Minimizing order picking distance through the storage allocation policy

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Abstract:

Continuously changing demand patterns force Logistics Service Providers to develop sophisticated solutions for minimization of the order fulfilment cycle. Being one of the most time -intensive processes in the field of warehousing, picking has the highest impact on the service level. In turn, from the warehouse perspective picking is the most labour-intensive activity and thus reasonably objective of continuous improvement. Scientific discussion emphasis various approaches to optimize the picking process: storage allocation, routing policies and batching algorithms.

The aim of this thesis is to answer the question **"How to minimize an order picking distance and improve picking efficiency through the more efficient storage allocation of the items?"**

As was revealed in the simulation existing random storage allocation has significant drawbacks, when it goes to the order picking distance. Favorable storage locations are misused for the items with the low picking frequency. Warehouse management is suggested to apply wireless scanners to improve picking and minimize transaction time between systems. It is recommended to implement COI-based allocation with affinity relation component, as an optimal solution with estimated average 90% improvement compared to random storage. The difference in the estimated picking distance between allocation policies increases with the increasing amount of the picking lines. Warehouse Management System should follow picking frequency aspect and affinity relation of the A-class items. ABC stratification is based on the picking frequency. Affinity relation is very important when storage allocation made for the items with the same COI-index, as additional criteria. In addition, availability of the future demand and strong information flow are considered as vital criteria during development of the storage allocation policy.

Keywords:	*Order picking, storage allocation, COI-based, random, ABC-stratification, affinity relationship*
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FOREWORD

This research project was executed as completion to the Master’s Degree Programme in International Business Management, at Arcada University of Applied Sciences, with focus on the improvement of the order fulfilment cycle though the more efficient storage allocation policy.

This research could not be possible without the help of many supporters. First and foremost, I would like to express my sincere gratitude to my supervisor: Siv Relander, Senior Lecturer in Business, at Arcada University of Applied Sciences, who was encouraging and positive through the whole research. Her guidance, patience, and support inspired and helped me enormously. Special gratitude to all the experts in management and outbound team of Vantaa warehouse for giving me opportunity to investigate picking process to improve the order fulfilment cycle. The was always valuable feedback and practical advices from the best specialists in the field of warehousing. I feel extremely fortunate, I got the chance to participate in the Master’s Degree Programme at the Arcada University of Applied Sciences. Truly wonderful and challenging time it was.

Finally, I would like to thank my family for making me happy every day, as well as my friends, who repeatedly provided creative ideas

Sincerely,
Vadim Smyk
Helsinki, February 2018

1 INTRODUCTION

Continuously changing demand patterns force Logistics Service Providers (LSPs) to develop sophisticated solutions for the optimization of the order lead time. Being one of the most time -intensive processes in the order fulfilment cycle, picking has the highest impact on the service level. In turn, from the warehouse perspective picking is the most labour-intensive activity in the outbound logistics flow and thus reasonably objective of the continuous improvement in the minds of warehouse management, focused to minimize expenses and increase competitiveness.

The storage allocation problem has been intensively researched in the scientific literature over the past fifty years. Nonetheless, the majority of the available algorithms is mostly not applicable when it comes to customizing the features of the Warehouse Management System (WMS), in order to understand and analyse demand patterns and historical order profiles. Typically, scientific literature provides a set of general recommendation related to the improvement of the picking process ignoring specific customer requirements and real-world demands.

It is notable, that logistics and warehousing solution providers usually overlooking storage allocation policy as a way to minimize the order picking cycle, limiting related with ABC-stratification, which, however, is not able to cover the potential demand fluctuation and full set of order and item profiles completely.

This chapter provides general information on the importance of warehousing and picking operation as a significant part of the order fulfilment process. It also introduces the aim and research question of the study, as well as methodology and limitation. List of acronyms used in this thesis provided in Section 1.8.

1.1 Background

There are various real-world situations, that have been studied to comprehend the factors affecting the efficiency of the order fulfilment process and mostly, reducing order cycle time is an ultimate goal, resulting in improved warehouse throughput, and high cost saving in the materials handling operations (De Koster 2006 p. 7).

According to Tompkins picking, as a part of the order fulfilment cycle, is the most labour-intensive and costly set of activities representing approximately 55% of the total warehouse operational costs, as shown in Figure 1. Order picking process has direct influence on the order accuracy and delivery time. Due to the large number of items in orders, the picking capacity constraint is considered as vital (Tompkins et al. 2010 p. 86).

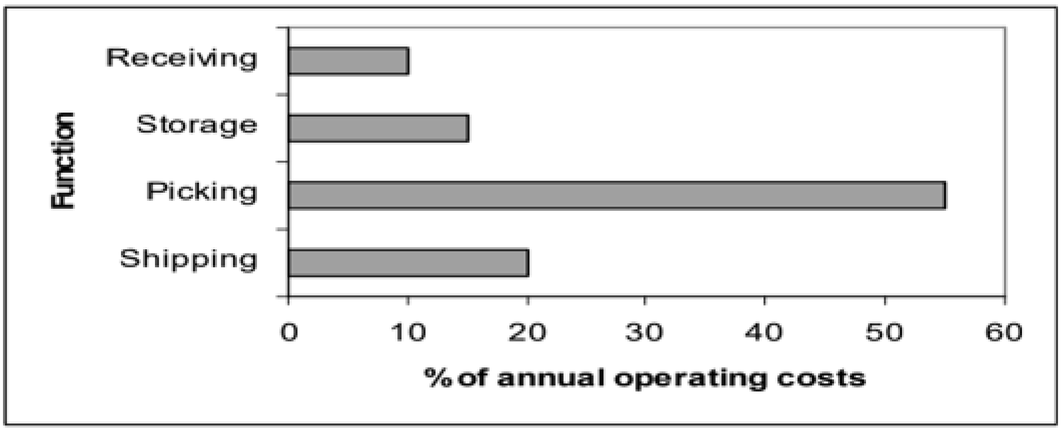

Figure 1. Operational costs in the warehouse (Wiley 1996)

Generally, the objectives of the warehouse are to reduce order fulfilment cycle, decrease costs and keep customer satisfaction on a high level. The warehouse is the connecting point between the main elements of the supply chain and a significant point in the informational and material flow. Nowadays warehouses are being driven by customers to expand distribution channels. On the other hand, due to the growing unpredictability of orders and higher requirements regarding SLAs, the importance of warehousing performance in value adding process has been increasing over the past decades (Goetschalckx et al. 2007 p. 18).

Managing order fulfilment processes becomes more multifaceted and complicated. The complexity of the order management, the ongoing challenge to keep customers satisfied, increased demand for SLAs, and tackling growing costs are among the major challenges warehousing LSPs are facing currently.

De Koster emphasizes that, more logistic solution providers consider cost reduction and improvement of productivity within own warehouses, as well as pay separate attention to the order picking process. Related activities play a significant role for LSPs, as they are continuously making efforts to optimize processes in order to improve customer satisfaction and decrease operational costs. De Koster shares Tompkins opinion about order picking being the most labour-intensive and capital-intensive operation in warehouses (De Koster et al. 2007 p. 34-35).

There are many comprehensive studies proving picking as a fundamental way to reduce order fulfilment costs. Scientific discussion emphasis various approaches to the optimize picking process: storage allocation, routing policies and batching algorithms. Storage allocation regulates where to keep items in order to decrease material handling costs. Routing and batching, on the other hand, defines the best possible batch and route to arrange picking process efficiently. McGinnis et al. observed that 32% and 38% of the order picking related studies are about storage allocation and routing policies, respectively (McGinnis et al. 2007 p. 15).

With dynamic fluctuations in Customer N demand, picking of its healthcare products in Vantaa warehouse has become a bottleneck of the order fulfilment cycle, which is one of the major KPIs of service level. The aim of the picking strategy is to improve level of service by optimizing order fulfilment cycle. Moreover, as picking process acknowledged as the most labour-, time- and cost-intensive activity, suitable picking strategy, results in the cost reduction. Therefore, Vantaa warehouse is actively searching ways to advance picking process to the new level and admits its highest priority, as the key element to improve efficiency and gain competitive advantage. Warehouse located in Vantaa, Finland and items considered in this work related to the healthcare sector, where delays or inaccurate picking might lead to way more serious consequences.

At the beginning of September 2017 many pharmacies and customers in Finland were out of the essential drugs due to new ERP system by Oriola couldn’t maintain logistics processes, as expected. As a result, on inappropriate picking orders were mixed and delayed. The situation was partially solved with the help of competitors. Besides drastic consequences for the customers and company reputation, Oriola reported that it had lost some 4 million euros in net sales, as distribution of non-pharmaceutical products were only partially possible in September, with all attention focused on the distribution of the most essential items (Aamulehti 2017).

According to Goetschalckx, a main priority for the picking process is to increase service level of the order fulfilment, and minimize overall lead time based on available labour and/or machines and capital (Goetschalckx 1990 p. 124). There are various studies conducted on the efficiency of different warehouse activities to offer picking improvement and cost reduction. Most of these studies emphasize picking travel time or travel distance to retrieve a complete order, as the objective to improve picking process (De Koster 2006 p. 23).

1.2 Purpose of the study

The purpose of this study is to reduce the order processing cycle in the Vantaa warehouse for customer N orders by developing a practical strategy for correct storage allocation of the items. Based on the outcomes of this study suitable allocation strategy has been selected and the set of recommendations have been provided to be integrated into WMS.

1.3 Research aims and objectives

The aim of this thesis is to answer the question **"How to minimize order picking distance and improve picking efficiency through better storage allocation of the items?"**

This study aims to cover following questions:

(i) define main criteria to be considered while developing storage policy for Customer N items;

(ii) analyse historical demand data and describe the current storage policy for Customer N items in Vantaa warehouse;

(iii) compare storage policies and determine practical allocation method.

This subject is close to the author as he has been involved in logistics processes and warehousing for almost ten years. Besides the strong desire to assist Vantaa warehouse in cost reduction, optimization in the order fulfilment cycle and improving in customer satisfaction, author can gain more experience and problem-solving skills in order to enhance efficiency for similar processes in own company.

1.4 Contribution

This work contributes to both efficiency of the warehouse operations, reduction of the costs and order fulfilment cycle, as well as improving level of service. As contribution to knowledge about storage allocation, as a part of picking strategy, this work brought more understanding to the question of warehouse management in the scope of the order fulfilment process. Optimization of the order fulfilment cycle minimizes the time required for item transfer to upstream outbound processes and any reverse movement or delay increases the number of operations, as well as the total costs of cycle.

1.5 Limitation

In this study improvement for the order picking process is developed through a storage allocation strategy for items of Customer N in Vantaa warehouse. Therefore, thesis is limited to the planning level. Operational level of the picking process, like routing strategies batching algorithms and order sequencing, as well as other warehouse activities and order fulfilment stages, as packing, loading or transportation are out of the scope. In addition, as order handling in Vantaa warehouse is done manually, study is limited to a picker-to-parts picking system, with automated picking systems left out of the scope.

As the focus of this study is on minimizing of the order fulfilment cycle through the storage allocation policy, possible changes in layout design of the warehouse or picking tools will not be considered. Since it takes long time to simulate all Customer N items, ABC- stratification is implemented, with simulation later concentrated on A-class items only. Method for selection and the related selection processes described in Chapter 3.

1.6 Research methods

The research of this work is conducted as a case study. According to Schirmer, a case study is a popular research method in the warehousing area, with the purpose to investigate specific problems within the limitation of definite conditions, circumstances, or processes. Benefits of the case study method include data collection and assessment within the scope of the process, integration of qualitative and quantitative data in the evaluation process, and the potential to cover comprehensive real-life states. This way the process can be examined on the micro level. Insufficiency of thoroughness, difficulties related to data assessment and lacking potential for generalizations of results are evidently shortcomings of the case studies (Schmenner 1997 p. 420).

On the other hand, according to Farooq, intense exposure of the case study offers grounds for generalization of the data for demonstrating statistical findings but has limited representatives and no appropriate classification. Other benefits of the case study are the intensity of the study and continuity of the assessment, with investigation and exploration of a process thoroughly and deeply based on the facts from the simulation. As potential drawbacks, Farooq emphasizes that case study method might have errors of the judgment, since it is rather a subjective method than objective and have no fixed limits. Case study research is also considered as more time consuming compared to other approaches of data collection (Farooq 2013 p. 5).

Yin states the case study research as an empirical investigation that examines a contemporary process within its real-life scope, when the restrictions between the process and the scope are not evidently shown, including implementation of numerous sources for quantitative prove. Others define case study research significance only as an investigative instrument (Yin 2009 p. 24).

Case study research is a methodology which can use either a qualitative or quantitative approach. Qualitative research is mainly investigative study, targeted at gaining an understanding of fundamental explanations, views, and drivers of the process. It offers deeper understandings about the phenomena and supports on developing concepts or suggestions for potential quantitative investigation. Qualitative research is likewise applied to discover trends and dive deeper into the phenomena. Qualitative data collection methods differ applying to unstructured or semi-structured approaches. Commonly approaches include focus groups, individual interviews, and participation or observations. The amount of samples is commonly minor, and respondents are chosen to satisfy a certain allocation (Racino 1999 p. 118).

Quantitative research is applied to quantify and analyze the phenomena by generating mathematical data or data that potentially can be altered into practical statistics. It is applied to quantify attitudes, processes, performances, and other specific variables and generalize outcomes. By implementing quantifiable information to frame empirical evidence and reveal outlines in an investigation, data collection approaches of the quantitative are much more organized than data collection approaches of the qualitative data, including different forms of surveys, interviews, longitudinal investigations, website interceptors, online polls, and methodical observations (Racino 1999 p. 119).

Assumptions and simulation of this thesis are based on historical data from WMS. Schmidt states that, generally, warehouses outbound activities are based on the enterprise management systems to manage the inbound, storage, relocations, and outbound of the items according to the customer demand. WMS keeps historical data, including specific characteristics of the customer items like weight and dimensions and warehouse design related information, like storage locations, allocation restrictions, and material handling tools.

Historical data is significant for allocation policies and can be utilized to formulate simple performance indicators to predict future demand (Schmenner 1997). Specific data, valuable for this research, might not be available in WMS and is collected from the warehouse specifications and process descriptions.

De Koster et al. defines simulation approach as extremely supportive in quantifying performances for complex processes where the analytical approach has been proven to be unfeasible (De Koster et al. 2007 p. 24). On the other hand, Rouwenhorst et al. concluded that an analytical study and a simulation study equally might not lead to a comprehensive solution in the real-world situation, and suggested that a combination of two approaches would be desirable (Rouwenhorst 2011 p. 116).

To answer the main research question, a suitable methodology must be selected. Figure 2 illustrates an overview of the stages engaged in this study.

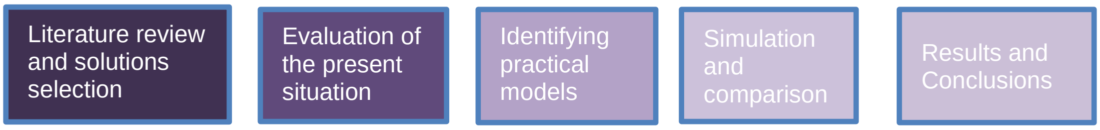

Figure. 2 Methodology overview

In the literature review chapter, main warehousing activities are introduced and place of the picking process and relationships between activities are defined, following by discussion about strategies for improving order picking process. Next potential of allocation policy to ensure required improvement is determined. Related assessment and comparison between allocation policies are conducted, in order to define the best possible practical solution to minimize travel distance of picking tours in Vantaa warehouse.

In the next part assessment of the present situation is conducted, to evaluate how appropriate existing random allocation strategy is in keeping required level of customer service, and what are the main criteria for the efficient order picking process. This part is concentrated on qualitative evaluation, which is valuable later in the process of modelling assumptions and determining parameters. Quantitively evaluation will be performed during simulation stage.

After potential options have been discussed, next part covers practical mathematical models in order to evaluate and compare selected solution in the simulation. This part includes limitation of potential samples by implementing ABC stratification. Next, proposed allocation policy and existing random policy are tested empirically in the simulation and compared to define which solution is considered to be the most effective under different circumstances. Subsequently, the underlying model is an abstraction of the real word, the optimization results are just suggestive of the real influence on actual performance. Based on the results of the simulation, the closing stage of the study concerns conclusions and recommendations on alternative having the highest potential for improvement.

According to the computational complexity theory, as a part combinatorial optimization concept, the complexity of a problem is defined as the complexity of the best algorithm that solves that problem. Cook et al describe discrete optimization or combinatorial optimization, as defining an optimal solution in a finite or countably infinite set of potential solutions. Optimality is defined with respect to criterion function, which value is to be minimized while modelling storage allocation strategy (Cook 2009 p. 6).

In relation to the storage allocation, combinatorial optimization problems can be quite limited in use due to a large amount of possible solutions, as well as due to constraints in the receiving of the certain item. For example, certain items cannot be allocated to all possible places due to measurements or specific storage requirements related to the nature of the items, as well as certain items cannot be stored together.

As the amount of variable solutions due to the several constraints, there is no practical possibility to use exact optimal solution model. ABC-stratification is used prior to the simulation, in order to limit the number of the item profiles, leaving less important out. To present optimization problem mathematically Linear Programming Problem is used for this study.

Heuristic methods are preferred over exact methods when the problem is so large or high dimensional that the exact methods might take too long. In turn, metaheuristics are on a higher abstraction level than heuristics and provide general-purpose search methodology that can guide an optimization (Rainer et al. 2009).

1.7 Structure of the study

This thesis includes five chapters. Chapter 2 introduces warehouse activities and picking process, following by discussion on order picking improvement strategies. Next allocation policies are presented, comprehensive analysis about strengths and weaknesses based on the literature review is made, following by the discussion on the specific methods most applicable in the case study in this work.

Chapter 3 introduces current picking process and layout of Vantaa warehouse and analyses historical order patterns. In this chapter assumption are made, ABC stratification is performed, a mathematical model for selected methods is formulated and the simulation model is introduced.

In Chapter 4, the results of the simulation are considered, and comparative analysis made, following by summary and a discussion on the findings.

Chapter 5 finalizes the study with conclusions, recommendations and potential suggestion for future works on the related topic.

1.8 List of acronyms

ABC-stratification – classification of the items into three categories

EOM/EOP- End of Manufacture/ End of Production

ERP- Enterprise Resource Planning

COI -Cube-Per-Order Index

GP- Generic Programming

KPI- Key Performance Indicator

LPP-Linear Placement Problem

LSP- Logistics Service Provider

OOS- Order Oriented Slotting

SCM – Supply Chain Management

SLA- Service Level Agreement

WMS-Warehouse Management System.

2 LITERATURE REVIEW

As discussed in section 1.5, the objective of this research aims to reduce picking travel distance in order to improve total order fulfilment cycle. The importance of the order picking improvement has been acknowledged largely and deservedly has been taking place as a subject for the various researches over the past 50 years, with the attention paid to the different aspects throughout the time.

Khodabandeh emphasizes that the importance of the order picking is valid for healthcare warehouses as well. As evidence, he provides a report by United Parcel Service, showing that picking and order fulfilment consumes 54% of the cost in the average healthcare distribution centre (Khodabandeh 2016 p. 12).

De Koster et al., discuss several recent trends both in manufacturing and distribution, which have made the order-picking design and management more important and complex. In manufacturing, there is a move to smaller lot-sizes, point-of-use delivery, order, product customization, and cycle time reductions. In distribution logistics, in order to answer new requirements of the customers, companies tend to accept late orders while providing fast delivery within tight time windows. Thus, the time available for the order picking becomes shorter (De Koster 2007 p. 123).

Gu et al. define the crucial roles of the warehouses in the supply chain performance. The major roles included "buffering the material flow along the supply chain to accommodate variability caused by factors such as product seasonality and/or batching in production and transportation (Gu et al. 2007 p. 5). Warehouse operation and management systems are discussed in section 2.1.1

Gu et al. describe order picking problem as one of the most challenging among the warehouse operation planning concerns (Gu et al. 2007 p 8). While there have been several investigations on the general order picking problem, little research regarding order picking for a healthcare warehouses was found. Reader may refer to Gu, Goetschalckx, and McGinnis, 2010 for detailed reviews on warehouse operation, design, and performance evaluation, as well as to comprehensive review of De Koster, Le-Duc, and

Roodbergen, 2007 on warehouse layout and picking operations. Methods for the order picking improvement are discussed in section 2.1.3.

2.1 Order picking process

Tompkins et al. describes an order picking, as the process of retrieving items from the storage in response to the customer request and defines picking as the most labour-intensive and costly process containing around 55% of the total warehouse operational expenses as shown in Figure 3 (Tompkins et al. 2010).

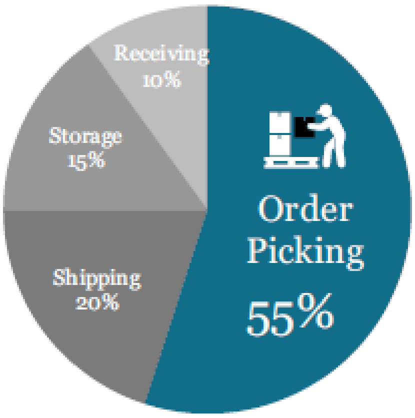

Figure 3. Warehouse expenses

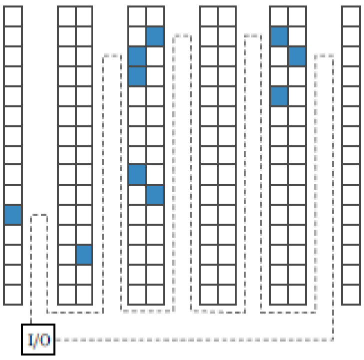

Figure 4. Example of order picking

Minimizing material handling cost or equivalently, traveling cost, traveling distance, or traveling time is one of the main objectives which researchers have strongly focused on when the goal is to improve order picking efficiency. Figure 4 represents order picking of multiple items in an aisles warehouse. Tompkins et al. showed that in fact, half of the order picker's time is spent on traveling (Figure 5). To the same conclusion went both De Koster et al. and Petersen by describing travelling of the order picker is the most time-consuming activity –usually estimated at about 50%. Therefore, typically the majority of the studies are dedicated to improve this vital process (Tompkins et al. 2010 p. 25).

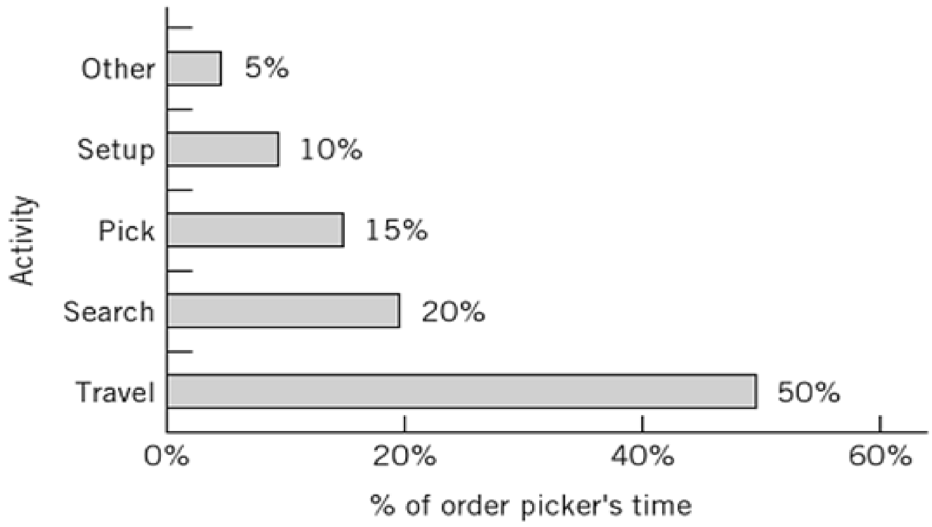

Figure 5. Typical distribution of an order picker's time (Tompkins et al. 2010)

2.1.1 Warehouse operations and WMS

De Koster et al. defines warehouse as a place where goods are received, temporary stored, and released according to the customer requests. As consolidation point between supply and consumption warehouse also provides value-added for order fulfilment and, is the place where packaging of goods according to the specific sales orders, customization, inspection and assembly are performed (De Koster et al. 2007 p. 131). Hausman et al. mentioned the efficiency of the order picking as a crucial factor considered at the stage of warehouse design. Correct storage allocation and suitable warehouse layout minimizes travel distance and the picking time, resulting in improvement of the total fulfilment cycle (Graves et al. 1976 p. 40).

According to Lambert et al. warehouses contribute to a multitude of the company's missions, as follow:

• Achieving transportation economies (e.g. combine shipment, full-container load).

• Achieving production economies (e.g. make-to-stock production policy).

• Taking advantage of quality purchase discounts and forward buys.

• Supporting the firm's customer service policies.

• Meeting changing market conditions and uncertainties

• Overcoming the time and space differences that exist between producers and customers.

• Supporting the just-in-time programs of suppliers and customers.

• Providing temporary storage of material to be disposed or recycled

• Providing a buffer location for trans-shipments (i.e. direct delivery, cross-docking) (Lambert et al. 1998 p. 15).

Heragu et al. defined these areas as forward and reserved areas. Items purposed to be kept in the warehouse for short period of time are stored in the forward area and therefore are located closer to inbound and outbound points to minimize traveling distance for pickers. On the other hand, items with less frequent demand are to be stored in the reserved area (Heragu et al. 2005 p. 317). Frazelle defines warehouse as an element having a critical influence on the service levels and operational costs of supply chain and agrees it is important that warehouses are designed and managed to be cost-effective and ensure efficiency of the picking processes (Frazelle 2002 p. 22).

Given the importance of the picking process it has been recognized as area where significant performance improvement can be achieved. To define a place of the order picking and classify its relationship with other warehouse operations Frazelle presented a unifying framework in Figure 6.

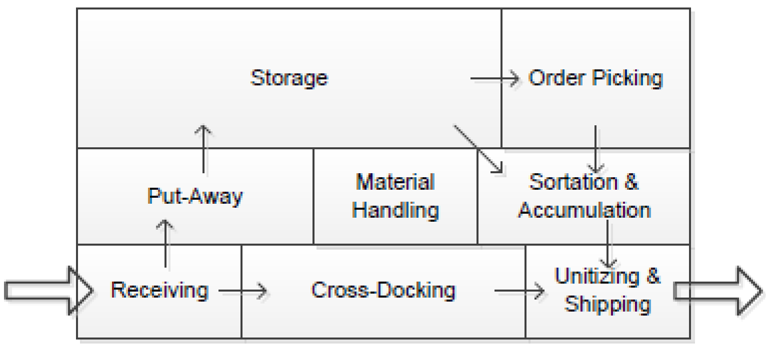

Figure 6. Framework for warehouse operations (Frazelle 2007)

De Koster defines several order picking systems which are created to optimize the order fulfilment cycle (Figure 7). Three main systems are distinguished according to the order picking approach: picker-to-item, item-to-picker, and automated picking. In a picker-to-item system, order pickers need to travel along the rack shelves to retrieve the items in their order lists. Same approach is used in the case warehouse of this study (De Koster 2006 p. 37).

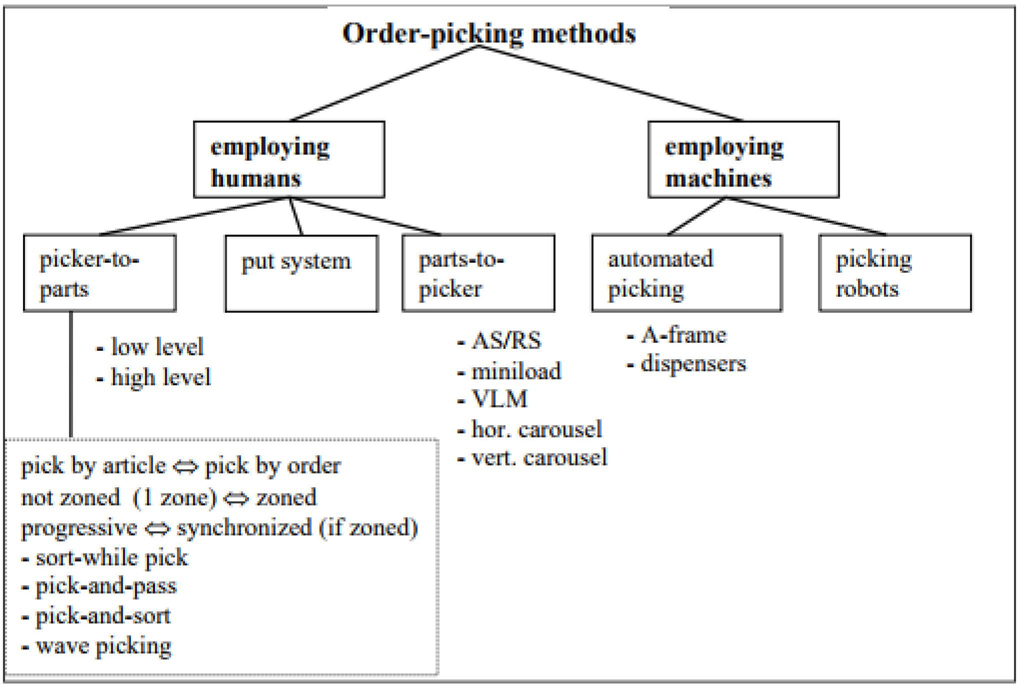

Figure 7. Classification of order-picking systems (based on De Koster 2006)

2.1.2 Warehouse layout and KPIs

De Koster et al. have conducted a comprehensive survey on warehouse layout with the special attention to the order picking. During this research related warehouse activities, like receiving, transfer, order consolidation and packing were studied. There are specific areas in the warehouse which serve specific requirements (De Koster et al. 2007, p. 63).

In order to measure the impact of a successful order picking strategy relevant indicators need to be defined. According to Cristopher lead time and fulfilment cycle are the basic measurements and performance indicators, but they are frequently not considered in relation to the warehouse throughput and cost efficiency. Order fulfilment cycle is defined as the time period between the moment order received by the warehouse to the point when goods being delivered at the customer request (Cristopher 2005).

As said above picking is both the more cost-intensive warehouse activity as well as being considered having the largest potential for improving order fulfilment cycle. Minimizing of the order picking is often a good place to start the overall effort to improve warehousing efficiency and customer satisfaction since it can be arranged without heavy capital investments (Cristopher 2005).

Hompel and Schmidt defined common KPIs for the order picking including the number of picks per time unit, the average travel distance per pick/ order, the average time per pick order. Cristopher mentioned that the average order picking time should be measured in relation to the average order size. As said above, since picker travel time is the most time-intensive activity with 50% share of the total order picking time, it is one of the most widely adopted measures for warehouse performance used in the scientific literature (Hompel et al. 2006).

According to De Koster, order picking policies are regarded as critical to warehouse performance and can be influenced by both internal and external elements (De Koster et al. 2007 p. 154). Examples of the internal factors are system characteristics and organizational and operational policies. These organizational and operational policies include storage, batching, zoning, routing and order release mode. Chan et al. add to this statement that, the efficiency of picking is also highly related to the class configuration and the way the warehouse has been designed. External factors include marketing channels, customer demand pattern, the state of the economy, etc. (Chan et al. 2011 p. 241).

2.1.3 Picking improvement policies

As described in the number of different works of Goetschalckx, De Koster, Jacobs, Frazelle, Meller and Tompkins, there are commonly three strategies used to improve order picking:

- assigning items to storage locations (tactical and operational level)
- order picker routing (routing) (operational level)
- grouping or batching all picks of the orders (batching) (operational level)

A related overview is presented in Figure 8. Storage allocation strategies and zoning strategies determine where to store the items to reduce material handling cost. Routing, batching and order release mode, on the other hand, determine the best sequence and route of the locations for storing and picking a set of items. As stated in the limitation part routing and batching algorithms will be out of the scope of this study (De Koster 2007 p. 211-213).

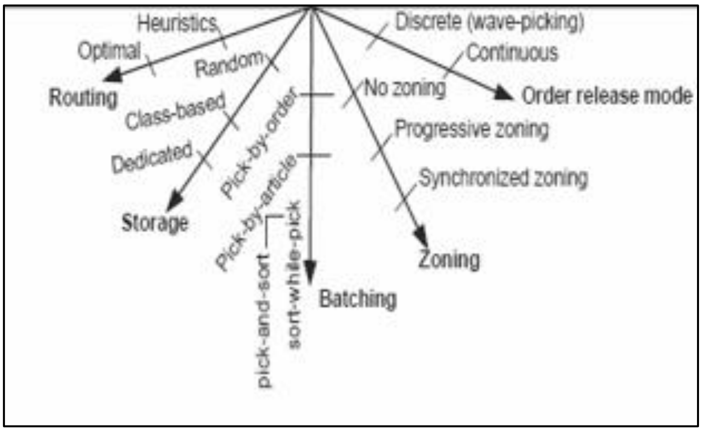

Figure 8. Order picking improvement policies (based on De Koster, 2007)

Petersen et al. suggest the use of travel distance to compare different allocation policies. In his opinion distance is better than time to measure performance, since the travel time could be influenced by the travel method, while distance will not (Petersen et al. 1997).

In order to describe the main factors affecting three main approaches for order picking optimization, Adil introduced wheel of order picking, as shown in Figure 9. The wheel is furthermore affected by physical attributes, like the warehouse design, the equipment used, as well as the information flows, like forecasting and warehouse management system. The information flow is needed in several ways to coordinate the flow of materials and provide the data about storage capacity, sales forecasts, and the information about items.

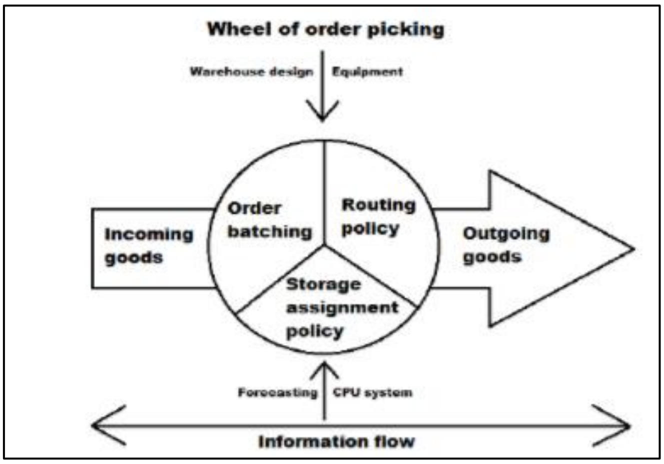

Figure 9. Wheel of the order picking. Factors affecting picking policies (Adil, 2008)

According to Tompkins et al., there is a gap between reality and academic research, when it comes to the order picking policies. Not all new picking policies have been studied sufficiently. The literature on the influence of the picker congestion is still limited and in practice, a selection of the performance indicators must be made on a case-by-case basis. There is still a shortage of case studies that consider the optimal combination of warehouse design, storage assignment, order batching and routing (Tompkins et al. 2010).

Rouwenhorst et al. made an extensive research on the order picking policies being considered already at the stage of warehouse design and came to the conclusion there is a lack of an academic data about warehouse layout approaches. Researchers concluded that in most of the cases selecting correct allocation policy in the scope of warehouse design is a complicated mission with many trade-offs between various targets at each consequent step. Many researches have introduced methodology dedicated to concrete real-life cases, but there has never been a consensus. This shows that a systematic methodology to the warehouse design process is required (Rouwenhorst et al. 2000 p. 493).

According to Le-Duc, previously most of the studies about the improvement of the order fulfilment cycle focused on the travel distance mitigation based on Pareto ABC- principle. In the real-world, however, due to the increasing fluctuation in the demand, allocation policy needed to be reviewed and adjusted over time for the reasonable utilization of warehouse space. In this scope demand forecast from customer integrated to warehouse management system could be supportive, as well as WMS self -analysis of historical shipping data for specific items will be needed in the future (Le-Duc 2007 p.131-133).

Having provided an overview of the warehouse activities, order picking and picking improvement strategies, next storage allocation policies are discussed.

2.2 Storage location assignment as a method to improve picking process

Storage allocation mainly influences the mean travel times, the occurrence of congestion, and the throughput capacity. Gu et al. extend the perspective, and claim that performance methods like cost, throughput, space utilization, and services can be used within the several evaluation methods. Evaluating performance, both through internal and external benchmarking is crucial to identify weak points in the picking process and determine how it might be improved (Gu et al. 2010 p. 11).

2.2.1 Definition of the storage allocation

De Koster et al. defines the storage allocation as, the set of rules which can be used to assign the incoming products to the storage locations in the storage zones. Correct storage allocation helps in the reduction of material handling costs and the improvement of space utilization (De Koster et al. 2007 p. 211). Peterson categorizes storage allocation to the family of assignment problems. Allocation challenges match two or more sets of factors, like machines, tasks, employees, materials, storage locations etc. to each other (Peterson 1999 p. 102).

According to Goetschalckx et al., a storage assignment policy is a set of rules which determine the warehouse allocation for different items finding the optimal locator to minimize the average travel and picking time required. Storage assignment policies suggest a location to store and pick up a specific item while satisfying different constraints placed upon the system (Goetschalckx et al. 1990 p 17-18).

2.2.2 History of the storage allocation

In the first instance Graves et al. introduced an accurate classification of the potential storage location assignment policies within a warehouse: original problem considered an identification of optimal storage locations and the major factors to be accepted during this process, which also Sharp (1989) and Frazelle (1990) decide to categorize in dedicated storage, random storage, and class-based storage Graves (1963).

Lynn et al. define four main criteria's when considering allocation of the items: compatibility, complementarity, popularity, and space. Compatibility refers to the possibility to keep items close to each other without concerns about corruption or damage. Substances, that are determined as incompatible must be kept in nonadjacent sites. Complementary items are frequently ordered simultaneously in the same order and ought to be located close to each other. Items with the high popularity in terms of the average number of picks should be stored closest to the order shipping area, since these items demand the highest number of tours to their location. Finally, the space factor considers products necessitating the minimum warehouse space and that those items are stored closest to the packing zone (Lynn et al. 1976). Sharp concludes that popularity is the most frequently suggested criteria to be taken into focus while warehouse managers are planning appropriate allocation policy for warehouse, not to mentioned, that popular items can be fairly defined as compatible as well (Sharp 1990 p. 26).

According to Chan et al., first researches on the topic have been mainly taken into consideration random and class-based storage policies. Related studies also typically investigated single-level rack warehouses, particularly when the outcomes are to be found based on a warehouse related simulation.

Chan et al. have presented a general classification of the various allocation strategies. They propose three broad categories:

- Random storage where all items are placed in a single class
- Dedicated storage where each item institutes its own class
- Class-based storage which provides an in-between distribution of items. Products are allocated to a class and each class has its own dedicated zone in the warehouse.

However, within this dedicated zone items were stored randomly, as described above in the study conducted by Larson (Chan 2011 p. 235).

2.3 Storage allocation policies

Most important allocation policies are described next. Popularity-based allocation suggested by Hesket, dedicated, random and class-based storage were introduced by Graves et al in 1976. Family grouping policy is newer and has gathered lots of attention in the literature during the last years.

In the Table 2.1 related works in the field of the allocation policies are summarized.

Storage allocation strategy	Related researches
Random	Hausman et al. (1976), Malmborg (1996), Larson et al. (1997), Pettersen (1999), Van den Berg (1999). De Koster et al. (2007), Roodbergen (2007), Chan (2011)
Dedicated	Goetschalckx and Ratliff (1990), Cormier et al. (1992), March et al. (1997), Elsayed (2005), De Koster et al. (2007), Chan (2011)
Class- based (ABC)	Hausman et al. (1976), Frazelle (1989), Cavinato (1990), Cormier et al. (1992), March, et al. (1997), Mahan et al. (2003) Le-Duc et al. (2005), De Koster et al. (2007) Goetschalckx (2007), Chan (2011)
Affinity-based Slotting, Family grouping	Kallina and Lynn (1976), Rosenblatt (1989), Frazelle (1989), Schuur (2006), Smith et al., Heragu (2009), Pitzer (2010)
Popularity-based (COI)	Heskett (1963), Kallina and Lynn (1976), Bhaskaran (1996), Schmenner et al. (1999), Aase et al. (2004), De Koster (2007), Goetschalckx (2007)

Table 2 1. Studies on the allocation policies

Based on the literature review the main allocation policies and respective benefits and drawbacks are summarized in the Table 2.2:

Allocation strategy	Definition	Benefits / Drawbacks
Random	assigns storage locations based on the first come first served basis, and the available space	Benefits - results in a high space utilization - easy to implement, balanced picker traffic Drawbacks - increased travel distance over other policies - only functions in a WMS controlled environment - material handling cost is frequently greater
Dedicated	fixed storage location(s) per product	Benefits - low-tech, easy to implement, pickers can memorize locations - typically reduces the material handling costs Drawbacks - low storage utilisation
Class-based (ABC)	Inventory is assigned a class based on some criteria (demand, value, size). Each class is assigned a zone of storage locations	Benefits - Uses the benefits of both random and dedicated storage - less congestion if used within class Drawbacks - Periodic demand review required - only reduces average tour length - warehouse resulting in a large amount of reshuffling of stock.
Affinity-based Family grouping	place parts, which are often ordered together, close to each other	Benefits - shorter picker tours, higher throughput Drawbacks - congestion issues and algorithm parameter tuning
Popularity-based (COI)	locations. position heavy and fastmoving products in accessible locations	Benefits - Reduction in travel time and distance - easy to implement, optimal under certain conditions Drawbacks - Aisle congestion - Unbalanced utilization of the warehouse

Table 2 2. Allocation policies and respective benefits and drawbacks

The various elements can influence the measurement technique and practical value of implemented allocation strategy:

- Limitation warehouse infrastructure and design (Hausman et al. 1976);
- The harmonizing of the inbound and outbound processes (Ratliff et al. 1990);
- Full box picking rate (Bhaskaran 1998);
- Estimated duration of the allocation strategy (Mahan et al. 2003);
- Ground level consumption rate, picking expenses and adjustability (March et al. 1997);
- Retrieval zones (Roodbergen 2007);
- Operational and reserved space expenses (Adil et al. 2008).

March et al. inspected a warehouse design with the approach aimed at the performance of single facility lift truck for pallet storage and retrieval. The idea was to attain the effective use of ground level maximizing the locator usage, by minimizing the travel distance and being strong enough to adapt to potential changes in the inventory levels and customer demand. A class-based allocation strategy was implemented to assign the ground level to classes based on the warehouse layout, compulsory number of locations and throughput. Each class was allocated to a dedicated warehouse zone. Though, within this dedicated zone items were stored randomly. Random storage ensures elasticity to adjust potential dissimilarities in inventory levels for items allocated to the class. Combination of two allocation strategies improved utilization of the ground level and flexibility, by reducing material handling costs (March et al.1997 p 124-127).

Gu defines picking frequency of the item as main criteria for allocation classification, where items are categorized by declining picking frequency and the classes with the highest demand are allocated the most easily accessible positions. On the other hand, Roodbergen et al. suggest the maximum warehouse space allocated by the group of items as criteria for a classification, where items are categorized within required warehouse space and groups with the lowest requirement are allocated to the most easily accessible positions (Roodbergen et al. 1999).

Finally, as combined approach, Cube-Per-Order Index has been widely presented in the scientific literature and is commonly considered as more efficient criteria than others. This classification takes into attention both the picking frequency and warehouse space utilization. Items are categorized by the increasing index value and the groups with the lowest value are placed in the most easily accessible positions (Goetschalckx et al. 2007 p. 23). Cube-Per-Order Index is discussed in detail later in this chapter.

2.3.1 Random storage allocation

According to Petersen et al., the main principle of random storage is to allocate all incoming items randomly, by choosing from all the obtainable locations with the identical probability randomly. The random locator assignment strategy would only function in a warehouse run by an automated WMS to keep track of the locations assigned to each item. Otherwise, the search-time of the items during the retrieval process would be seriously affected. Therefore, random allocation approach was not popular before first fully automated WMSs were available on the market (Petersen et al. 1997 p. 418). Hausman et al. argue that random allocation typically results in a warehouse with the racks full around the shipping area and progressively emptier towards the back (Hausman et al. 1976 p 213).

De Koster et al. define random allocation as a “closest open location storage” strategy in which the first vacant location found by an employee during the warehouse inbound becomes a potential candidate location for the incoming items. The most important advantage of random storage policy is the high warehouse space utilization, since any available locator in the picking zone converts can be used directly saving warehouse space for other same customer products or other customers (De Koster 2007).

Likewise, it might be beneficial in terms of handling costs and efficiency, as time spent on inbound process is reduced, which can be valuable in case of continuous stream of incoming shipments waiting for inbound. However, the number of picking tours in the retrieval process is expected to rise. For this reason, random allocation will provide highest improvement if implemented in WMS with automated picking. In this sense warehouse managers should take into consideration relation between time saved on the inbound and additional efforts on picking process, which varies from one warehouse environment and type of items to another. Sharp as well agrees that the results of random allocation in a low space requirement at the expense of increased travel distance (Sharp 1990 p. 31).

Peterson et al conducted a simulation study to compare static random allocation and class-based allocation. Evidently, with the growing demand and the number of items the amount of savings brought by the different allocation policies might decrease. Additionally, it was determined that class-based allocation required substantially fewer traveling distance than random allocation. Though, considering work balance a random allocation typically covers the entire picking zone more smoothly resulting in the decreased rate of congestion (Peterson et al. 2004 p 140). Simulation identified trade-offs, for example, between the space utilization and travel time by applying for various allocation strategies, showing the interdependence between picking zone and an optimal allocation strategy.

According to Van der Berg, random allocation is regularly used as performance baseline in the scientific literature. Nowadays a real-world operation with barcode scanners is not that complex, outbound staff movement is well-adjusted across the warehouse, and utilization of the locators is high. On the other hand, mistakes, or confusion in the picking of the visually comparable items are not expected, if they are not placed close to each other. For these reasons, according to Kolfer, large retailers such as Amazon, implement chaotic locator allocation in distribution centres. The main disadvantage of the random allocation is that it regularly results in the longer order picking tours. In case picker travel distances are not a bottleneck, random storage assignment is a surprisingly decent allocation policy (Van der Berg 2007 p. 127).

2.3.2 Dedicated storage allocation

According to De Koster, dedicated storage is assignment of items to a fixed, exclusive storage location or set of locations. A drawback of the dedicated storage is that the locations are reserved even for items that are not currently in stock. Furthermore, for each item adequate space must be reserved such that the maximum potential inventory level can be placed. Consequently, the space utilization is the lowest among all allocation strategies leading to the high warehouse rent costs for LSPs (De Koster 2007 p. 153).

A benefit of dedicated storage, especially before automated WMS, is that order pickers become familiar with the location of the items, which may speed up retrieval. This is especially important in the case with compatible items, which are often picked together. Using continuously same order pattern allows to develop familiar routing pattern, decreasing both the picking time for customer and materials handling cost for warehouse. Before the common implementation of warehouse management systems, this was the most practical technique to arrange inventory. In dedicated storage, a vacant location is not reserved to keep another item (Gu et al. 2010 p. 15).

Neuteboom claims, that, repeatedly, in retail warehouses dedicated allocation matches the layout of the facility. Such storage approach might save picking and replenishment time for both customers and the staff in the stores since all goods are logically grouped. Neuteboom concludes that, dedicated allocation might be supportive in case weight of the items fluctuates. Heavy items must be stored on the lowest levels of the pallet and light items are to be kept on top. By placing goods in the order by weight and routing the order pickers accordingly, a decent loading sequence can be attained without extra efforts (Neuteboom 2001).

Dedicated assignment policy might be functional in the picking zones, where a bulk area reserved for replenishment of the items that can be arranged, for instance, using principles of random allocation. In this context, the benefits of dedicated allocation still hold, with drawbacks being insignificant, since dedicated locator assignment is implemented only to a minor zone (Neuteboom 2001).

Due to continuously increasing amount of various techniques and mechanisms to define exact dedicated locator to serve the specific customer demand patterns, minimizing the picking travel distance and the total order fulfilment cycle, dedicated storage is the most used policy in warehouses.

2.3.3 Class-based storage allocation

De Koster et al. describe the concept of the class-based allocation, as combination of random and dedicated allocation strategies. The idea behind, is to division the inventory items into classes. Each class would have an allocated zone, where any space available within the class is randomly used by the items fitting to that class. Random and class-based storage are also known as shared storage policies, as both allow different products to successively occupy the same location. In the inventory management, a traditional approach for composing products into classes based on popularity is Pareto's distribution. Classification related to the work of Italian sociologist and economist Vilfredo Pareto "85% of the wealth of the world is held by 15% of the people". In the scope of storage allocation, the main principle for classification is that the more frequently demanded class covers only about 15% of the items kept in warehouse but contributes to about 85% of the turnover. Every class is then allocated to a dedicated zone of the warehouse (De Koster et al. 2007 p. 143).

Allocation policy within the zone is random. In some way classes are defined by demand frequency, such as the pick volume. More frequently demanded items are commonly defined as A-class items, and less frequently requested items as B-class items, and so on. Typically, the amount of classes is constrained to three, while in some situations more accurate classification into smaller groups could potentially provide with the additional benefit minimizing travel times (De Koster et al. 2007 p. 147).

Hausman et al. conducted simulation study with the main effort on allocation of the whole pallets to aisle, in order to optimize inbound and picking. Outcomes of this simulation demonstrated the class-based allocation strategy being relatively better than, the popularity- based and random allocation. Results of the study were only perceived as pilot and temporary due to the fact that comparison at that time haven't included interleaving provided by modern WMS (Hausman et al. 1976). Nevertheless, outcomes still held for the specific warehouse situation that was studied, showing that during planning phase available equipment for the inbound and picking processes, type of items to store and time requirements have vital significance and should be considered together in connection with potential of the existing WMS.

Petersen et al. constructed a simulation study, to demonstrate that the popularity-based storage outperforms the class-based storage, when it goes to employed distance of the picking tour. The gap between the two goes in accordance with the class partition policy, for example, the amount of the classes, the rate of the total volume per class, and the routing strategy implemented in the specific warehouse. Nevertheless, Petersen et al. offered to utilize the class-based approach with 2 to 4 classes in real – world implementation, as it is more efficient to execute than the popularity-based storage. Class-based allocation does not involve a full compulsory list of the items ranked by the picking frequency and it necessitates less time to manage compared to the dedicated storage (Petersen et al. 1997 p. 413).

Van den Berg concludes, that in case with the moderate size warehouses 6-class is the best possible solution. The gain of this allocation technique is that items with higher demand can be placed next to the I/O and simultaneously the flexibility and low storage space requirements of the random storage are valid. To place the incoming shipments appropriately in the separated class dedicated zones, vacant locations must be offered, consequently demanding more space with the amount of the classes. Finally, class-based allocation requires more rack space compared to the random allocation (Van den Berg 1999 p. 118).

There are different opinions for distribution of the A-, B- and C-class items in the low-level picker-to-part systems. McDowell proposes that every aisle must cover only with one specific class. Referring to above described configurations for the desirable location by Petersen et al. the most desirable dark zones include A-class items, less dark zones covered with B-class items and the light zones with C-class items accordingly (McDowell 1991 p. 95).

Based on a closed simulation for the approximation of the picking-time, Le-Duc improves the distribution of zones for the class-based storage. According to the results of the experiment the across-aisle storage configuration is near to optimal. Later, Le-Duc extends related outcomes for other routing strategies claiming, that there is tight connection between storage and routing policies. Routing policies defines the best possible locator assignment policy, as well as warehouse dimensions, and the amount of the items obtained by the picking tour. However up to these days there is no fixed regulation to categorize a class configuration in the scientific literature (Le-Duc et al. 2007 p. 129).

Adil et al. introduced an optimal technique for configuration of the storage class, considering zone reduction, the available warehouse space and the material handling costs by comparing class-based allocation and dedicated allocation. One of the main practical outcomes of this study was the rule for class creation. In case only material handling costs are considered, the dedicated allocation runs with the minimum expenses, and in case classes are shaped in accordance to the cost of the reserved space, a fully random allocation produced the lowest cost. Nevertheless, they emphasized, that, in case material handling costs and reserved space costs are simulated together still a class-based allocation was the optimal (Adil et al 2008, p. 507).

2.3.4 Affinity-based or family storage allocation

Lynn et al. define two items as correlated, similar or affine if they are frequently demanded together, for instance in the same customer order or within the same time period. In warehousing affinity described as the probability that pairs of items will occur in the same order or batch. Once affinity data has been revealed, it is possible to use it in various ways to minimize the picking time through the better allocation strategy. In many circumstances it might be practical to store similar items together, for instance in the same pallet or bin, to reduce picking time. With order picking from multiple areas, intentional distribution of correlated items across these areas might be beneficial in balancing the workload (Lynn et al. 1976).

According to De Koster et al., the affinity-based allocation is the unique in considering the potential connection between the items. For instance, certain item can be frequently demanded together with another item. In this situation, it may be practical to keep these two items next to each other. Evidently, the grouping of the items can be aligned with some of the previously mentioned allocation strategies. For instance, class-based storage can be combined with the group related items. Nevertheless, the distribution for class allocation will be dictated by the number of the specific group features (De Koster et al. 2007). Rosenblatt et al. evaluated the space requirements for the random and the affinity-based allocation and provided empirical evidence, that the affinity-based allocation increases the space requirements (Rosenblatt et al. 1989 p. 168).

In the scientific literature, there are two types of affinity observed. The first technique is called the complementary-based technique, which contains two major phases. In the first phase, it clusters the items into groups based on a measure of the strength for simultaneous demand. In the second phase, it locates the items within one cluster as close to each other as possible. For finding the distribution of clusters, typically item type with the largest demand should be assigned to the location closest to the packing zone, while De Koster proposes to take into account also the space requirement. This is also known as Cube per Order Index, which is discussed in detail later in this chapter. The second type of family-grouping technique is called the contact-based technique. This method is similar to the complementary method, except the use of contact frequencies to the cluster items into groups (De Koster, 2006 p. 45-49).

Wäscher defines a contact frequency between item 1 and item 2, as the amount of times that an order picker retrieves either item 1 directly after item 2, or item 2 directly after item 1. Nevertheless, the selection of the picking method is reliant on the location of the item groups, showing the solid connection between item location and picking method. Since finding a combined best solution for both tasks is not a realistic tactic, contact-based solution methods alternate between the two problem types (Wäscher 2004 p. 67-69).

In order to formulate the rule for the affinity of the items, Frazelle et al. present a statistical method that identifies pairs of items that are affine and should be stored close to each other. They perform a simulation study to compare random storage and correlated assignment and confirm that affinity-based allocation can potentially decrease the number of the required pickings by 30-40% (Frazelle et al. 1989 p. 25-27).

The restrictions of correlated allocation are relatively challenging. It requires available statistics about the relationship between items which might not be offered in a warehouse with 15,000 various items – approximately 75 million product pairs. Another constraint for comes different characteristics of items such as safety issues, like flammability, product fragility, shape, weight, etc., which limits the choice of storage allocation policy (Van den Berg 1999 p. 115).

2.3.5 Popularity- based storage allocation

Originally Heskett defined popularity-based policy, as distributing items over the warehouse storage zone corresponding to their turnover, as the only definition of popularity. The items with the largest sales volumes are placed at the most reachable locations, typically next to the packing and shipping area. Items with the low demand are assigned somewhere towards the back of the storage (Heskett 1964 p. 12).

On the other hand, Hausman refers to popularity of items as basic determination and accentuate that popularity can be considered in various ways and not only limited by turnover rates, as the terminology is not a constant, popularity of the items is frequently bound with the number of storage/picking requests per item, as well as amount of the picks per items are also in use (Hausman et al. 1976 p. 131).

According to Lynn et al. a real-world execution of the full-turnover strategies would be the most efficient in case it united with the dedicated allocation. The main drawback is that the demand fluctuates constantly over time and the variety of the popular items alter frequently. Every demand modification would involve a new batch of the items ordered and the storage would end up with big volumes of the locations to rearrange. An answer would be to apply for rearrangement once per period (Lynn et al. 1990). De Koster et al. emphasize that the loss of flexibility and accordingly the loss of warehouse efficiency is potentially significant when warehouse management is trying to adopt full-turnover storage policy (De Koster et al. 2007 p. 97).

The implementation assignment strategies based on the demand frequency commonly involve a more ‘data intensive’ approach than random allocation, as order and inventory statistics must be managed in order to rank and allocate items. In various practical situations this data may not be offered, for instance, due to the variety of popular items alters too rapidly to shape reliable statistics (De Koster et al. 2007 p. 101-113).

Hausman defined inventory turnover as the cost of items sold divided by the average inventory level. Turnover frequency is calculated as the amount picking requests per time period. On the other hand, frequency demonstrates the average storage time per item.

Once warehouse specific criteria for popularity are defined, items are ranked and allocated to warehouse zones in descending order, with the most desirable locations reserved for the most popular items (Hausman et al. 1976 p. 42).

Petersen et al. suggest four different configuration that are typically implemented to define the “desirable” locations, called diagonal, within-aisle, across-aisle, and perimeter volume-based storage. As shown in Figure 10, the perfect configuration determined mutually by the position of the inbound and outbound point (I/O) and the related distance or picking tour time between locations. Dark areas are highly desirable storage locations, light areas are less desirable. A within-aisle configuration is potentially suitable for situations when rearrangement of items will cause huge materials handling costs, for instance for wire-guided forklifts, required to bring themselves into line before they might access an aisle. An across-aisle configuration might be more applicable to balance picker circulation across multiple aisles. Finally, the diagonal configuration is a compromise between the within and across aisle models (Petersen et al. 1997 p. 424).

Petersen et al. discuss that this configuration should be extended to examine the total time to complete a picking tour by taking into consideration the picking time difference in warehouse location. The time to pick up an item to be contingent on the height of the storage location in addition to size and weight of the demanded item. Warehouse locations above the picker’s shoulder or below the picker’s waist require more time to retrieve. The area between the waist and shoulders is called the “golden zone” and naturally items with higher demand are placed there (Petersen et al. 1997 p. 426).

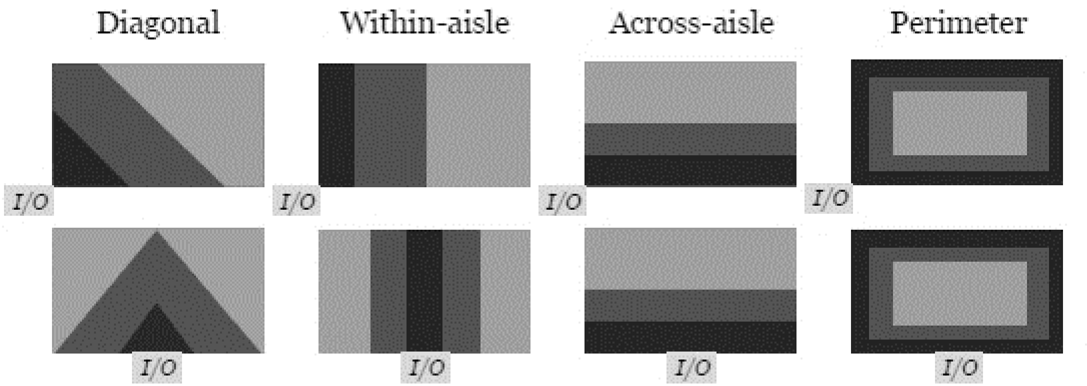

Figure 10. Configurations, typically implemented to define “desirable” locations

Mahan et al. inspected a tactical and strategic planning to demonstrate various alternatives for improvement of order fulfilment cycle. On the tactical level they utilized principles of turnover based allocation. To define frequently demanded items, ABC stratification was implemented in this research. Such analysis facilitated company to keep items in the suitable locations and the two characteristics utilized to distinct products into groups were: the proportion of part numbers and the rate of inventory value. Values: quantity per period and the cost per unit were defined in accordance with customer demand (Mahan 2002 p. 71).

Having provided an overview of the main storage policies, next the oldest and generally, the most frequently used allocation to reduce the amount of travel Cube per Order Index (COI) is discussed and presented in the scope of different allocation policies.

2.3.6 Cube per Order Index (COI)

Originally introduced by Heskett in 1963 the Cube-per-Order Index (COI) defined as the ratio of the item's total space requirement to amount of picking tours required in accordance with customer demand. The original heuristic involved placing the items with the lowest COI value next to packing zone, allocating items that combined a high demand frequency with a low space requirement in the most desirable locations. Items were then allocated progressively starting from the packing zone by increasing the COI. There are numerous simulations considering the storage allocation in relation to the COI. This approach is extensively studied by Heskett et al., 1963, Francis et al 1967, Harmatuck 1977, Bhaskaran,1988.

According to De Koster, mathematical models of the COI-method emphases distributing of the required space for each item by its turnover, with the subsequent ranking of the items from the lowest to the highest COI-index. Next, following a space-filling curve, the highest ranked the COI items are allocated to the most desirable locations. Lynn presents advantages and disadvantages of the COI, and practical rules on the implementation of the COI-method (De Koster et al. 2007 p. 278).

Hodgson investigated practical value of the COI-method in the scope of popularity- based storage, describing index as the relation of the item's total necessitated space to the amount of picking tours compulsory to satisfy its demand during a specific period. Allocation algorithm involves assigning the items with the lowest COI-index next to the packing and shipping area (Bhaskaran 1998 p. 83).

The COI-method has been proven as optimal allocation approach by numerous authors under different time, circumstances, available WMS and warehouse layouts. Based on simulation study Francis provided empirical evidence that the COI-based allocation decreases distance of the picking tour under certain assumptions and Frazelle configured the COI-method as a linear program, and examined the heuristic in relation to the linear program demonstrating that the settled configuration built in this simulation would not interrupt with the main principles of the COI-method (Frazelle 1989). Bhaskaran also proved evidence about advantages of the COI-method, when it goes to the assignment of the items to minimize travel distance during storage/retrieval and suggested to distinguish the COI as separate allocation policy (Bhaskaran, 1998).

Lynn et al., define the real-world situation where the COI-method is the most efficient, and observed the critical warehouse infrastructure and layout elements, obligatory for the efficient utilization of this approach. Theoretical assumptions were mainly designed based on the original outcomes of study by Heskett. Lynn et al provide an accurate guidance which way the COI-method can be implemented, by determining obligation for the heuristic to be optimal and used a linear program as well as to show the optimality of the COI with application to the specific simulation case and warehouse layout (Lynn et al. 1976).

Bhaskaran implemented the COI-method to a multiple picking zone layout and demonstrated that under Euclidean distance the COI-method provides with the minimum picking tour distance. Additionally, The COI-method had been proven reasonable in the simulation study with the target on minimizing material handling expenses. In the scope of dynamic demand fluctuation, the COI-method wasn’t constantly being able to provide the optimal solution (Bhaskaran 1998 p. 90).

Lynn sees the great disadvantage of the COI-method in its static nature. Order rates for different items repetitively fluctuate –mostly due to the seasonal demand. Consequently, the COI-method requires frequent reviews of the actual demand situation and timely relocation of the items, causing additional operational expenses. Additionally, for moderate size warehouses, where order picking is performed using sequencing or batching, the COI-method fails flexibility in allocating items that occur in the same picking tour next to each other. Therefore, the probability of allocating such items together, while they are not used in the same sequence is very high, causing additional traveling. Thus, product correlation should be considered in the scope of the warehouse location assignment (Lynn 1976 p. 28).

According to Caron et al., the major drawback of the COI-method is that it does not consider the affinity relationship between ordered items. This approach could be advanced by adding elements of affinity or class-based stratification. Algorithms and heuristic would be settled to provide a solution to the allocation layout problem, and the heuristic should include comparability aspects (Caron et al. 1998 p. 534-539).

Bhaskaran conducted a simulation using the COI-method for full box picking and introduced models to compare dedicated allocation and random allocation using the closest open location to assign the items. These allocation strategies were evaluated with the relation to the total item space requirements, order picking cycle times and WMS reaction time. Random allocation only reached a 65% space usage compared with the 100% space usage of the dedicated allocation. Nevertheless, random allocation had a higher rate of the available space covered (Bhaskaran 1998 p. 92).

One should distinguish another valuable and frequently implemented approach - Order Orienting Slotting from Cube-per-Order Index, even though both methods have a lot in common. Order orienting slotting is presented next.

2.3.7 Order Orienting Slotting

Regularly, outbound team goes along with the exact route to retrieve order items, where the picking tour is bounded to the picking list and the routing policy configured in WMS. Consequently, it is of major significance to investigate the retrieving sequencing once allocating items to warehouse zones. The literature on Order Oriented Slotting (OOS) is rather scarce. Originally Frazelle tried to tackle this and suggested a heuristic approach to group items into areas in accordance with the combined likelihood that pair of items would be repeatedly appearing in the same orders (Frazelle 1989 p. 155).

Schuur et al. suggested a storage policy named Order Oriented Slotting. The idea of OOS assimilates the retrieving regularity between products with their unbiassed popularity to allocate them a warehouse locator, minimizing the overall picking tour distance for all the orders. The main idea of OOS is to keep products, frequently appearing together in customer demand orders, next to each other. OOS approach contains solving two subproblems simultaneously: allocation of items to storage locations and execution of the order picking tours for all the orders. Often singular structure of the given routing strategy allows formulation of the correlated OOS problematic as a Linear Programming Problem. For moderate size warehouses, one can solve this LLP to optimality. Accordingly, the value of the above-mentioned heuristics can be verified (Schuur et al. 2009).

The OOS policy offers a decent solution to the allocation of items. However, the OOS model has a major drawback. There is almost zero functionality in case when the order retrieving method includes batching. OOS might only be competent when each item is picked in a static sequence within other items. This approach forbids the same specific item to occur in different picking orders. In a batching situation, items may be demanded in several orders with various subitems to be retrieved in tours with different travel distances.

As stated in sections 1.7 and 1.8 in order to concentrate on the most significant items ABC-analysis has been implemented to narrow down the amount of samples.

2.4 ABC-stratification

ABC analysis was already discussed in the scope of the class-based allocation. In order to concentrate empirical research on the most valuable items from the picking point of view, ABC-analysis has been conducted. According to Cheng ABC-analysis is an approach to categorize objects, actions, or processes based on the relative significance. This technique is regularly applied in warehouse management where it is used to categorize storage items into clusters in accordance with the total annual spending, or total stockholding expense.

Pareto analysis is applied to reach related ordering. Considering warehouse and picking specifically the primary task in the analysis is to classify principles which make a selective level of control for relevant items. Two thinkable criteria are the picking frequency of item and its value. Combining both intensive management is extra imperative frequently demanded items with a high unit value. On the other hand, in case with non-popular, low value items, the cost of the special attention might overweight the benefits and the modest level of control would be enough (Cheng 2010 p. 76).

Frazelle defines the relevance of the items as the combination of criteria and suggested classification which offers warehouses to categorize items into three classes:

- A – items with the highest relevance;
- B – items with moderate relevance;
- C – items with low relevance (Frazelle 2002 p. 26).

Frandsen suggests using picking frequency in the below classification to accomplish original analysis based on the value of the item:

- A-items correlated for 80 % of the picking frequency;
- B-items correlated for 15 % of the picking frequency;
- C-items correlated for 5 % of the picking frequency (Cheng 2010).

Since the main goal of this thesis is to decrease order fulfilment cycle by minimizing picking distance order frequency is relevant. However, the total amount of the items demanded during a specific period is not suitable for the picking frequency classification, as picking tours vary from in accordance with the certain features of the items. For example, demanded amount in 1000 pcs for item A might be requested to fulfil in one order and 100 pcs of item B might - 1 pcs per order, resulting in more picking times and distance to travel. Depending on the dimensional characteristics of the items, the amount retrieved within single picking tour might fluctuate significantly, for example, one storage locator might be sufficient to store 100 pcs of item A, while 10 pcs of larger item B might require 10 separate storage locators. Consequently, it is reasonable to categorize items by the number of pickings during the specific period, as this would reflect time spent on retrieval of each item.

Evidently, there are other criteria that represent relevance to the customer, especially in B2B business, like delays in picking for more expensive items might lead to more problems for the customer and consequently to the greater amounts of complaints from the customer. Specifically, for picking of the pharmaceutical items nature of the items plays the crucial role in classification, as some drugs might be required at once in relation to the lifesaving event and delays for less relevant towels can be partly acceptable. Another useful characteristic for classification is the amount of urgent orders for specific items.

According to Frazelle, there are following steps to be taken to implement an ABC analysis:
1. Categorize the items from largest to smallest of the selected criteria;
2. Compute percentage of each item in relation to the total volume of the selected criteria;
3. Compute each item accumulated criteria starting with the highest value;
4. Categorize items into classes in accordance with the Pareto's rule (Frazelle, 2002).

The goal of the ABC-analysis in this study is to define A-class items with the high picking frequency, with high value and relevance for the end consumer and thus, less acceptable for delays, as well as represented in urgent orders. Due to the relevance of these A-class items, it is recommended to keep all items close to the packing zone in order to reduce order picking distance and order picking time. In the scope of storage allocation implementing ABC-stratification represents class-based storage and, therefore allocation strategy in this thesis is the combination of different storage policies: popularity-based (COI) and family-based allocation (affinity relation), with the additional detailed allocation for relevant A-class items based on simulation (class-based).

3 METHODOLOGY AND PRESENT SITUATION

This chapter focuses on the empirical part of this study. It starts with methodology overview. Next, case company with the focus on warehouse layout, the historical pattern for customer orders and importance of forecasting are introduced. Chapter 3. continues with the analysis of the historical shipping data and ABC-stratification, following by COI-index definition for the current case and ranking. Next, sampling, and mathematical method are presented. Finally, simulation related assumptions and constraints are introduced, random and the COI-based locations for A-class items assigned and order sets are generated.

3.1 Introduction

To minimize picking travel distance a methodology that combines simulation and optimization was developed. Individually every phase has a core objective which is determined as follow:

- First Simulation concentrated on formulation of problem and generating model, objective function, as well as related picking constraints and parameters that are going to be used throughout the experiments;
- Optimization is used to compare the existing random allocation strategy with the option selected based on literature review: the COI-based allocation; in details how, a potential storage allocation strategy influences the average distance of the picking tour to retrieve the full order.

The emphasis of this study is to define the settings under which different allocation strategies diminish the overall length of picking tour. 61 order sets are generated randomly to be tested in the simulation. By reviewing historical order patterns, the goal is to demonstrate the conditions under which chosen allocation strategy might have more benefits than the existing one. For instance, in case similar items occur in different orders, an allocation strategy that assigns these items next to each other would minimize the average distance of the picking tour. On the other hand, in case all the items demanded by customer consistently without specific frequency, a random allocation strategy would be the optimal solution. Two allocation policies are compared: the existing random allocation and the COI-based allocation. Optimal storage locations are determined based on the distance of the picking tour to retrieve all required items under fulfillment of the customer outbound order.

It is assumed, that there is no shortage for simulation items throughout the picking process and there is a sufficient amount to satisfy all order sets of the simulation. Likewise, it is assumed that the item replenishment is immediate, and it occurs as soon as a storage location becomes empty.

The difficulty of the optimization method in the scope of storage allocation goes in accordance with the range of potential solutions and is time-intense for large-scale processes. As a result, it is not practical to implement developed mathematical model directly for all Customer N items, and therefore to handle this concern, ABC stratification is conducted to concentrate research on the most significant A-class items. This way existing 1000-items optimization, is limited to 200- items and simulation is conducted for the smaller amount of samples to achieve results in a much shorter time, as well as obtained results might be used as the base for the larger scale heuristics later.

The objective measure used in the simulation is picking tour distance. This measurement approach is the most regularly implemented one in the related studies and, according to De Koster et al., is directly correlated to the items retrieval time in the manual order picking systems. In addition, as stated before, travelling is the greater part of the whole retrieval cycle, pointing out its importance in the structure of the warehousing expenses (De Koster et al. 2007 p 113).

3.2 Warehouse processes and historical data

Simulation data for the empirical part was obtained from the review of the case company related orders and inventory information in WMS system. Additionally, an observation of the picking process was carried out at the Vantaa warehouse. For assessment of the simulation research data, as well as for ABC-analysis, Microsoft Excel and NetLogo simulation software were used. Dynamic data has been applied as the main basis for retrieving order line related information. The secondary data set is restricted to a 6-month period from Aug 2017 to January 2018.

Information obtainable from the WMS can be divided into the static data and the dynamic data:

- Static data: available inventory, warehouse locators reserved and used, average inventory rate and utilized space rate, locator assignment policy;
- Dynamic data: the most frequently demanded items, inventory operations, picking orders, relocation, lines per order, orders per item, items per specific period, picks per location, order picking cycle, order fulfillment cycle.

Additionally, the evaluation of the picking process is organized by monitoring the time warehouse outbound team is spending on the different stages of order picking. This has been made to ensure the classification of the time distribution provided in theoretical part with traveling being the most time intense activity generally, as well as to make sure there are no additional specific warehouse or customer order related features or attributes affecting picking process or traveling distance in particular. There were no such features found during observation and simulation period with travelling, evidently, being the most time intense stage of the picking process in Vantaa warehouse.

3.2.1 Material handling and picking process in Vantaa warehouse

In its present structure, the materials handling process in Vantaa warehouse can be classified into four main activity groups: receiving, inbound, order picking, and outbound. The process flow in Figure 11 demonstrates the common warehousing procedure related to handling of the single order cycle. Depending on the direction all activities can be further divided into inbound logistics flow and outbound logistics flow.

The incoming flow of the order cycle initiates with the arrival of the direct shipments from the factory or distribution center or reverse transportation from the customer site. Commonly, in accordance with the agreed logistics procedure and transportation mode, the direct deliveries are unloaded either by the transportation service provider or handled by the inbound staff of the Vantaa warehouse.

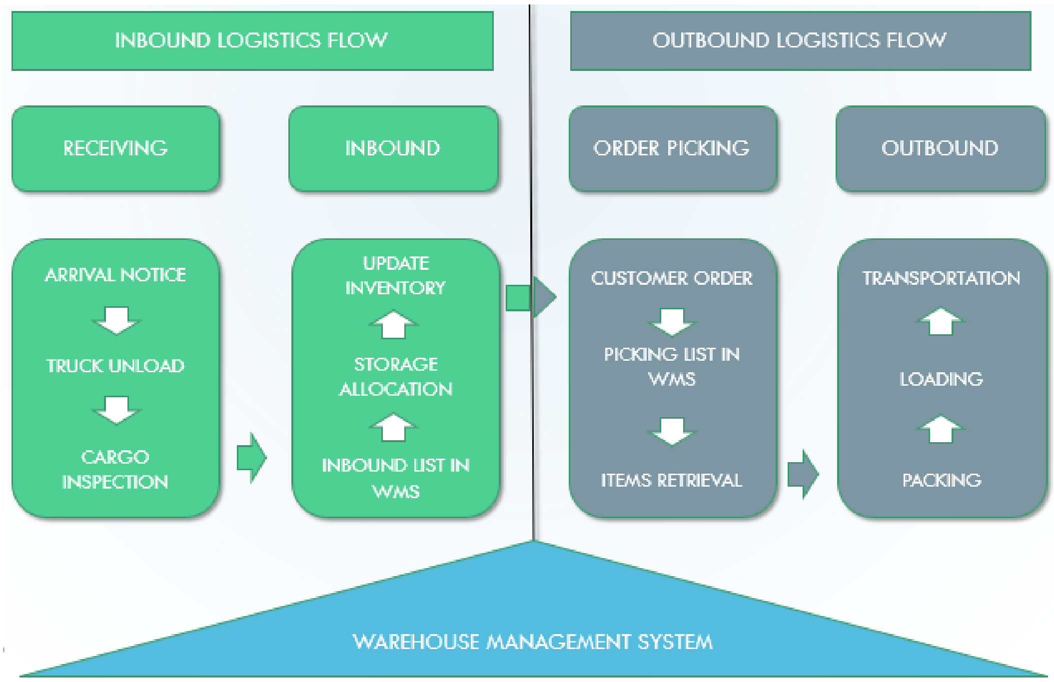

Figure 11. Material handling process in Vantaa warehouse

As soon as the goods have been unloaded to the inbound zone, packages are momentarily examined for physical damages and discrepancy; wholes, broken boxes, any possible inconsistency compared to customer order, arrival notice and transportation documents, should be reported immediately to both transportation agent and customer, as well as marked in related sections of the shipping documents.

As a rule, internal sides of the boxes cannot be examined directly during receiving due to the time restriction, as well as the consistency of the items inside the packages cannot be verified. Potential special cases for the discrepancy of box content are handled separately between parties afterwards. In case no any issues appear, and no further investigation required, warehouse inbound team sign and receive related shipping documents without additional remarks, accepting the accountability for any potential discrepancy and damage on the package level later.

The allocation part of incoming flow initiates after an inbound order note or packing list is transferred from customer ERP to WMS. All included goods are placed in the receiving zone by that time. The inbound staff, normally with an assistance of lift-truck or pump, transfer and locate goods to a storage position. Storage location for each item is defined by WMS during acceptance of the customer order notification from the customer ERP and marked in the inbound order note. As soon as the inbound order note has been completed and fully scanned with RF scanners inbound team approves new items to inventory in WMS and customer receives related notification in the ERP.

Presently, while random storage allocation is in use, WMS distributes storage locators in accordance with the configured rule for incompatible items due to the pharmaceutical nature of the components, which must be placed in nonadjacent locations. No complementarities, popularity, demand frequency, affinity issues are taken into consideration by WMS, neither continuous evaluation of demand patterns are implemented. It is assumed, that the main practical outcome of this thesis would be to provide set of recommendation within the given allocation method to be integrated into WMS in order to take above-mentioned features into account while making the distribution in the future

Outbound part of the outgoing flow initiates with the order picking process, when specific items are demanded in the ERP for the new sales order. Sales data integrated between the customer ERP and WMS, and the last one automatically configures delivery note and picking list, which is handed over to the warehouse outbound team. Outbound team member moves to the first storage location in the picking list, recovers the demand amount of items, and continue to the next location. As soon as all required items are picked successfully, they are transferred to the packing zone. This part covers another strategy of order picking improvement, called routing. Routing policy defines in which order picking lines are positioned. Typically picking order can be completed in the single picking tour, as well as this is assumed for the simplicity of the simulation study.

Currently, when it goes to the picking of the customer N orders in the Vantaa warehouse, there is S-Shaped routing policy configured in WMS. As stated in the limitation part this work is focused on solving allocation problem as the method for the picking improvement, and routing and batching are out of the scope. For that reason, S-Shaped routing, shown in Figure 12 is assumed to be fixed during the simulation period. Under this strategy, outbound team member starts picking tour by entering the aisle next to the packing zone. Any aisle corridor having at least one item should be entered across over the entire length, without any backtracking. Corridors without locations mentioned in picking lists are passed over. Once all required items are collected, the order picker returns with the shortest possible way back to the packing zone. However, since there is no backtracking allowed, it is assumed that picker would need to finish until the end of the last corridor, he has accessed.

Additionally, heuristics are frequently applied to define best possible routes. The selection of an appropriate routing strategy goes in accordance with the specific features of the customer orders, picking aisle design, and available inventory tools. For example, s-shaped is empirically proven as having best results in case the density of the picking per aisle is large (De Koster et al 2007 p 112). It is assumed that an optimal picking tour distance will result in an optimal return distance as well. For more information regarding routing and batching reader may refer to De Koster et al, 2007 and Smith, 2001. Improvement of the picking through the different routing or batching method might be a potential topic for future investigation.

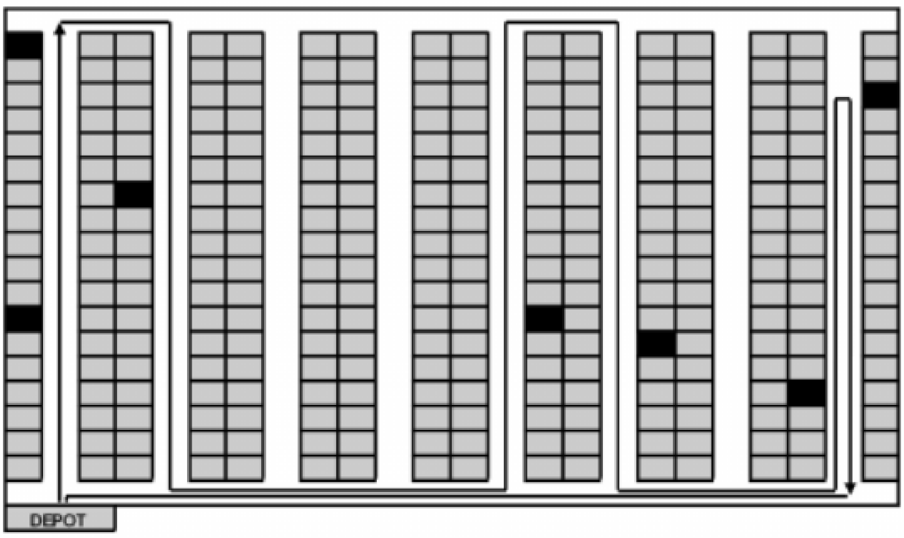

Figure 12. S-shaped routing policy in Vantaa warehouse, with the black squares as picking items.

A frequent practice is that the same outbound team member is in charge of the whole outbound order outbound cycle including packing the items. In the loading zone orders are sorted and packed for departure. After all, items have been scanned as being picked, RF scanners are used to update order status in WMS and notify transportation department to collect packed shipment from the loading zone. After shipment is booked outbound team member prints out the delivery labels, transportation documents, and other customer-related documents and enclose on the package.

As soon as these activities are completed, items are transferred to the transportation zone, where they are departed to the final destination. It is important to point out, although modification of order picking tools is out of the scope of this work, it is recommended to upgrade RF scanners to wireless ones, with related data being updated into the WMS and ERP directly after the corresponded process has been completed. This way, there is no need to spend time by travelling to the packing area and connecting scanner to PC to download customer outbound order, as well there is no need to manually upload successfully picked orders to WMS to update order status and trigger a booking for transportation. From the customer side, implementation of wireless scanners might require a certain amount of investment, as well as the additional arrangement to get separate WLAN- channel.

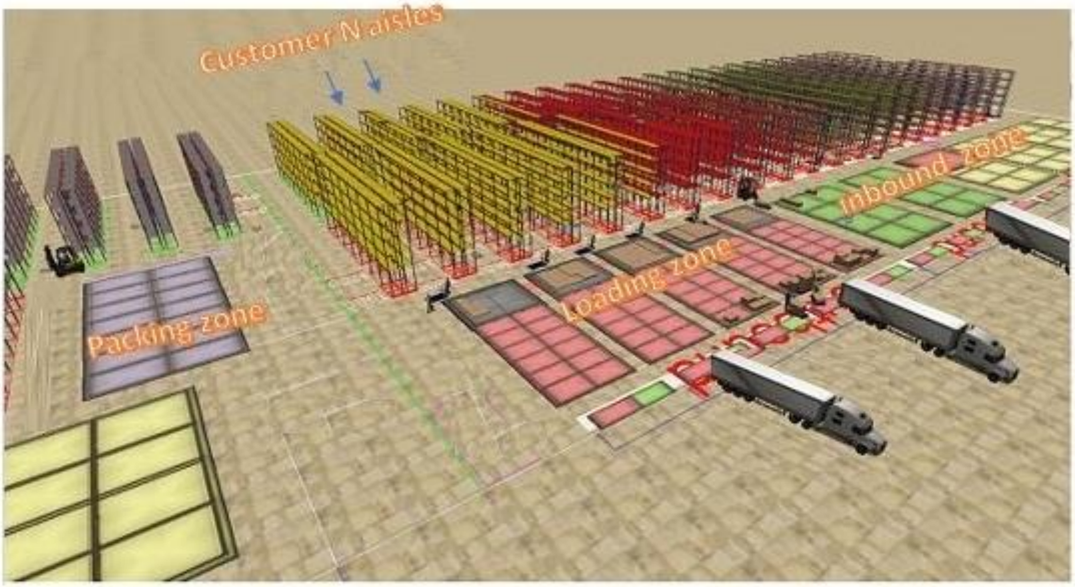

Figure 13. The layout of Vantaa warehouse

As shown on the layout Figure 13, Vantaa warehouse is flat two-dimensional rectangular warehouse with single inbound and outbound zone placed in the front of the warehouse next to unloading and loading gates, with loading gates located closer to packing zone. The warehouse includes 15000 pick locations and thirty aisles with 500 storage locations per aisle and 250 locations on each side. Since Vantaa warehouse is not dedicated to processing only Customer N items and has cooperation with multiple customers, there are two aisle X and Y reserved for Customer N items in the "golden zone", close to the packing area. Each aisle has the upper part and the lower part as shown in the layout with total 1190 storage locators available and 238 locators with five different levels, starting from the floor level: A, B, C, D, E, F It is assumed that ground level A locators are preferable to use for allocation. To present the time spent of retrieval of items from the higher levels, each additional level increases conditionally picking distance by three meters, compared to retrieval from the same place level A. Congestion and availability of picking tools for higher locators are not taken into consideration. For simulation simplicity amount of possible levels will be limited to four levels: A, B, C, D.

Shipments arrive on the pallet and leave either on the pallet or without it. Storage locations are identical in height, width and length. Furthermore, four cross aisles are utilized for changing the corresponding aisles, starting from packing area until loading zone. The packing area, where order retrieval process begins and ends is positioned in the right edge of the backcross aisle.

Although in real-life a storage locator is occupied with different items combined in batches according to the FEFO warehousing technique for picking items, for the simplicity of the simulation it is assumed that each locator includes similar items. This simplification is partly offset by the fact, that items combined in batches have normally strong affinity relation with the same demand popularity and therefore are frequently ordered together. In case of high demand for all batch items, ABC-analysis would classify all to the same group and considering compatibility features simulation would suggest storing them next to each other. On the other hand, non-popular B- and C-class items with less movement and demand are out of the simulation. At the time of the simulation, 70% of dedicated storage locations reserved for Customer N items were utilized due to seasonal demand fluctuation. As stated above, in this simulation there is always enough quantity of required items to fulfill customer order and picking is performed to complete one order at the time, as well as one picking order completed in one picking tour and therefore replenishment and sequencing issue are not considered in this work.

3.2.2 Historical order data and forecast

Based on the historical demand data, complementary items with high affinity relationship should be located close to each other, to minimize picking tour. However, based on the observation, allocating non-affinity items with comparable package size and design might lead to confusion, delays and picking mistakes. For that reason, it is recommended to mark names for each item visibly on the inventory, as well as to keep non-affinity items distanced from each other. Based on the observation, there are no additional allocation constraints based on the nonstandard weight or volume, requiring specific storage locators for particular items.

Typically, amount of picking lines in the outbound list has crucial importance. Orders with the greater amount of picking lines correspond to a comparatively efficient order fulfillment, whereas the less lined picking is more time-intensive. This occurs due to the typical handling cycle per line is higher for the pickings of single items. For the period between August 2017 and January 2018, there were 6914 outbound order requests from Customer N provided, with total 23243 order lines. Table 3.1 represents the amount of orders for various picking lines, with the amount of picking lines 1,2 and 3 having significantly more demand.

However, due to the reason, that retrieval process for such minor amount of picking lines requires relatively less traveling distance, simulation is focused on more complex 11 variations of orders with the amount of picking lines from 4 to 14 and 1854 total order lines during the simulation period. Figure 14 illustrates an average proportion of total orders for each number of the picking lines requested from August 2017 to January 2018, which are picked up for the simulation and Table 3.2 represents simulation share or each variation of the picking lines.

Amount of orders	Lines per order	Amount of orders	Lines per order	Amount of orders	Lines per order	Amount of orders	Lines per order
3035	1	80	11	6	19	1	30
1127	2	58	12	5	28	1	29
751	3	53	14	5	22	1	27
485	4	48	13	4	39	1	32
334	5	29	15	3	33	1	26
228	6	24	16	3	31	1	36
168	7	16	17	3	23	1	55
153	8	13	18	3	35	1	42
130	9	11	21	3	24	1	53
117	10	7	20	2	25	1	

Table 3.1. The amount of the orders for various number of picking lines

Forecasting is a useful tool to estimate future need and allocate potentially more vital items with separate SLA, closest to the packing zone. Although Customer N cannot provide any forecast, the historical urgency of the order for specific items will be considered separately as the additional attribute for more favorable storage allocation, in case there are related items with equal picking frequency and demand. The simulation covers specific items with special picking urgency and separates agreed lead time, even though according to the classification of ABC-stratification, they are categorized as B-class and C-class items with low picking demand. It is important to point out, that due to the demand fluctuation, the compulsory requirement for WMS system is to analyze dynamic demand data over the agreed period and update ABC-stratification and distribution principles of the allocation policy. It is also recommended to request associated information from the Customer N about, for example, EOM/EOP items, in order to arrange related relocation.

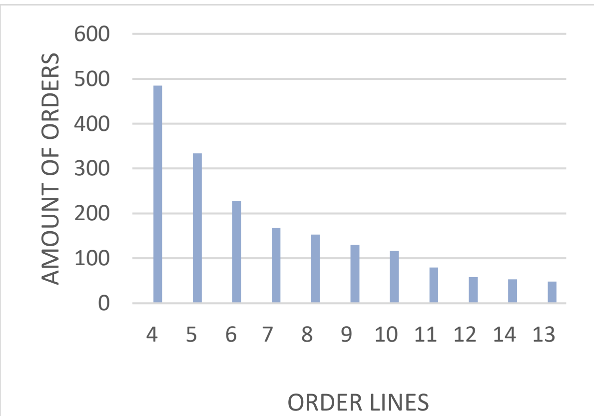

Figure 14. Simulation picking lines per order

Picking lines per order	Amount of orders	Share of orders	Simulation orders
4	485	26%	16
5	334	18%	11
6	228	12%	7
7	168	9%	5
8	153	8%	5
9	130	7%	4
10	117	6%	4
11	80	4%	3
12	58	3%	2
14	53	3%	2
13	48	3%	2
TOTAL	1854	100%	60

Table 3.2. Orders variations for the simulation

3.3 ABC-stratification

As mentioned in Chapter 1, in order to simplify simulation and provide the set of recommendations for allocation based on the empirical results, simulation is focused only on the most important A-class items with high picking frequency as the criteria for stratification and number of order lines per period as a parameter. As Vantaa warehouse is 3PL LSP for Customer N, with the same agreed lead time and warehouse rent fee, picking frequency was selected as main criteria for stratification as being the most relevant. It is not appropriate to use quantity in general as items might be requested with different quantity per order, for example, 1000 pcs of item X can be requested in one order line and 20 pcs of order Y in 20 order lines. Therefore, picking of item Y requires 20 times more traveling, than picking of item X, with total demand 50 times more than item Y.

Items are classified into three different categories, with A-class items corresponding to the 80% of the picking lines; B –class items corresponding to 15% of the pickings; and C-class items corresponding to the remaining 5% of pickings. According to the picking orders for the 5-month period, from totally 942 Customer N various items stored in Vantaa warehouse totally 902 (95%) different items were picked for Customer N orders, with 783 (82%) items required at least two times, 403 (42%) items required at least 10 times, 119 (13%) items required at least 50 times and 59 (6%) items required more than 100 times. As presented in Table 3.3, 18024 picking lines outbounded from August 2017 to January 2018 of total 23243 picking lines covered by 200 most frequently picked items, meaning that 22% of items represent 78% of the picking. In a deeper analysis, there are 15 items with 4450 order lines, meaning 1.5 % of the items is 20 % of the total ordered lines.

Item class	*Amount of items*	*% of items*	*Amount of order lines*	*% order lines*
A	*200*	*19%*	*2089*	*78%*
B	*413*	*39%*	*321*	*12%*
C	*450*	*42%*	*268*	*10%*
	1063	***100%***	***2678***	***100%***

Table 3.3. ABC stratification based on the picking frequency

The difference in order lines between the most picked item I1 and the second most popular item I2 is 234 picking lines and respective demand variance between I2 and the third popular I3 is 73 picking lines. Otherwise, distribution for the 200 most picked, A-class items is relatively smooth, which is shown in Figure 15. Statistically, in fewer picking claim, B-class items are placed behind or above A- class items, and the least picked C -class items placed even further or higher, with the A-class items occupying floor level.

It should be pointed out, that based on the historical allocation data some of the B- and C-class items are reserved for A-level locations. Despite shorter picking distance for A-level locations, retrieval of the items from higher levels of the aisles requires special tools, like higher picker lifts. Even though the availability of related picking tools is out if the scope of this work, potential shortage as well as congestion to access aisle might lead to delays in the picking process. With A-class items located in A-level such impact is minimized.

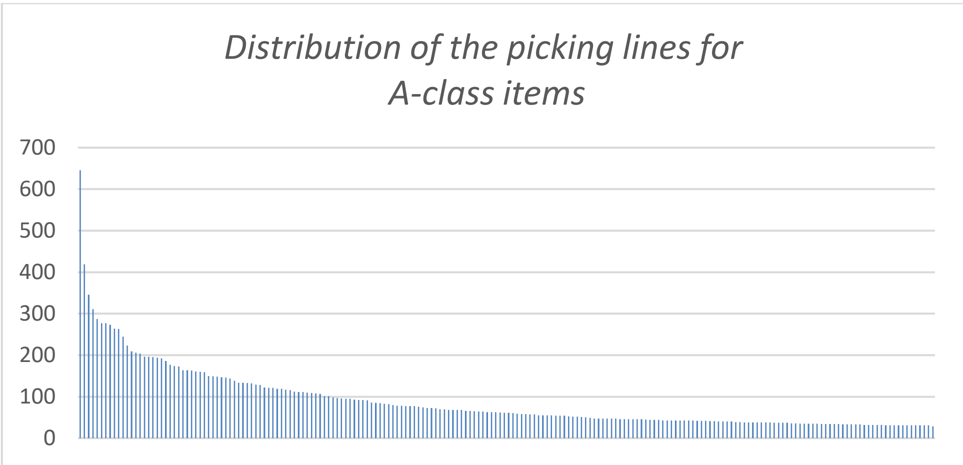

Figure 15. Distribution of the picking lines for A-class items

3.4 Simulation

While simulation research for this thesis has the goal to generate practical solution by optimizing objective functions and compare given methods, there are some assumptions should be applied to keep it more controllable and to ensure generalization towards other studies related to the allocation policies in the healthcare sector. This section also discusses the mathematical method to solve optimality problem, introduces the objective function, as well as describe the run of the simulation.

3.4.1 Model Assumptions

There are following assumptions applied in this work. Warehouse layout related assumptions already discussed in section 3.2:

- **Pallets and aisles.** All items are kept, and more than one box items are transferred on euro-pallets. Euro-pallets are assumed to be the same size 1.2m x 0.8m, weight 20kg, and structure and these features have no impact on the allocation or picking distance and time. The width of the picking aisles is assumed to be one unit. Only floor levels are utilized to place items, meaning that there is no additional time needed for handling higher levels in racks.

- **Packing zone and warehouse tools**. There is one universal packing zone where all items should be delivered after retrieval and from which they will be later picked up by transportation department to end receiver. Items were delivered and retrieved using a forklift truck in required condition, as well as picker itself has sufficient skills to manage truck. There is no relocation, renovation or wall-to-wall stocktaking happening at the moment of order picking. The dimensions of the warehouse and the position of the picking zone and aisles are static. The reverse zone is not considered, either movements of other pickers causing congestion or additional traffic or aisle access/exit delay.

- **Future demand and inbound locations.** There is no forecast available, so historical order pattern is used for simulation. There are always available warehouse locations for new inbound. Reserved volume and picking process are simple linear models and it requires around x times of the warehouse units to place and keep x pallets as well as it requires around x times for the picking team member to retrieve x items.

- **One item- one locator.** One item occupies one storage locations and quantity is always enough to satisfy the order. Typically, inbound batches from the factory are containing items to satisfy around 10 -15 outbound orders, and therefore situations, when picker should visit multiple storage locations to collect are rare and not require special attention in the scope of the simulation.

- **Orders assumption.** Based on ABC-analysis, it is supposed that the inventory stores 200 different items simulation items. Utilizing these 200 items and historical shipping data, 60 outbound orders of different proportions and amounts are created. As stated above, the order scope differs between 4 and 13 items, created within the scope of the normal distribution matrix. Although, selection if the items for simulation is random there is an affection based on popularity and affinity of the items. Every outbound order is a solo simulation move. Some items due to the security reasons cannot be stored next to each other. For the simplicity this constraint is out of the scope of the simulation.

In case there are too many items with high picking frequency are placed next to each other, it might end up in higher traffic density for the specific aisle, with pickers waiting for access. In this situation, the WMS might choose to distribute these items over the aisles with the same picking distance from packing zone. However, such items should not have affinity relations, i.e. used frequently to satisfy same type or orders or customer demand, as well as the inbound distribution of storage locators for these items, might be analyzed and manually adjusted in the WMS.

3.4.2 Mathematical optimization method

Allocation distribution in Vantaa warehouse can be presented as the Linear Placement Problem (LPP). According to Cheng, the LPP is a complex non-polynomial combinatorial problem, with all the potential solutions of positioning x items is x-factorial. Morse first tried to define correlation index to present interdependency between books and bookshelves as a part of allocation combinatorial problem. He suggested that as soon as the correlation indices are defined through the heuristic algorithm, a location *yi* is allocated for next item *i* along a linear categorization range, showing the optimal order of the books (Cheng 2010).

Cheng later proposed the more practical solution, with the intention, to reduce the length of cable, linking a group of nodes. The algorithm initiates with minimal steps and steadily alters to more comprehensive steps. Implementing the LPP to the order picking, the goal is to define the most appropriate storage locations, so the traveling time and distance among same order items is reduced. At each stage, the most suitable set of items to the closest accessible position is acknowledged and assigned to the set of the storage locations starting from the closest potential storage locations. The solution generation is accomplished when every item has been allocated. LPP might not be the valid method in case the expressive functions are sampled from the original situation. To investigate a batch of items with random size, historical order pattern data with picking frequencies items and distances from storage units to the packing zone are implemented as the set for LPP method.

Genetic Programming (GP) is another mathematical approach, which recently has been gaining popularity, investigates allocation problem by matching objective functions as a substitute for solutions for this problem, like it is done in case of LPP. By implementing GP corresponding area for objective functions can be optimized in simulation using historical data to generate proper solution competently for future allocation. (Mantel et al. 2009 p 311-313). GP is also more efficient when simulation contains more than 500 items, which is however not beneficial in the case of allocation in Vantaa warehouse due to the simulation focused on A-class items only.

3.4.3 COI-ranking and objective function

As stated in Chapter 2, The COI-index is the proportion between compulsory storage space to keep an item and picking or demand frequency for this item. Initial practical step is to determine the COI-index by dividing the assigned storage space of each item by its picking frequency and rank COI in non-increasing order. As the compulsory storage space by every item is considered as equal, neither relevant for this simulation, the COI relationships is transformed based on pure picking or demand frequency. The picking frequency is the number of orders that requires a specific item. Next step is to rank items from the lowest to the highest COI-index. Table 3.4 illustrates the calculated the COI-indexes for the simulation items. Afterwards, the highest ranked COI items are assigned closest to the packing zone.

Item ID	COI index	Item ID	COI index	Item ID	COI index	Item ID	COI index	Item ID	COI index	Item ID	COI index	Item ID	COI index
1	646	30	159	59	101	88	68	117	52	146	42	175	34
2	419	31	150	60	98	89	68	118	51	147	42	176	34
3	346	32	149	61	97	90	68	119	50	148	41	177	34
4	311	33	148	62	96	91	66	120	49	149	41	178	34
5	287	34	147	63	95	92	66	121	47	150	40	179	33
6	277	35	146	64	95	93	65	122	47	151	40	180	33
7	277	36	144	65	93	94	64	123	47	152	40	181	33
8	273	37	138	66	92	95	64	124	47	153	40	182	33
9	264	38	134	67	92	96	63	125	47	154	39	183	33
10	263	39	134	68	91	97	63	126	47	155	39	184	32
11	245	40	133	69	86	98	63	127	46	156	38	185	32
12	223	41	132	70	85	99	62	128	46	157	38	186	32
13	209	42	129	71	84	100	61	129	46	158	38	187	32
14	206	43	128	72	83	101	61	130	46	159	38	188	32
15	204	44	122	73	82	102	60	131	46	160	38	189	31
16	196	45	121	74	80	103	59	132	46	161	38	190	31
17	196	46	121	75	78	104	58	133	45	162	38	191	31
18	195	47	119	76	78	105	58	134	44	163	37	192	31
19	194	48	119	77	77	106	57	135	44	164	37	193	31
20	192	49	117	78	77	107	57	136	44	165	37	194	31
21	186	50	116	79	77	108	55	137	43	166	37	195	31
22	177	51	112	80	76	109	55	138	43	167	36	196	31
23	174	52	111	81	74	110	55	139	43	168	36	197	31
24	173	53	111	82	73	111	55	140	43	169	35	198	31
25	164	54	110	83	73	112	54	141	43	170	35	199	31
26	164	55	109	84	72	113	54	142	43	171	35	200	29
27	163	56	108	85	70	114	54	143	43	172	35		
28	161	57	107	86	70	115	53	144	43	173	35		
29	160	58	101	87	68	116	52	145	42	174	34		

Table 3.4 COI-indexes for simulation items based on the picking frequency

Next applicable variables for COI-based allocation are considered, with following notations:

P = amount of packing zones, which is limited by in assumption part and equals 1

i = amount of items

l = amount of inventory locators

d_{pa} = picking distance from packing zone p to locator a

x_{ja} = 1, if item j is allocated in storage locator a; otherwise 0

$f(x)$ = distance of the picking tour; single order completed

The assumed picking tour distance (1) between storage locator a and the packing zone p is determined as follows:

$$(1)\ f(a) = \sum_{b=1}^{P} d_{pa}$$

LPP mathematical model (2) for item j is determined as follows:

$$(2)\ \min D = \sum_{j=1}^{i} \cdot \sum_{a=1}^{l} \cdot x_{ja} f_a$$

s.t. $a = 1,2,3 \ldots.l$ $\quad x_{ja} = (0,1)$

$j = 1,2,3 \ldots.i$ $\quad \sum_{j=1}^{i} . x_{ja} = 1$

Standard LPP algorithm was simplified as there is no additional packing zone, required spare by items is irrelevant and equals 1, the order is collected in one picking tour. By calculating *f (a)* and renumbering storage locations and order items, as well as assigning new storage locations based on renumbering above LLP model is solved to optimality.

3.4.4 Scope of the simulation.

At the first stage of the simulation is to allocate items in the warehouse according to existing random allocation policy and based on the COI-distribution matrix. The goal is to define the settings for which comparable storage allocation policies lead to reducing in the overall picking distance to retrieve all outbound orders, by running simulation for existing random allocation and proposed the simplified COI-based model.

A sample calculation for picking distance concerning the retrieval of multiple items for single outbound shown in Figure 16, with green zone representing the most favorable locations with back to back travelling distance less than 40 meters.

Allocation data for existing random storage allocation policy is taken from available inventory lists from the six months period of observation. As stated in Chapter 2, under random storage policy, each item can be randomly allocated to a vacant storage location in a warehouse, regardless of picking frequency, affinity, or compatibility. Consequently, each vacant storage location has theoretically the equal likelihood of being nominated for allocation by the WMS. Figure 17 demonstrates the existing storage assignment of simulation items with prioritizing based on the inventory and shipping data for the last six months. The numbers in the square box represent the items stored in the locations.

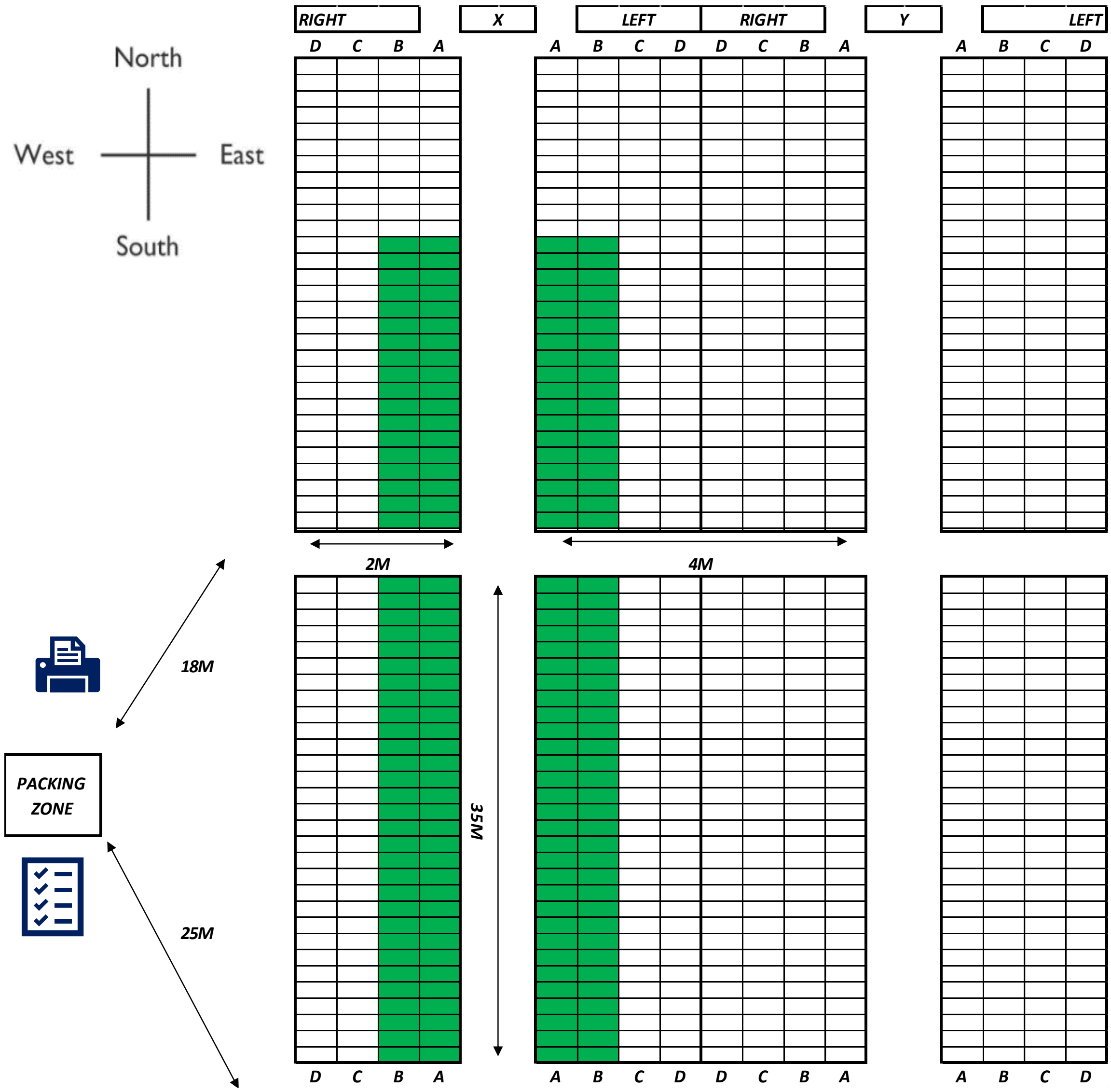

Figure 16. Travel distance to the simulation storage locators, meters

Based on the review of the current inventory list can be concluded, that not all items with high picking frequency are located close to the packing zone, as well as numerous items with the 2-3 picks over the last six months located on the ground level A without any benefit for the picking process.

In the following stage the minimal distances of the storage locations to packing zone should be defined for alternative based on COI-allocation method.

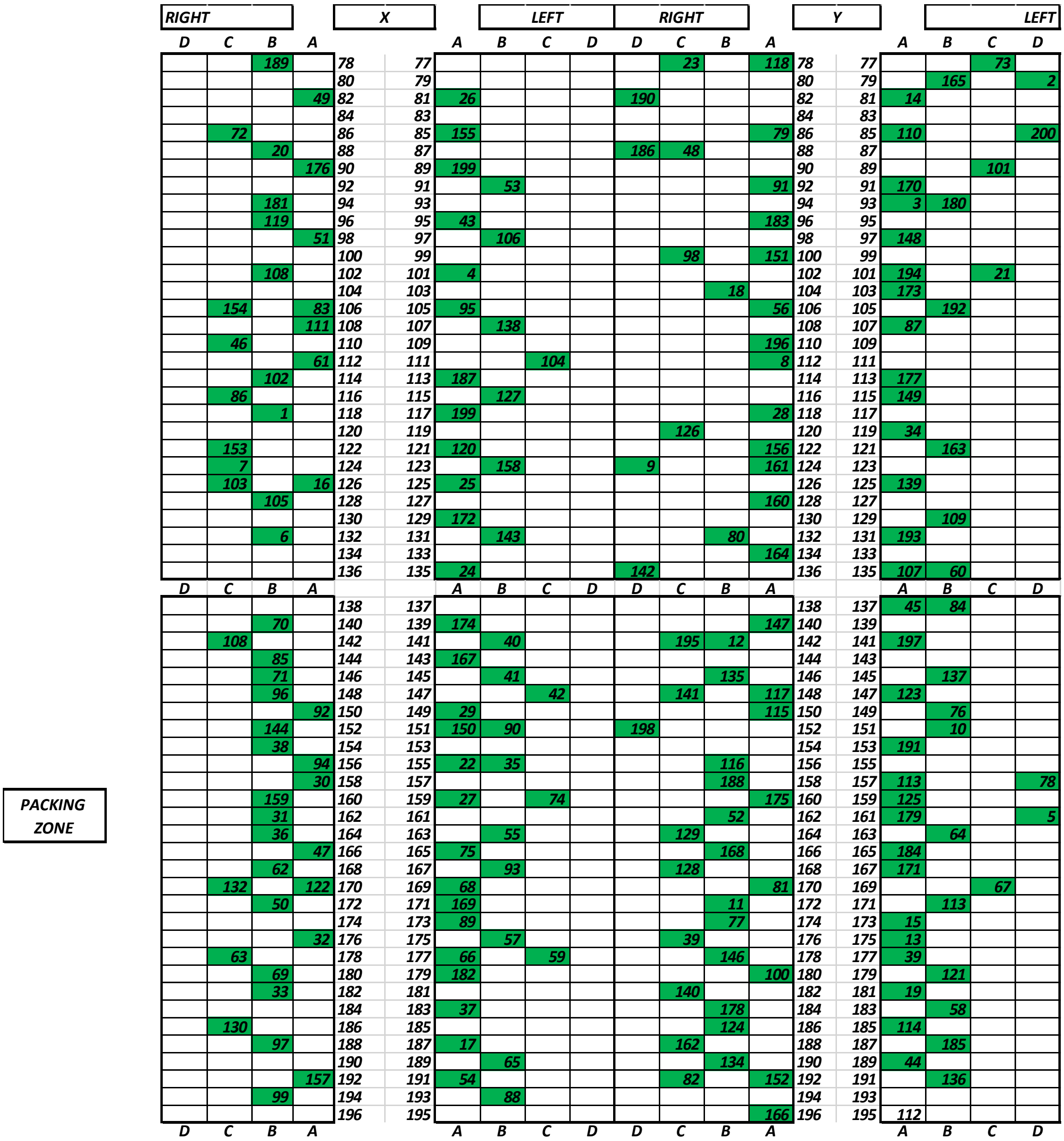

Figure 17. Storage assignment of the simulation items based on the current random allocation

As soon as the minimal distances are defined, the next phase is to allocate items with a higher COI-index or the picking frequency to a storage location next to the packing zone. For that reason, item 1 has obtained key storage location closest to the packing zone with minimal retrieval tour distance 40 meters.

Figure 18 represents the assignment of items according to the COI-based allocation method including manual adjustment for affinity items based on the principles compatibility described in the scope of the OOS-allocation policy, meaning that compatible items are allocated close to each other. Items a and b have the index of affinity equal if they are requested once in the same order. Affinity relationship indexes are distributed based on analyzing of the shipping data and customer orders. Compatibility rate has been determined based on the amount of times same items are ordered together by analyzing the shipping data over the past 6 months.

It is assumed that the COI-based allocation would provide a more optimal solution than the random alternative, since it considers both picking frequency and affinity relations between items in the scope of storage allocation. In terms of the affinity relation items, it is assumed that items *i* and *j* have the affinity rate 1 in case these items are required for the same order. Consequently, if *i* and *j* items required for 4 simulation orders affinity relation for these items is 4. The greater affinity relation value for items i and j is the closer related items should be located to each other, or in the real-world even share the same storage location. Affinity relations rates calculated based on the historical order patterns for the last 6 months.

The following step is to compute the total picking travel distance for the 61 order samples, which are generated randomly for this simulation. Since routing strategy is the limited in the assumption part outbound team member is instructed to follow S-shaped routing strategy, as well as picking list has storage locations listed in respective order. Under this strategy, the picking initiates by accessing the storage aisle closest to the packing zone.

Every aisle including at least one sample is crossed over the complete length. Aisles without items to retrieve are not considered. As soon as the last item is order list is collected, the picker returns to packing zone. Randomly selected simulation sets presented in Appendix 1. It should be pointed out, that due to the real-world demand, and based on the actual order data, the amount of samples for items from 1 to 12 with the highest picking frequency was adjusted manually, so item 1 included in 90% of the samples, item 2 in 50% of the samples, and items from 3 to 12 at least in 20% of the samples.

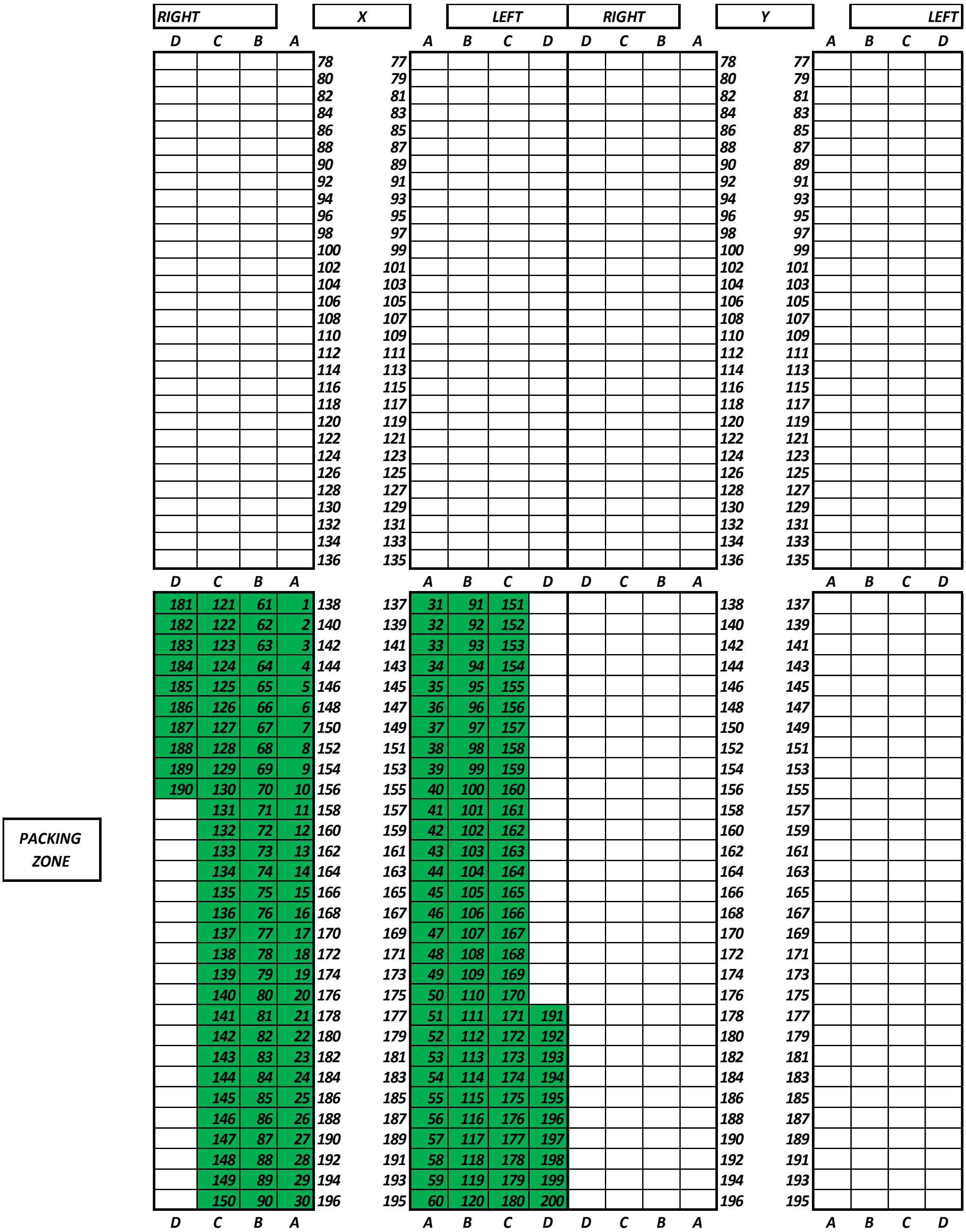

Figure 18. Storage assignment of the simulation items based on the COI rule

As simulation software NetLogo is used, which is a great choice for warehousing related optimality research, with huge amount of adjustable configuration features to emphasize essential processes and get accurate and real-world representing results. Depending on the first item in the picking list, picker enters to the picking isles either through the corridor between upper and lower isle or starts picking by the first or last location to the picking isle. Simulation items and share of the picking lines are presented in Figure 19.

Simulation number	Picking lines													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	1	47	2	66										
2	3	25	12	1										
3	176	74	105	1										
4	93	2	58	14										
5	11	49	184	1										
6	1	10	156	3										
7	41	136	5	2										
8	105	1	42	85										
9	37	76	5	24										
10	53	6	57	95										
11	9	161	12	2										
12	91	36	71	1										
13	12	19	68	2										
14	1	47	7	46										
15	2	143	17	44										
16	1	28	40	52										
17	2	40	181	6	103									
18	1	79	44	148	17									
19	1	110	61	12	98									
20	2	136	13	3	8									
21	1	35	180	93	185									
22	1	112	32	11	71									
23	3	7	102	63	77									
24	2	5	109	54	87									
25	1	33	65	134	40									
26	7	105	59	34	72									
27	2	64	33	10	124									
28	1	122	23	72	6	60								
29	1	29	13	12	9	138								
30	2	168	46	76	7	28								
31	1	24	74	107	30	90								
32	2	142	30	27	153	49								
33	1	80	46	30	20	8								
34	5	13	176	71	12	25								
35	1	181	42	83	19	43	3							
36	2	37	156	68	177	98	9							
37	1	138	45	51	5	19	6							
38	1	129	173	14	10	7	5							
39	2	126	44	56	117	12	4							
40	1	98	170	8	3	9	15	10						
41	1	32	27	51	93	71	185	6						
42	1	11	61	14	40	75	79	3						
43	2	89	61	45	12	82	35	165						
44	1	79	188	26	85	77	54	4						
45	1	93	84	160	17	11	13	132	7					
46	2	200	5	42	114	35	27	89	12					
47	1	26	134	59	102	7	28	61	4					
48	1	110	8	18	80	48	92	77	42					
49	1	4	98	74	16	12	36	22	68	9				
50	2	104	17	124	19	62	195	8	26	11				
51	1	44	7	136	70	147	21	57	38	17				
52	1	60	89	42	74	94	128	38	9	7				
53	1	88	33	69	152	6	183	19	124	55	10			
54	2	117	33	89	27	156	23	52	91	76	3			
55	1	27	70	55	15	111	46	77	47	115	6			
56	1	86	94	66	16	91	15	170	17	27	33	6		
57	9	18	114	85	56	1	142	104	147	73	3	13		
58	2	44	89	146	72	45	64	95	14	130	26	4	9	
59	1	80	22	52	122	47	103	5	16	149	65	35	116	
60	1	10	58	13	163	77	48	100	17	146	88	29	57	61
61	1	49	31	106	76	23	51	91	132	54	27	99	21	8

Picking lines per order	Amount of orders	Share of orders	Simulation orders
4	485	26%	16
5	334	18%	11
6	228	12%	7
7	168	9%	5
8	153	8%	5
9	130	7%	4
10	117	6%	4
11	80	4%	3
12	58	3%	2
14	53	3%	2
13	48	3%	2
TOTAL	1854	100%	60

Figure 19. Simulation items and related share of the picking lines

It is assumed that traveling distance for one simulation order is minimized in case picker enters only one corridor and exists from moving directly back to packing zone. After the simulation has been run for all samples, the total travel distance of random and the COI-based allocation policy is calculated and compared.

4 RESULTS AND DISCUSSION

In this section, simulation results are presented and comparison between random storage allocation and the COI-based storage allocation, as well as an assessment of previously made assumptions is provided. As was defined in Section 3 two simulation features were pointed out: allocation policy and A-class items based on the highest picking frequency. Two allocation policies were compared in the scope of the simulation: existing random allocation and the COI-based allocation with the addition of the affinity relation.

4.1 Summary of results

The simulation was conducted for 61 order sets, consisting of A-class items, with the amount of the picking lines varying from 4 to 14. Accordingly, for both comparable allocation strategies, simulation results are presented in this section, with order items randomly picked using historical order patterns. However, even though the likelihood of occurring in the simulation order is identical for all A-class items, in order to take the real-world demands under consideration more intense 70% of simulation picks were items from 1^{st} to 100^{th} ranked in accordance with the piking frequency.

As stated in Section 3, the COI-based storage policy allocated all simulation items on the both sides of the nearest aisle X: items 1-60 to level A, items 61-120 to level B, items 121-180 to level C and rest items allocated to level D of the upper part of left side and lower part of right site. This way WMS could calculate optimal routing solution to start picking tour. In the random allocation items allocated to all 8 possible sides (aisles X, Y; left, right sides; upper, lower racks) and four possible levels (A, B, C, D) randomly. As can be seen from warehouse layout in case to minimize travelling distance random items should be allocated to the same corridor: both side of the lower rack of the same aisle.

This way picker is able to retrieve all order items by entering and exiting the same corridor.

In order to minimize the simulation period, relatively minor amount of picking order samples was implemented. In this sense affinity relation between different items might not be so visible. This fact would represent the random allocation as more appropriate in the situation when the amount of sets is minor. Though, with the increasing amount of the simulation samples, the affinity interaction between items becomes more visible, with fewer benefits from random storage, since neither affinity relation nor the popularity of items considered in the scope of the random allocation policy.

Considering that according to the literature review the COI-based storage allocation policy with affinity relation component is the most item picking focused approach among the rest of the alternative allocations random allocation is compared to it. The aim of this assessment is to confirm the capacity of the COI-based allocation to find the optimal solution that reduces the travelling distances to retrieval required items for Customer N orders. Table 4.1. presents total travelling distance for each simulation order set and related amount of picking lines for alternative allocation policies.

According to the simulation results in sample order sets the COI-based alternative obtained a better solution than the random allocation, resulting in average 90% improvement for order picking distance. This result indicates that COI-based allocation is significantly better than the random alternative, as well it is essential to take into consideration both picking frequency and affinity relations between items in the scope of storage allocation.

Consequently, it is concluded that the COI-based allocation with affinity relation component provides the more optimal solution than that could be achieved by the existing random allocation. Comparison for each simulation set is shown in Figure 20.

Random allocation			COI allocation			Random allocation			COI allocation		
Simulation	Amount of picking lines	Picking distance	Simulation	Amount of picking	Picking distance	Simulation	Amount of picking lines	Picking distance	Simulation	Amount of picking lines	Picking distance
1	4	170	1	4	85	32	6	149	32	6	94
2	4	166	2	4	82	33	6	140	33	6	85
3	4	164	3	4	94	34	6	173	34	6	91
4	4	217	4	4	85	35	7	214	35	7	103
5	4	166	5	4	91	36	7	150	36	7	100
6	4	160	6	4	88	37	7	176	37	7	91
7	4	205	7	4	88	38	7	172	38	7	88
8	4	167	8	4	85	39	7	169	39	7	94
9	4	142	9	4	85	40	8	179	40	8	91
10	4	152	10	4	85	41	8	164	41	8	97
11	4	192	11	4	88	42	8	208	42	8	91
12	4	134	12	4	88	43	8	226	43	8	97
13	4	205	13	4	85	44	8	208	44	8	100
14	4	167	14	4	82	45	9	226	45	9	100
15	4	218	15	4	88	46	9	232	46	9	97
16	4	211	16	4	82	47	9	226	47	9	94
17	5	149	17	5	91	48	9	226	48	9	94
18	5	202	18	5	91	49	10	223	49	10	91
19	5	170	19	5	91	50	10	220	50	10	103
20	5	135	20	5	88	51	10	226	51	10	97
21	5	218	21	5	97	52	10	208	52	10	97
22	5	167	22	5	88	53	11	220	53	11	109
23	5	220	23	5	91	54	11	229	54	11	97
24	5	214	24	5	88	55	11	179	55	11	94
25	5	173	25	5	91	56	12	214	56	12	100
26	5	146	26	5	88	57	12	202	57	12	106
27	5	214	27	5	91	58	13	232	58	13	106
28	6	146	28	6	91	59	13	226	59	13	106
29	6	217	29	6	88	60	14	229	60	14	106
30	6	175	30	6	91	61	14	232	61	14	100
31	6	134	31	6	91						

Table 4.1. Order picking distance for simulation sets

In the scope of the average affinity relation rate is 2.5; some items like item 3 and item 5 has affinity relation rate 6. It was assumed that affinity relation would add favor to the COI-based allocation over random allocation, but due to the simulation only focuses on A-class items and there are enough A-level for the all items with higher affinity interaction, as well as the amount of simulation order sets is limited, the affection of the affinity is limited. For example, locating items with higher affinity relation rate to the neighboring locators or even to the same locations would minimize retrieval period with fewer times to stop during picking. However, the main attention of this thesis is on the traveling distance and there would be no affection on the length of the picking tour from such allocation.

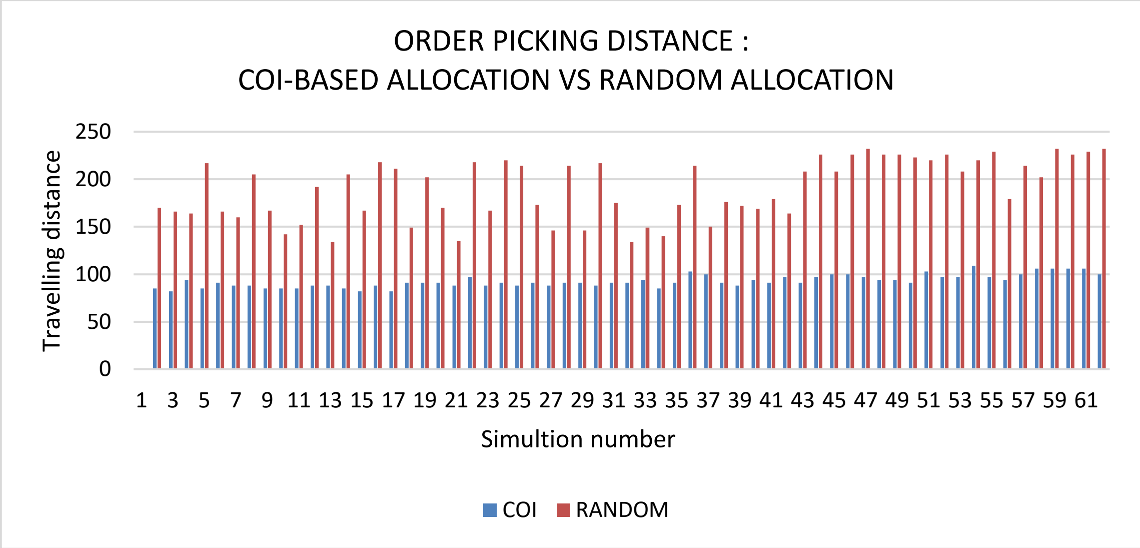

Figure 20. Comparison of the order picking distance for the simulations samples

Affinity aspect of the OOS-storage allocation has also practical significance, when it comes to the reduction of the warehouse operational costs. However, OSS-allocation has some additional complexity compared to the other allocation policies, applying to the demand popularity as a basic principle, which might be challenging to implement in a short period of time.

Total order picking distance for all simulation order sets with the COI-based storage allocation is more than two times less than in case with the random storage allocation as illustrated in Figure 21.

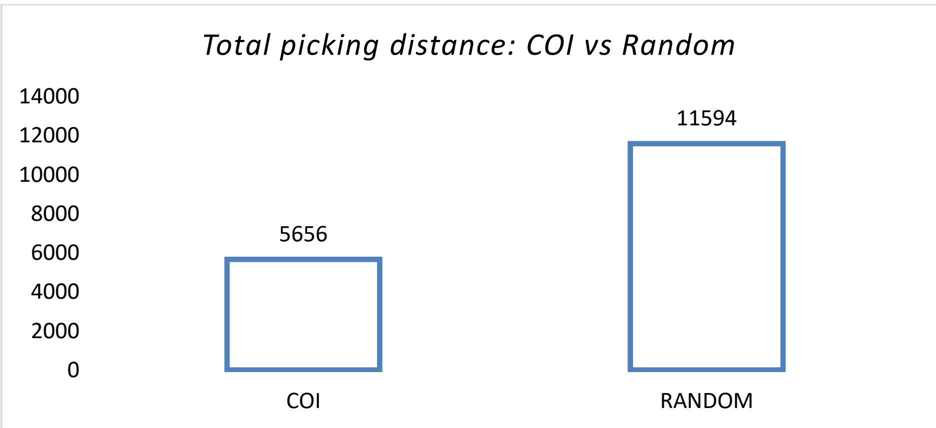

Figure 21. Total order picking distance for the simulation samples

In terms of the relation between the amount of the picking lines for the simulations order set and picking travelling distance, the uncertain conclusion might be that the length of the retrieval tours rises together with increasing amount of picking lines. This conclusion is confirmed by simulation results for the COI-based allocation, with distance increasing due to additional transportation needed to retrieve items from higher aisle levels. However, for random allocation this is not the case, as the even greater amount of picking lines might be randomly allocated to the same single corridor, with minimized travelling distance to perform order picking, like in the simulation order sets, number: 32, 33, 36, 55. With the correct allocation, the amount of the picking lines does not impact the picking distance. Related distribution of the interaction between the amount of the picking lines and picking distance shown for both random allocation and the COI-based allocation in Figure 22.

Figure 22. Distribution of the picking distance to the amount of the picking lines

In order to gain the more comprehensive understanding of achieved results, a statistical investigation was completed on the simulations order sets to determine possible irregularities.

4.2 Verification and validation of the model

In case an approach used in the simulation is to be implemented in the future investigations and in general, verification and validation is an important aspect of the approach development procedure. The purpose of this additional investigation to determine any possible irregularities demonstrating a fault data in the calculations of the simulation. Validation of the simulation data in the scope of the further investigation related to the allocation in the healthcare warehouse might be under concern in case samples are not disseminated in the proper way. According to Reis it is essential to take into account that no simulation or mathematical method could be fully confirmed or validated. At maximum researchers might get proof on the results of the simulation, since simulations are a simplified demonstration of the real-world situation having less potential constraints and therefore it's not possible to reach a perfect representation of reality (Reis 2010 p. 97).

To understand whether the simulation approach applied to categorize the grounds is, in fact, effective, the approach should be verified. Verification is determined as guarantee that theoretical assumptions for the potential capacity of the linear or generic program to solve optimization problem consistent with practical execution. At each step of the simulation, approach and data were verified to improve reliability, as well as to indicate whether there are any exceptional cases requiring the additional extension of the scope. All assumptions that were made during modelling were checked with one or more experts from logistics and supply chain management.

To define whether the simulation approach represents real-world problems rationally at each step of the simulation design reasonability of respective results are assessed together with supply chain experts and representatives from Vantaa warehouse. In case some of the assumptions are not reasonable or practical, assumptions were corrected or replaced to ensure representation of reality

In order to verify and validate the simulation model used in this work following actions were implemented:

- As stated above simulation was designed step by step, with wide-ranging testing every phase, as well as discussing parameters and result with logistics and warehousing experts.
- The mathematical approach and the simulation were documented from the beginning making it transparent and open for discussion and correction.

- Debugging the approach through NetLogo, to confirm no simulation software lags are presented in the final form of the simulation.
- Stress testing the simulation approach with a large amount of samples and picking lines. Each storage allocation policy was tested in specific conditions, like allocation of thousand items or picking of the order with all items.

In addition to verification, the simulation responds to practical requirements and problems of the real-world, as follows:

- Data validation: inventory records and shipping information exported from warehouse WMS system, used for the simulation are valid and represents real-world. The representatives of Vantaa warehouse provided historical data.
- Face validation: the assumptions and constraints of the simulation are valid. All assumptions are discussed and confirmed by experts in the warehousing field and supply chain, as well as observation in Vantaa warehouse done by the author during multiple visits.
- Process validation: the stages in the simulation are clear, reasonable and match the procedure in Vantaa warehouse.

4.3 Discussion

Random allocation is regularly implemented as a reference line for storage assignment optimization in the scientific literature. Likewise, random policy splits different processes more consistently across numerous warehouse zones and therefore minimizes the probability of congestion in case if numerous retrievals happen simultaneously. Warehouse management traditionally has a solid trust in random storage allocation, due to its capacity to manage inventory systematically, which allows outbound personal to handle orders more resourcefully. Though, with the development of WMS and RF tags, data on the item in stock and locators are permanently available, as well as the system can use different patterns to suggest the best possible location for the items, based on selectable settings. Nevertheless, the warehouse managers not willing to deviate from traditional approaches in storage allocation or afraid to adopt new policies, which partly explains why other popularity and affinity-based assignment strategies are not widespread. Another reason might be in continuous adjustment of demand patterns, where popularity of the items could alter significantly in the short period of time. Adjustment to new demand frequency requires regular reviews of the recent orders, as well as close cooperation with customer side to update patterns timely. As the result, additionally, there might be a need for relocation of the items, which is extra workload and cost for the warehouse.

However, benefits of the storage assignment policy, like the COI-based allocation, which takes under consideration demand frequency and affinity relation are comparatively greater, than the potential cost of possible relocation, due to the changed patterns of the customer orders. It divides warehouse into the specific zones and allocates items to these zones in accordance with the order frequency. This way, regularly required items are located in the most favorable locations near the packing zone and items with the strong compatibility are located close to each other or tend to share the same location. Generally, in case there significant difference in the picking frequency the COI-based storage reduces allocation costs and time, but the results of the simulation model developed in this work provide evidence, that it also reduces picking distance and improves picking efficiency remarkably compared to the existing random allocation.

The COI-based allocation, as assumed outcomes in the lowest estimated picking distance for each simulation set and in total. The main reason for this is that COI based allocation takes into consideration both popularity of the items and affinity relation and proposes allocation accordingly. Another explanation is the dilapidated tendency of the calculated distance achieved by the COI-based storage, due to the limited amount of aisle corridors to visit, which is always only 1 for A-class items in the scope of the simulation. In the real world situation with all 1000 items of customer N available for potential order, it is to be expected that in 70% of the cases picker would access the corridor of lower part in the aisle X, which is located near to the picking zone and rest of the cases picker would need to follow to the upper part of the aisle X or following aisles to retrieve items with low demand frequency. In any case with random allocation, the amount of corridors to be visited during retrieval is more likely to be higher than those in the COI-based allocation. Additionally, random storage allocates inefficiently items with low picking frequency close to the picking zone and to the ground levels, wasting unreasonably favorable locations. Potentially, the shortcoming of the COI-based allocation that it demands more inventory space, compared with random storage, by keeping locations reserved for certain items, even there are no items However, in case WMS tracks changes in the customer order data or requesting approximate forecast data, as well there is strong information support from the customer side, reserved empty locations can be reassigned accordingly to match the actual need.

The outcomes of the simulation also evidently point out that in most of the cases, the difference in the estimated picking distance increases with the increasing amount of the picking lines. A larger amount of the picking lines leads to an advanced concentration of items per corridors. Since the COI-based allocation assigns all simulation items to the same corridor calculated travelling distance remains almost on the same level. On the other hand, in case with random allocation with the increasing amount of picking lines distribution among the storage corridors increases, which in the long run requires the order picker to access most of the corridors. In the simulation model, around half of the order sets 28 /61 necessitates access all four corridors when allocated by random policy, with 95% need to access all, for order sets with eight or more picking lines.

Therefore, it is relevant for WMS system to be able to continuously analyze dynamic order data to reevaluate popularity and affinity over time and redistribute indexes timely. In addition, warehouse management in cooperation with the customer should make a decision, whether it is reasonable to make relocation of the items to respond to the new demand pattern. Another benefit of the relocation would be to combine boxes with the small amount of the same item to one location for more efficient space utilization. It is essential for the customer to be involved in the relocation process and provide additional forecast data to evaluate popularity and affinity relation. In case change is not radical, relocation time and cost might be equal or more compared to the situation, if additional time would have been spent for picking without relocation made. With more advanced cooperation between warehouse and customer in this scope, as well as with smoother information flow, the more progress in order fulfillment reduction, work efficiency, and costsaving can be achieved.

5 CONCLUSIONS AND RECOMMENDATIONS

In this chapter, all the important conclusions and result discussed in the preceding chapters are summarized. Additionally, there is a set of suggestions provided to minimize picking distance and improve order fulfillment efficiency, as well as possible topics for future research listed.

5.1 Conclusions

This study transformed earlier investigation and theories into practice and completed a case study. The master thesis presented here has the objective to minimize order picking distance in healthcare warehouse, by implementing the best possible storage allocation strategy. This was performed by conducting a simulation investigation based on the historical shipping data and the sets of assumptions made according to the literature review, process constraints, as well as author’s own experience. The two comparable allocation strategies that were simulated are:

- Random storage
- COI-based storage with affinity relation component

Order picking problem defined as one of the most challenging among the warehouse operation planning concerns. In overall, previous order picking related studies discussed three strategies used to improve order picking:

- assigning items to storage locations (tactical and operational level)
- order picker routing (routing) (operational level)
- grouping or batching all picks of the orders (batching) (operational level) (Gu et al. 2007 p 8).

Petersen et al. suggest the use of travel distance to compare different allocation policies. In his opinion distance is better than time to measure performance, since the travel time could be influenced by the travel method, while distance will not. In general, it was concluded that in most of the cases solving allocation problem in the scope of warehouse design is complicated mission with many trade-offs between various targets at each consequent step. Many researches have introduced methodology dedicated to solve concreate real-world problems, but there has never been a consensus (Petersen et al. 1997 p. 390). According to Le-Duc, in the real-world however, due to increasing fluctuation in demand, so allocation policy needed to be reviewed and adjusted over time for reasonable utilization of warehouse space (Le-Duc 2007 p.131-133).

Having provided an overview of the warehouse activities, order picking and picking improvement strategies, next the storage location assignment problem was discussed. De Koster et al. defines the storage location assignment problem as, the set of rules which can be used to assign incoming products to storage locations in storage departments/zones. Storage allocation helps in the reduction of material handling and the improvement of space utilization (De Koster et al. 2007 p. 211). In the first instance, Graves et al. introduced an accurate classification of the potential storage location assignment policies within a warehouse: original problem considered an identification of optimal storage locations and the major factors to be accepted during this process. Random, dedicated, and class-based storage were introduced by Graves et al in 1976, popularity storage by Hesket in 1963. Family or affinity grouping policy are newer and have garnered lots of attention in the literature during the last years.

According to Petersen et al., the main principle of random storage is to allocate all incoming items randomly, by choosing from all the obtainable locations with identical probability randomly, in the fast picking area (Petersen 1997 et al. p. 418). De Koster et al. defined random allocation as a "closest open location storage" strategy in which the first vacant location found by an employee during the warehouse inbound becomes a potential candidate location for the incoming items (De Koster 2007). Most of the researches agreed results of random allocation in a low space requirement at the expense of increased travel distance. In his simulation study Peterson determined that random allocation required substantially more traveling distance than class-based allocation. Simulation identified trade-offs, for example between space utilization and travel time (Peterson et al. 2004 p. 140). According to Van der Berg random allocation is regularly used as performance baseline in the scientific literature (Van der Berg 2007 p. 127).

According to De Koster, dedicated storage is the assignment of the items to a fixed, exclusive storage location or set of locations. A drawback of dedicated storage is that a location is reserved even for items that are not currently in stock. The space utilization of this policy is lowest among all allocation strategies leading to the high warehouse costs. A benefit of dedicated storage, especially before automated WMS, is that order pickers become familiar with the location of the items, which may speed up retrieval. This is, however, not the case presently with the more advanced WMS systems managing all inventories. Due to continuously increasing the amount of various techniques and mechanisms to define the exact dedicated locator to serve specific customer demand patterns, minimizing the picking travel distance and the total order fulfilment cycle, dedicated storage is the most used policy in warehouses (Petersen et al. 1997).

De Koster et al. describe the concept of class-based allocation, as a combination of random and dedicated allocation strategies. The idea behind is to division the inventory items into classes. Each class would have an allocated zone, where any space available within it is randomly used by the items belonging to that class. In inventory management, a traditional approach for composing products into classes based on popularity is Pareto's distribution (De Koster et al. 2007 p. 143).

In the scope of family-based allocation policy, Lynn et al. define two items as correlated, similar or affine if they are frequently demanded together, for instance in the same customer order or within the same time period. In warehousing affinity described as a probability that pairs of items will occur in the same order or batch. Once affinity data has been revealed, it is possible to use it in various ways to minimize picking time through better allocation strategy. Frazelle performed a simulation study to compare random storage and family assignment and confirm that affinity-based allocation can potentially decrease the number of the required pickings by 30-40%. According to the authors own experience affinity relation can be combined with other popularity- or class-based assignment policies, resulting in the less time and distance picker spends in the retrieval process (Frazelle et al. 1989 p. 25-27).

Originally Haskett defines popularity-based policy, as a distribution of items over the warehouse storage zone in accordance with their turnover, as the only definition of the item popularity. The items with the largest sales volumes are placed at the most reachable locations, typically next to the packing and shipping area (Heskett 1964 p. 12). On the other hand, Hausman refers to popularity of items as basic determination and accentuate that popularity can be considered in various ways and not only limited by turnover rates. This is especially, the case for outsourcing warehousing, with an aim to improve order fulfilment efficiency having order picking frequency or volume as popularity measurement criteria (Hausman et al. 1976 p. 131). According to Lynn et al. a real-world execution of the full-turnover strategies would be the most efficient in case it united with the dedicated allocation (Lynn et al. 1990). The main drawback is that the demand fluctuates constantly over time and the variety of the popular items alter frequently. Petersen et al. constructed a simulation study, to demonstrate that turnover based storage outperforms class-based storage, when it goes to employed distance of picking tour (Petersen et al. 1997 p. 424).

One of the most used methods of the popularity-based allocation is Cube-per-Order Index (COI). Originally introduced by Heskett in 1963, the COI defined as the ratio of the item's total space requirement to amount of picking tours required in accordance with customer demand. This approach is extensively studied by Heskett et al., 1963, Francis et al 1967, Harmatuck 1977, Hodgson et al. 1982, Bhaskaran, et al.,1988. Allocation algorithm involves assigning the items with the lowest COI-index next to the packing zone. According to Caron et al., the major drawback of the COI-method is that it does not consider the affinity relationship between ordered items. This approach could be advanced by adding elements of affinity or class-based stratification. Both these aspects were considered in the simulation of this thesis.

Regularly, outbound team goes along with the exact route to retrieve order items, where the picking tour is bounded to the picking list and the routing policy configured in WMS. Many researches described this process as Order Oriented Slotting, which can be considered as a method of the affinity-based policy, which considers historical order patterns in the scope of allocation. Combination of COI-based storage assignment with picking frequency as criteria and affinity relation was selected as potential allocation method to compare with existing random allocation used in Vantaa warehouse.

To concentrate empirical research on the most valuable items from the picking point of view, ABC- stratification has been implemented. Frandsen suggests using picking frequency in the below classification to accomplish original analysis based on the value of the item. In the scope of storage allocation ABC-stratification represents class-based storage and, therefore allocation strategy in this thesis is the combination of different storage policies: popularity-based (COI) and family-based allocation (affinity relation), with the additional detailed allocation for relevant A-class items based on simulation.

In order to minimize traveling distance for picking was developed a methodology that combines simulation and optimization. 61 order sets are generated randomly to be tested in the simulation. The optimal storage locations are determined based on the distance of the picking tour to retrieve all required items under fulfillment of the specific order. The objective measure used in the simulation is picking tour distance. Simulation data for the empirical part was obtained from the review of the case company related orders and inventory information in WMS system and an observation of the picking process carried out at the warehouse located in Vantaa.

Next warehouse and material handling activities described with special attention to the order picking process and historical order data were described. Warehouse layout was presented, and assumptions made to constraint simulation. The assumptions made might not fully characterize a real-life picking process and order patterns, but with the selected constraints, the simulation could be conducted the in a reasonable time. With the review of the historical order pattern based on the shipping data over the past 6 months, order frequency was determined to complete ABC-stratification. This resulted in 200 A-class simulation items with representing 19% of the total Customer N items in Vantaa warehouse and 79% of the total picks. Next, a mathematical optimization method - Linear Placement Problem was presented and comparison with Generic programming provided. Based on the historical shipping data, COI-indexes for the simulation items were distributed, variables and the objective function for the COI-based allocation presented, following by introducing of the simulation scope and travel distance calculation method. Next simulation items were assigned to storage locations based on the existing random allocation using historical inventory data, as well as in accordance with on COI-based allocation using COI-indexes. Affinity relation was determined based on historical shipping data and allocation for the items with the same COI index value was manually adjusted to keep these close to each other. Items for the simulation order sets were randomly selected from 200 A-class items, with the distribution of the picking lines from 4 to 14 made based on the historical order data.

There are numerous conclusions that appeared during this thesis work to be pointed out in this chapter. As was expected, in all simulation order sets the COI-based alternative with the affinity relation component obtained a better solution than the random allocation; resulting in average 90% improvement for order picking distance. This result indicates that the COI-based allocation is significantly better than random alternative, as well it is essential to take into consideration both picking frequency and affinity relations between items in the scope of storage allocation. Consequently, it is concluded that the COI-based allocation with affinity relation component provides the optimal. Total picking distance for all simulation order sets with the COI- based storage allocation is more than two times less than in case with the random storage allocation. With the increasing amount of the picking lines, improvement with the COI-based storage allocation becomes greater accordingly. Numerous of the favorable storage locations wasted for the rarely demanded items.

5.2 Recommendations

In this section, based on the conclusions found throughout this study, set of recommendation is provided in order to improve picking order and minimize related retrieval distance.

Order retrieval process is the most labor-intensive and costly among warehouse activities, and therefore minimizing the order fulfillment cycle is the high priority and beneficial to both customer and warehouse. Order receiving, travelling, searching, and collecting are the key steps in the order retrieval cycle, with travelling as the most time-intensive component. Consequently, the main goal of this study was to find out the storage allocation strategy and specific constraints to be taken into account in order to minimize order picking distance. To achieve this goal, the study aimed to cover following questions:

(i) define main criteria to be considered during development of the storage policy for customer N items.

It is recommended that WMS should follow picking frequency aspect and affinity relation of the main A-class items. ABC-stratification is based on the picking frequency. To follow all items is complicated and unnecessary, which only may lead to a confusion and the higher material handling cost for relocation. Affinity relation is very important when storage allocation made for the items with the same COI-index, as additional criteria. Another implementation of affinity would be in case with low demand items, since the COI-based allocation would suggest assigning the item further from packing zone and WMS might still consider allocating them closer to the compatible items with the high demand. In order to configure WMS correctly, rules, when affinity relation can be applicable over the COI-index for low demand items should be further investigated and this is a potential topic for the future research. In addition, availability of the future demand and strong information flow are considered as vital criteria during the development of storage allocation policy.

(ii) analyze historical demand data and describe current storage policy for Customer N items in Vantaa warehouse.

As was revealed in the simulation random storage allocation has significant drawbacks, when it goes to order picking distance. Efficient utilization of the storage locations, as the main benefit of the random allocation is currently not relevant for Vantaa warehouse, as well as with the timely evaluation of demand frequency, this minor weakness of COI-based allocation can be minimized. Based on the review of historical order data, there are significant differences between the items in the order frequency, like 19% of the items picked in 78% of the orders and therefore random allocation relatively inefficient. Favorable storage locations are misused to an unreasonable inventory of the items with low picking frequency. This leads to inevitability to consider popularity and affinity in the scope of storage allocation described in the research question (i). It is recommended to concentrate allocation of the A-class items to the lower part of the picking aisle X, close to packing zone. This way order can be retrieved from the single corridor and WMS will be able to arrange picking list based on the most efficient routing policy. In case of numerous orders are picked simultaneously WMS could vary corridor access point to minimize connection between pickers. Warehouse management is suggested to apply wireless scanners for picking to minimize transaction time between systems.

(iii) Compare storage allocation policies and determine practical allocation method.

Based on results of the simulation it is recommended to implement COI-based allocation, which results in minimum picking distance and consequently shorter order fulfillment cycle. The main advantage for Vantaa warehouse is to have Customer N satisfied with the potential increasing amount of business for Vantaa warehouse. Warehouse would have the ability to handle more orders and more customers with the same cost level. Customer N would benefit from improved order fulfilment cycle, fewer delays and own satisfied customers.

5.3 Suggestions for future research

The following recommendations for future research were identified during the thesis process:

- It is suggested to consider a diverse or radial inventory configuration and compare performance of the COI-based allocation, to confirm if results in this study can be extended to other warehouse layouts;
- Different routing policy, with the COI-based storage assignment policy as a constraint as the way to improve order picking can be investigated. Amount of order samples, simulation items and picking lines might be different;
- Batching policy for healthcare warehouse;
- Picking strategies, where affinity relation can be applicable over the COI-index for low demand items should be further investigated.;
- Replenishment strategy for the healthcare warehouse based on the allocation;
- Cost and process of relocation of the items with dynamically changing demand pattern, in case with the COI-based allocation.

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