
2719102	2719102-3	3100115287	3100115287-400	Customer Order	2012-08-09	65 - Bike	101000	BACKPAC RENAULT J81	12	3,00	3,54	4
2720199	2720199-5	3100116111	3100116111-100	Customer Order	2012-10-03	61 - Load carriers	101004	Load carrier Volvo Y286	36	3,00	5,73	12
2721511	2721511-2	3100116234	3100116234-400	Customer Order	2012-09-07	61 - Load carriers	101063	LC VOLVO V70 00-	16	1,00	1,11	16
2721511	2721511-3	3100116234	3100116234-400	Customer Order	2012-09-07	61 - Load carriers	101063	LC VOLVO V70 00-	16	1,00	1,11	16
2724088	2724088-3	3100113780	3100113780-400	Customer Order	2012-08-17	61 - Load carriers	101004	Load carrier Volvo Y286	36	3,00	5,73	12
2724403	2724403-2	3100116399	3100116399-100	Customer Order	2012-09-19	61 - Load carriers	101039	LC VOLVO V40 -04	24	1,00	1,11	24
2724403	2724403-8	3100116636	3100116636-900	Customer Order	2012-09-19	61 - Load carriers	101063	LC VOLVO V70 00-	16	1,00	1,11	16
2724403	2724403-9	3100116636	3100116636-900	Customer Order	2012-09-19	61 - Load carriers	101063	LC VOLVO V70 00-	16	1,00	1,11	16
2724404	2724404-12	3100116400	3100116400-100	Customer Order	2012-10-10	61 - Load carriers	101004	Load carrier Volvo Y286	36	3,00	5,73	12
2724404	2724404-6	3100116400	3100116400-800	Customer Order	2012-10-10	61 - Load carriers	101063	LC VOLVO V70 00-	32	2,00	2,23	16

Figure 48 Order data sample, provided by the Thule Group (Risholm, 2014).

Appendix D – Full and Partial Pallet Compilations

Table 23 Compilation of the outbound volume and unique pick lines (Risholm, 2014). A ratio for the different storage areas is also created by multiplying their respective percentage weight.

	High season	Number of pallets	Percentage of total pallets	Outbound volume: Number of pallets ordered in even full, partial pallets or both	Outbound volume: Percentage of total pallets ordered in even full, partial pallets	Outbound volume: Average number of pallets per day ordered in even full, partial pallets or both	Unique pick lines: Number of unique picks	Unique pick lines: Percentage of unique picks	Unique pick lines: Number of unique picks ordered in even full, partial pallets or both	Unique pick lines: Percentage of unique picks ordered in even full, partial pallets or both	Unique pick lines: Average number of unique picks per day	Storage area sizing: reserve vs. picking: Combined weight, percentage of pallets*percentage of unique pick lines	Storage area sizing: reserve vs. picking: Ratio of full vs. partial pallets outbound volume and number of unique pick lines
General pallet area	Full pallets	18 133	77%	14 639	62%	164	7 698	11%	6 830	10%	77	0,085	29%
	Partial pallets	5 507	23%	5 189	22%	58	61 948	89%	61 080	89%	686	0,207	71%
	Both partial and full			3 811	16%	43			868	1%	10		
	Total	23 640		23 640		266	69 646		68 778		773	0,292	
	Flow rack												

	Low season	Number of pallets	Percentage of total pallets	Outbound volume: Number of pallets ordered in even full, partial pallets or both	Outbound volume: Percentage of total pallets ordered in even full, partial pallets	Outbound volume: Average number of pallets per day ordered in even full, partial pallets or both	Unique pick lines: Number of unique picks	Unique pick lines: Percentage of unique picks	Unique pick lines: Number of unique picks ordered in even full, partial pallets or both	Unique pick lines: Percentage of unique picks ordered in even full, partial pallets or both	Unique pick lines: Average number of unique picks per day	Storage area sizing: reserve vs. picking: Combined weight, percentage of pallets*percentage of unique pick lines	Storage area sizing: reserve vs. picking: Ratio of full vs. partial pallets outbound volume and number of unique pick lines
General pallet area	Full pallets	16 942	75%	14 524	64%	85	6 837	8%	6 282	7%	37	0,057	20%
	Partial pallets	5 617	25%	5 402	24%	32	83 065	93%	82 510	92%	485	0,231	80%
	Both partial and full			2 633	12%	15			555	1%	3		
	Total	22 559		22 559		133	89 347		89 347		526	0,289	
	Flow rack												

Compilations of all SKUs, the outbound volume, and the number of unique pick lines ever to be ordered in full or partial pallets, as well as even full, partial pallets or both can be found in Tables 23 and 24. The breakdown is conducted for the general pallet storage area, and for both high and low season.

Table 24 Compilation of the number of SKUs ever to be ordered in full or partial pallets, as well as even full, partial pallets or both (Risholm, 2014).

	High season	SKUs: Number of SKUs	SKUs: Percentage of total SKUs	SKUs: Number of SKUS in even full, partial pallet or both	SKUs: Percentage of total SKUs in even full, partial pallets or both
General pallet area	Full pallets	350	15%	317	14%
	Partial pallets	1343	58%	1 323	57%
	Both partial and full			85	4%
	Total	2306		2 306	
	Flow rack			354	15%

	Low season	SKUs: Number of SKUs	SKUs: Percentage of total SKUs	SKUs: Number of SKUS in even full, partial pallet or both	SKUs: Percentage of total SKUs in even full, partial pallets or both
General pallet area	Full pallets	368	16%	337	15%
	Partial pallets	1588	69%	1 566	68%
	Both partial and full			79	3%
	Total	2306		2 306	
	Flow rack	354	15%		

Appendix E – Demand Skewness Low Season

The level of skewness in demand for full pallet picks, partial pallet picks and pick from flow racks during low season can be viewed in Figures 49, 50 and 51.

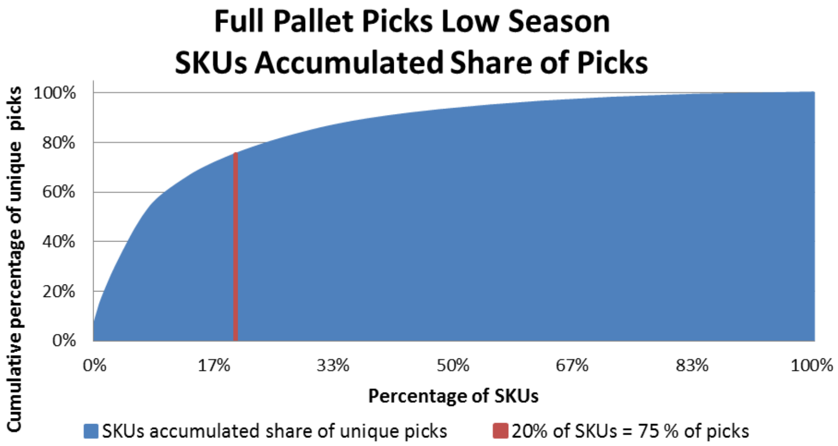

Figure 49 The percentage of SKUs picked in full pallets during low season that represent a certain accumulated share of all unique pick lines. The red line indicates the level of skewness: medium to high.

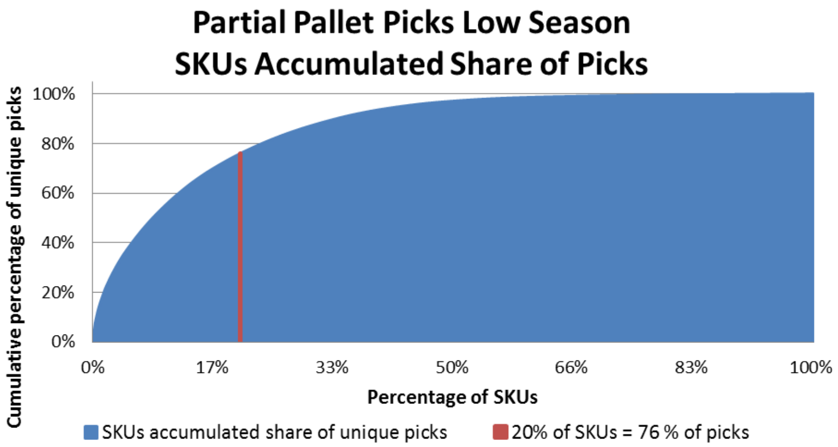

Figure 50 The percentage of SKUs picked in partial loads during low season that represent a certain accumulated share of all unique pick lines. The red line indicates the level of skewness: medium to high.

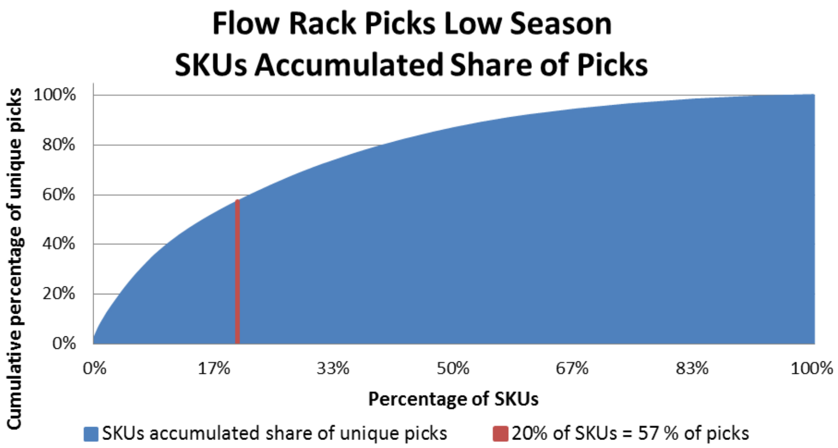

Figure 51 The percentage of SKUs picked from flow racks during low season that represent a certain accumulated share of all unique pick lines. The red line indicates the level of skewness: medium.

Appendix F – Sample of SKU Classifications in High and Low Season

The popularity of SKUs i.e. the number of unique picks per days and the corresponding A-, B-, C, or D-classification can differ a lot between high and low season. The sample in Table 25 below illustrates this by presenting the popularity of some SKUs picked in partial pallets and their high and low season classifications. Table 28 shows the criteria for the classes.

Table 25 Sample of SKUs picked in partial pallets, sorted by picks per day during high season (Gildebrand & Josefsson, 2014).

	High Season		Low Season	
Item numbe	Picks per day	Class	Picks per day	Class
532002	6,427	A	0,453	C
754002	5,562	A	0	-
920013	4,742	A	0,506	B
561000	4,629	A	1,694	B
922013	4,596	A	0,406	C
970003	4,348	A	1,629	B
931000	4,180	A	0,612	B
973002	3,955	A	1,182	B
889200	3,472	A	1,706	B
1500034368	3,022	A	1,724	B
928000	2,910	A	1,235	B
760000	2,831	A	1,871	B
183022	2,798	A	1,876	B
183030	2,573	A	1,959	B
970801	2,551	A	0,735	B
960100	2,539	A	1,959	B
958500	2,011	A	0,076	D
184003	1,966	B	1,765	B
963100	1,944	B	1,529	B
910401	1,933	B	0,729	B
532000	1,888	B	2,035	A
183006	1,876	B	1,759	B
184002	1,831	B	1,941	B
940000	1,831	B	0,624	B
183073	1,820	B	1,571	B
949008	1,708	B	1,041	B
959300	1,697	B	0,176	C
910301	1,685	B	0,618	B
620801	1,663	B	1,712	B
861000	1,652	B	1,947	B
968001	1,629	B	0,624	B
873000	1,404	B	0,365	C
538000	1,326	B	0,429	C
832000	1,292	B	0,453	C
943005	1,292	B	0,465	C
100016	0,910	B	0,076	D
920000	0,831	B	1,371	B
923001	0,764	B	0,918	B
141726	0,742	B	0	-
921001	0,742	B	1,253	B
931100	0,730	B	0	-
805300	0,663	B	0,176	C
911000	0,539	B	0,094	C
821000	0,483	C	0,129	C
141239	0,472	C	0,276	C
141622	0,438	C	0,335	C
726000	0,393	C	2,759	A
727000	0,393	C	2,624	A
323000	0,360	C	0,341	C
141281	0,348	C	0,200	C
141660	0,315	C	0,212	C
802000	0,303	C	0,224	C
183092	0,292	C	0,235	C
739000	0,270	C	2,394	A
1500043215	0,258	C	0,253	C
1500014671	0,213	C	0,271	C
694500	0,146	C	0,453	C
2004365080	0,034	D	0,535	B
2004705247	0,034	D	0,518	B
591040	0,011	D	0	-
2004705230	0,011	D	0,376	C
2004125090	0	-	0,524	B
2004255095	0	-	0,376	C

Table 26 Classification criteria in *x* picks per day.

Class	High season	Low season
A	$x \geq 2$	$x \geq 2$
B	$0.5 \leq x < 2$	$0.5 \leq x < 2$
C	$0.08 \leq x < 0.5$	$0.09 \leq x < 0.5$
D	$x < 0.08$	$x < 0.09$