Rotterdam School of Management
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AN EVALUATIVE FRAMEWORK FOR PICK AND PASS ZONE PICKING SYSTEMS

Master Thesis

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PREFACE

EXECUTIVE SUMMARY

The changing landscape of customer demand has put a strain on warehouse operations. As more services are shifted from producers further down the supply chain, warehouses have to handle a wider range of services. Therefore, efficiency optimization is key in maintaining a competitive advantage. The main limitation that managers have to tackle is the human aspect involved in one of the core warehousing activities – order picking. Multiple methods have been designed to increase picker productivity, each with its own benefits and drawbacks. Pick-and-pass order picking is a system which is relatively easy to implement that improves order picker productivity and is popular in practice due to its relative simplicity and ease of implementation.

The goal of this thesis is to study the interaction of specific elements that make up a pick-and-pass system in order to find the most efficient design. Five decision variables are selected based on the effect that they are expected to have on the system performance, as well as based on the current literature limitations. These are the number of segments and zones per segment, the implementation of a block-and-recirculate protocol, the addition of shortcuts which totes can travel through to avoid long distances that are not necessary, and finally, storage policy. For each of these variables, a set of parameters are selected, which then form the policy sets to be studied. The policy sets are modelled using the Zone Picking module of the Material Handling Simulation Package software.

An experimental setup is provided, which sets the number of orders per simulation at 1,000. The source will launch a new tote into the system according to an exponential distribution with the rate of 0.0167 totes/ second. For each policy set, 20 simulations are run, after which results are recorded. The data set generated through simulation includes the average throughput time of the totes, the make span of the simulation, the total, investment, and operational costs.

The throughput time for a customer order is determined as the time elapsed from the order arrival in the system to the moment the tote is packed and ready to leave. For each policy set, this is averaged across all customer orders in a simulation run and between all 20 simulations. The make span is also the average of the 20 simulation run make spans. For each simulation run, this is determined as the time from the launch of the first tote into the system until the last customer order has been fulfilled and packed. The total cost is calculated as the sum of investment and

operational costs. The operational cost includes strictly the labor cost. The investment cost accounted for in the analysis is the proportion of the cost to create the system that is depreciated during the make span of the policy sets.

Using the outcome of the MHSP simulation, models are analyzed using Data Envelopment Analysis (DEA), which determines the relative efficiency of each model in relation to the most efficient point in the set. DEA allows multiple inputs and outputs to be analyzed together using a minimum number of assumptions. In this study, DEA will calculate the minimum achievable throughput time using the minimum total costs.

The outcome of DEA suggests that the most efficient policy sets have a small number of zones and segments, use shortcuts to connect the two directions of the main conveyor at various points to allow totes to skip parts of the warehouse, and store SKUs based on a class-based policy, rather than using random storage. All additional analyses support the use of a small number of zones as long as it can accommodate the demand level of the source. This results in lower average throughput times and make spans, but also in lower total costs.

Next to the number of zones, the introduction of shortcuts impacts the average throughput time by 7.4%. This is a very strong effect that is relatively easy to implement given a U-shape layout for a warehouse. Although it does not have a strong impact in the current study, class-based storage does result in slightly better performance than random storage, which supports previous research studies. In the current study, the effect on average throughput time was not significant (0.34%), which could be attributed to the low skewness of the ABC storage policy. DMUs which allow totes to recirculate in the system are less efficient than those that do not. This contradicts existing literature and could be explained by the use of a low demand rate, which causes only a few of the totes to recirculate, as congestion does not build up too quickly.

More research is needed to assess the relative efficiency of the block-and-recirculate protocol. The current study uses a low demand rate to avoid specific policy sets from blocking. This results in a low efficiency of recirculation. However, the potential of this protocol to reduce throughput time is tremendous for systems with high demand rates. This study can easily be expanded by including more decision variables, or by selecting different parameters for the current ones and assessing their interaction under different situations.

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1. INTRODUCTION

Supply chain management has evolved throughout the decades to tackle consumption trends head on. Globalization has increased companies' global footprint, challenging supply chain managers to craft innovative solutions that cater to increasing customer expectations of low costs, high service levels, and high product customization. To respond to these market changes, companies must maintain flexibility and foster collaboration throughout the supply chain, supported by flawless information systems whenever possible.

As a critical part of the supply chain, warehousing has shifted roles to support companies in addressing these trends. From its original function of storing products, warehousing has evolved to encompass sourcing, processing, inbound and outbound distribution, and reverse logistics. The ability to cope with manufacturing trends such as shorter response times, higher variety of SKUs, shorter life cycles and higher return rates has changed warehousing significantly. Value-adding services, such as labeling, custom packaging, quality control, and bundling have become an integral part of warehousing (Harrington, 1998).

One of the drawbacks of offering such a broad service package is the inherent complexity. When the number of services performed by a warehouse is too large, performance begins to decline (Harrington, 1998). The reason for this is increased labor, which lowers productivity and response times, while increasing error rates. One of the most labor intensive and costly warehousing activities is order picking, which is the process of retrieving products from storage to fill customer orders. It accounts for as much as 55% of operating costs (Drury, 1988; Tompkins et al., 2003), which in turn amount to approximately 20% of total logistics costs (ELA/AT Kearney, 2004). Consequently, efficiency improvements and cost reduction efforts in order picking systems can have a strong impact on the bottom line.

One of the most powerful tools to address order picking costs is zoning, whereby the storage area is divided into multiple zones and each order picker is assigned to one or more of the zones (Petersen, 2002; Gu et al., 2007). Order pickers travel within smaller regions, in which they can locate products faster, shortening the time spent searching (De Koster et al., 2007). Additionally, the allocation of pickers to zones lowers congestion and reduces travel time. These advantages are fundamental in tackling the main non-value adding activities, travelling and searching, which make up 70% of picker's time on the job (Tompkins et al., 2003).

There are multiple types of zoned picking systems. However, this thesis will only study one of them, namely pick-and-pass. In pick-and-pass systems, each customer order is assigned a tote, which travels through the system sequentially visiting zones which contain ordered items. The order pickers complete the order with the items in their assigned zone and pass the tote to the next order picker. This type of order picking is also called progressive zone picking or sequential zone picking. An alternative fixed zone picking system is synchronized picking. Hereby, pickers will work in parallel on retrieving SKUs from their zones and place the items on a conveyor; orders are sorted and consolidated downstream. Compared to synchronized zone picking, pick-and-pass is particularly suitable for systems which host a wide selection of SKUs and serve a high demand, composed of small to medium-sized customer orders (Manzini, 2012).

1.1. PROBLEM STATEMENT

Zoning has a strong potential to improve performance by tackling the most significant non-value adding activities of order picking. Consequently, one would expect research on the topic to be abundant. Given the existence of multiple types of zone picking systems and the numerous variables that are needed to create such a system, research specifically addressing decision variables for each type of zone picking system, and their effect on performance, is limited.

Decision factors addressed are for instance the zone size, number of zones (De Koster, 1994), aisle configuration, stocking policy, batching (Mellema and Smith, 1988; Petersen, 2002), zone configuration (Petersen, 2002), and depot location (Eisenstein, 2008). However, Chen et al. (2010) underline the lack of studies addressing the interaction of multiple decision factors. Similarly, Rouwenhorst et al. (2000) and De Koster et al. (2007) remark the limitations of existing research in addressing the effects of multiple policy decisions combined, and the strong dependencies that exist between different policy choices. Therefore, there is a significant opportunity to contribute to existing literature by studying several decision factors in combination.

In those studies where multiple variables are used as input, the output is typically a single factor, such as service level, travel time, or utilization of space or labor. The tradeoffs and interaction of performance metrics, however, is addressed sparingly in literature.

Together, the potential to contribute to existing supply chain management literature, and to provide assistance to practitioners in designing responsive and cost efficient zone picking systems, form the basis of the research question addressed in this thesis.

1.2. RESEARCH OBJECTIVE

This thesis aims to guide practitioners through the design of pick-and-pass order picking systems by studying the effects of a set of decision variables on multiple performance metrics. Rather than proposing a single optimal solution, the policy set will be assessed using Data Envelopment Analysis (DEA), which allows for the selection of a set of high performing designs.

For the study to be relevant, the input parameters should have a strong impact on system performance. The performance metrics, on the other hand, should be selected based on the significance they are awarded by practitioners. Both input variables and performance metrics are essential in designing a framework that can subsequently be used as a guide in determining the most suitable policy combination for practitioners.

1.3. RESEARCH QUESTION

In order to achieve the objective stated above, the study will attempt to answer the following question:

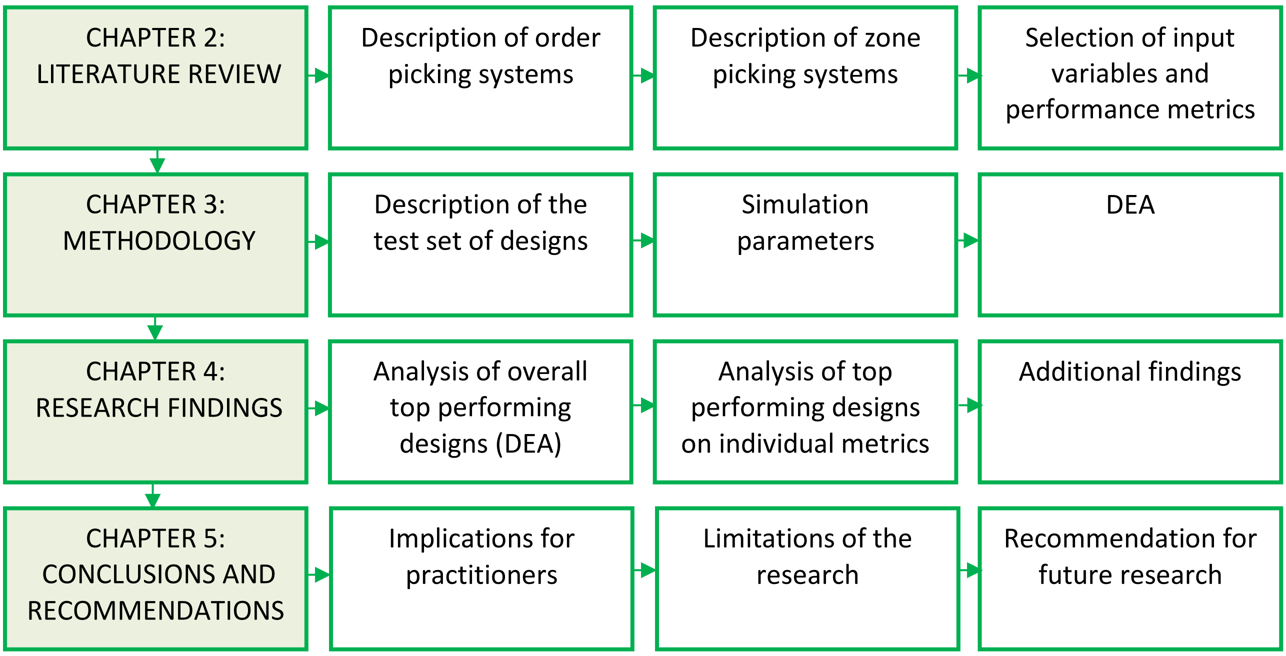
What is the most efficient pick-and-pass design based on DEA, in terms of the following decision variables: 1. number of segments; 2. number of zones per segment; 2. allowing totes to recirculate; 3. allowing totes to use shortcuts when possible; 5. using random versus class-based storage?

In addition to the main research question, the following set of sub-questions will be answered:

1. *What pick-and-pass designs minimize total cost?*
    a. *What pick-and-pass designs minimize investment cost?*
    b. *What pick-and-pass designs minimize operating cost?*
2. *What pick-and-pass designs minimize average throughput time? Throughput time is defined as the amount of time from the moment a customer order arrives in the system until the customer order is fulfilled, packed, and ready to be shipped.*
3. *What pick-and-pass designs minimize the make span?*

1.4. APPROACH

To answer the research questions, the thesis will be structured as follows. A literature review is conducted in Chapter 2 to describe order picking, zone picking and existing research on system design. The review will further serve to identify the most important policy decisions in designing a pick-and-pass system. Chapter 3 elaborates on the methodology used to answer the research questions. It will describe the input variables which form the test set. The test set will be modeled in a zone picking simulation program. The performance metrics generated through simulation will further support the selection of top performing designs using Data Envelopment Analysis (DEA). Chapter 4 will provide a summary of the research findings. In this chapter, the main research question is answered through an analysis of overall high performing designs, as resulted from Data Envelopment Analysis (DEA). The research sub-questions are answered through analyses of high performing designs on each performance metric of interest. The final chapter expands on the implications for managers and possible applications of the research findings. It concludes with the limitations of the current study and directions for future research. A visual depiction of the approach is provided below.



2. LITERATURE REVIEW

As previously stated, order picking is the process of picking products from storage to fill customer orders. Additionally, it includes scheduling and releasing the orders to the shop floor, as well as discarding the collected items (De Koster et al., 2007). De Koster et al. (2007) distinguish between conventional (manual picking), and automated warehouses. As most warehouses use systems in the latter category (De Koster et al., 2007), this study addresses manual order picking systems alone.

There are three types of conventional order picking systems: picker-to-parts, parts-to-picker, and put systems. In picker-to-parts systems, the order picker walks to the aisle to pick the product from the shelf, which is either reachable by the picker directly - low level - or may require a lifting device for the picker to reach the item - high level. Low level systems are encountered most often in practice (De Koster, 2008) due to their simplicity, low setup cost and low maintenance cost (Yu, 2008).

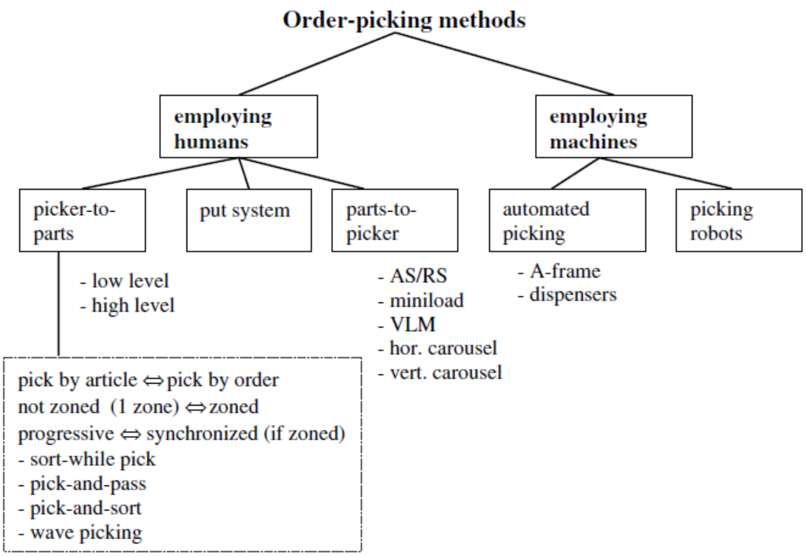


Figure 1 - Classification of order picking systems (De Koster, 2007)

In parts-to-picker structures, an automated storage and retrieval system (AS/RS) or a carousel will transport the items to the picker. After the items are picked, the AS/RS or carousel restores the remaining products to the storage space. Productivity is higher in such systems, but they are more expensive than picker-to-parts systems, and once installed, changes to the system are very costly (Yu, 2008). Finally, put systems entail the retrieval of items from storage, often in a tote or bin, from which order pickers can allocate items to the right customer order. They are effective for a large number of order lines with high time sensitivity (Yu, 2008). Figure 1 illustrates the different types of order picking systems.

The literature on order picking systems tackles four main operational matters. These are zoning and batching, layout, storage, and routing. The following sections address each of these except batching, which is not relevant to this thesis.

2.1 ZONING

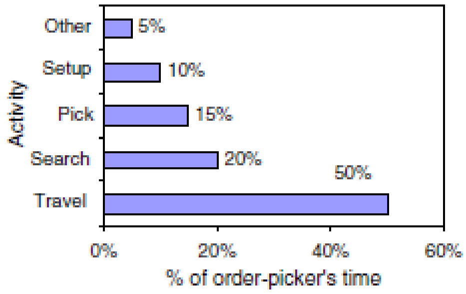


Figure 2 - Order picker time distribution (Tompkins et al., 2003)

A major "waste" identified in order picking systems is the travel and searching time of order pickers, which is estimated to account for as much as 70% of total working time (Tompkins et al., 2003) (see Figure 2). One of the most effective ways to shorten this wasteful time is separating the storage area of a warehouse into zones. Each order picker is then designated to one zone. As order pickers become more acquainted with their assigned area, they can locate products faster on the shelves, reducing searching time. Additionally, the time spent walking to the item is shortened due to the smaller covered surface (Yu, 2008) and traffic congestion is reduced (De Koster et al., 2012). However, despite the benefits of zoning, it has been addressed in literature only sparingly (Choe and Sharp, 1991).

In designing a zone order picking system, managers can choose between three strategies. If an order is only processed in one zone at a time and is passed on from one zone to the next until fully completed, the system is using a progressive zoning strategy, or pick-and-pass. Alternatively, order pickers could pick items for the same order simultaneously, all of which then go through a consolidation process before packing. This type of system is called synchronized zoning. While order integrity is lower than pick-and-pass due to the sortation and consolidation process, synchronized zoning has a faster response time (Jane and Laih, 2005). A limitation of both pick-and-pass and synchronized zoning is the delineation of the zones, which remain fixed in the system over time. This results in a need to balance the amount of work across zones, which can be a cumbersome task (Manzini, 2012). Failure to balance the workload can result to congestion in overloaded zones and inactivity in others, resulting in poor picker utilizations (Yu, 2008). A more recent trend in order picking is using bucket brigades, whereby pickers will pass the order to the next picker in the line as he/she is no longer working busy. The handover eliminates idle times and order build-up and generates a natural workload balance (Yu, 2008). In an application of bucket brigades, Bartholdi and Eisenstein (2005) found that next to eliminating the need to balance workload across zones, the throughput rate is increased compared to pick-and-pass systems. Although highly practical and attractive, bucket brigades have an application shortcoming, which is the requirement of a line-layout for the picking system (Yu, 2008).

An important, yet understudied topic in zoning literature is the division of the picking area into zones such that performance metrics are optimized (De Koster et al., 2012). De Koster et al. (2012) note that no studies in literature address zone number optimization under the assumption of identical zone size and aisles per zone. In the study conducted by Petersen (2002), different zone configurations are assessed on the travel distance within the zone. However, this study only answers part of the question, as zones have a pre-set storage capacity while aisle length and number vary. Instead, De Koster et al. (2012) make the assumption that the number of aisles is constant across zones and zones are identical in storage capacity in order to measure the optimal number of zones in a system. By varying the order size and pick list size, they measure the average throughput time in a batch order, synchronized zone picking system. An interesting study would be a similar analysis conducted in a pick-and-pass zone picking system, which would assess the optimal number of (identical) zones for different storage policies, routing policies and layout specifications.

2.2 LAYOUT

The design of the layout is a sensitive issue with strong implications for the travel time. Caron et al. (2000) found that the layout can affect the travel distance by more than 60%. There are several decisions to be made in this regard. At a strategic decision level, layout can translate to the process flow of the warehouse, which generally includes receiving, storing, picking and shipping, but can also include sorting, accumulating, packing or other additional processes, depending on the services performed in the warehouse (De Koster et al., 2007). At a tactical level, layout can translate to the number of segments and zones that make up the overall order picking system as well as their configuration within the warehouse. Van der Gaast et al. (2012) distinguish between single-segment and multi-segment routing. In the former, the main conveyor belt forms a loop to which all zones are connected. Alternatively, the system can have multiple segments, which totes only enter if they need to visit a zone within that segment. Multiple segments perform better in terms of throughput due to shorter travel distances of the totes. However, this benefit comes at the expense of higher investment and space requirements (Van der Gaast et al., 2012).

In both single and multiple segment pick-and-pass systems, a significant limitation is the congestion of the system. This happens especially at the beginning of the system, where totes may need to wait until a segment becomes decongested to enter the queue for a zone. Segment or zone blocking leads to inefficient use of resources, as pickers in subsequent segments may be temporarily idle (Van der Gaast et al., 2012). Additionally, blocking of the system impacts throughput time significantly. The solution to this problem is studied by Van der Gaast et al. (2012) by introducing a block-and-recirculate protocol. Hereby, when a segment or a zone's buffer space is fully occupied, the tote will not be allowed to enter the segment, but instead continue its path through the system and return to the segment at a later time. The main conveyor forms a loop, rather than a U-shape, which allows the tote to return to the zones it previously skipped (see Figure 3). They find that minimizing the number of zones and segments to be visited results in the highest performance. Additionally, the use of a block-and-recirculate protocol significantly improves throughput times and lowers congestion, therefore solving the limitation posed by standard pick-and-pass systems.

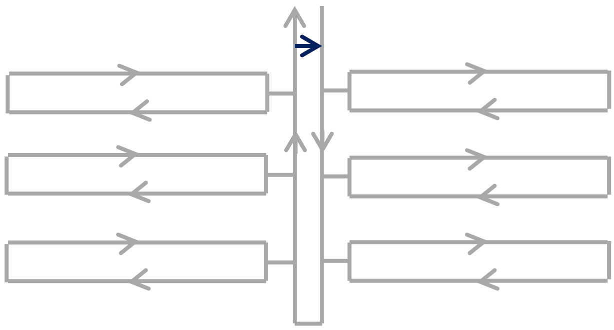


Figure 3 - Layout of a block-and-recirculate protocol configuration

An additional opportunity to reduce the distance travelled by totes in a pick and pass system is the introduction of shortcuts in the main conveyor loop. When the system configuration allows, totes should not have to travel across the entire main conveyor, but instead skip parts of the conveyor where it does not need to visit zones. Figure 4 exemplifies such shortcuts. Given the strong potential to reduce throughput time, the addition of shortcuts serves as a valuable analysis parameter.

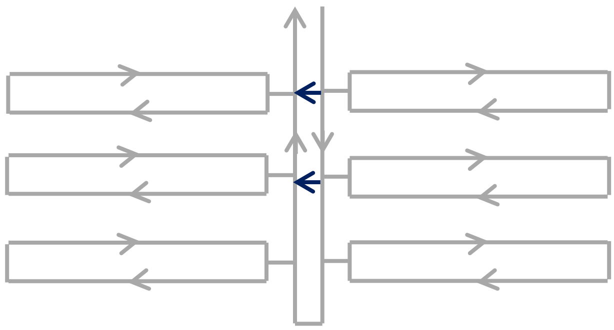


Figure 4 - Layout of a system with shortcuts

In addition to more tactical layout decisions, numerous researchers explore the effect of zone layout choices on travel distance and cost minimization. According to De Koster et al. (2007), the main decisions to be made in the planning process are the location of the depot, the length and number of aisles, the use of cross aisles and the number of storage blocks.

In relation to the depot location, aisles can either be parallel (see Figure 5), or perpendicular (see Figure 6). Both layouts have been considered in multiple studies (see Bassan et al., 1980; Rosenblatt and Rolls, 1984; Caron et al., 2000), usually with the goal of travel distance minimization. Roodbergen (2001), for example, studies aisle configurations that lead to minimal average tour length based on pick list and warehouse size. For layouts with no cross aisles, he finds that the optimal depot location is in the middle of the front cross aisle. A different study conducted by Roodbergen and Vis (2006) also targets average tour length minimization and further considers the effect of storage types in a cross aisle warehouse design. The results also show that the optimal solution is placing the depot in the middle of the front cross-aisle.

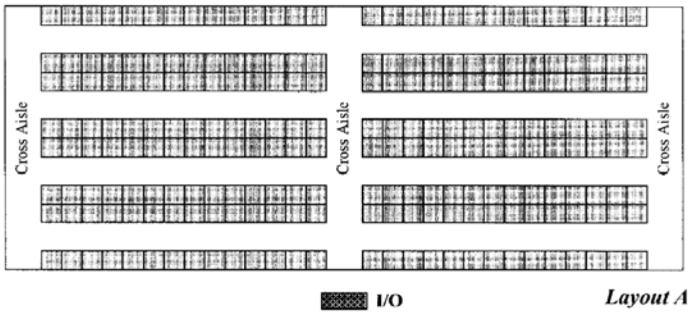


Figure 5 - Parallel aisles (Caron et al., 2000)

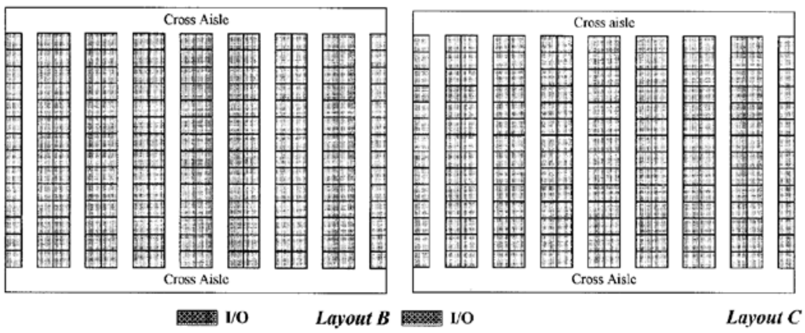


Figure 6 - Perpendicular aisles (Caron et al., 2000)

A second matter of interest in layout design is the number and length of the aisles. Several researchers study the effect of these variables on tour length using different routing and storage policies (Kunder and Gudehus, 1975; Hall, 1993; Caron et al., 1998, Caron et al., 2000). Kunder and Gudehus (1975) derive the number of aisles that minimizes travel distance as a function of aisle length and number of picks in each trip. Hall (1993) observed that the number of picks per trip influences the ideal number of aisles which minimizes distance travelled. Caron et al. (2000) remark the strong interdependency between layout and storage design. Their study shows that in warehouses with random storage or Cube-per-Order-Index (COI) storage with a low skewed ABC curve, the best performance is achieved with layouts that have the minimum possible number of aisles. Petersen (2002) uses simulation to find the impact of aisle length and the number of aisles on travel time in zone order picking systems. The results show the optimal number of aisles is dependent on zone size. More aisles are preferred for large zones and short pick lists, whereas fewer aisles are better for small zones and long pick lists. Petersen's (2002) research also clarifies the link between zone picking system and aisle length and number, when aisles are perpendicular to the main conveyor. They state the significance of order size, number of zones and batch size on determining the optimal setup. Pick-and-pass is characterized by short pick lists and many small zones, meaning that a larger number of aisles will have the strongest effect in reducing picker travel. Whereas wide and shallow aisles are preferred for sequential zone picking, in batch picking the long pick lists for each zone suggest that fewer aisles are more efficient in reducing travel.

Closely connected with the aisle length and number is the inclusion of cross aisles. Researchers seem to agree that the use of cross aisles is generally beneficial and decreases travelled distance (Roodbergen and De Koster, 2001a; Roodbergen and De Koster, 2001b; Vaughn and Petersen, 1999). Vaughn and Petersen (1999) look into the impact of increasing the number of cross aisles on picking efficiency. The addition of cross aisles is increasingly beneficial as the ratio of aisle length to cross aisle width rises. Roodbergen (2001) finds that travel time is lowered when the warehouse has two blocks rather than one for small pick lists (less than 50 items). However, for large pick lists, small warehouses should have only one block. Roodbergen and De Koster (2001b) analyze the impact of cross aisles on performance additionally taking into consideration that the route selected should minimize the travelled distance.

2.3 STORAGE

After selecting a layout for the zones, managers must choose a storage policy. Most often used are random storage, closest open location storage, dedicated storage, full turnover storage, and class based storage (De Koster et al., 2007).

In random storage assignment, products are allocated arbitrarily to one of the available spaces. It can only be applied to computerized warehouses and while it is the easiest policy to implement, it is not ideal (Le Duc and De Koster, 2005) It is suitable for warehouses which have a space limitation, as they are highly space efficient. However, this comes at the expense of increased travelled distance (Choe and Sharp, 1991). In warehouses that are not computerized, pickers may follow a similar assignment pattern, called closest open location storage. As the name suggests, pickers will store items in the first available location they find. This leads to a high utilization of the front of the warehouse and low utilization at the back (De Koster et al., 2007). According to Hausman et al. (1976), when items are moved only by full pallets, random and closest open location storage achieve similar performance levels.

A third policy is dedicated storage. Hereby each product has a designated storage location, leading to inefficient space utilization. However, pickers can memorize the locations of each product, which decreases the overall searching time (De Koster et al., 2007). Thus, dedicated storage is more appropriate for situations where warehouse space is inexpensive and fast order fulfillment is vital. Additionally, dedicated storage is extremely powerful when combined with other policies. Yu (2008) marks that two sets of rules are described in research studies as the base for dedicated storage. They are Cube-per-Order-Index (COI) and volume based strategies (either by frequency or turnover).

The COI is the ratio of the space required to store the product to the number of trips necessary to fulfill the product's demand (Heskett, 1963; Heskett, 1964). Intuitively, low COI products are stored closer to the depot whereas high COI products are stored further away. COI is the best strategy to minimize picker travel in single-block warehouses (Jarvis and McDowell, 1991). COI is a type of turnover storage, whereby the highest turnover generating products are located closer to the depot (De Koster et al., 2007). Full turnover storage suffers from a significant drawback. When product demand and variety fluctuate, the method does not perform well, requiring frequent reshuffling. Caron et al. (1998) further remark that this method is more information intensive than random storage, making it a less attractive storage assignment. A benefit of volume based policies is that picker travel time is diminished (Petersen, 2002). Petersen (2002) finds that volume-based storage is superior to random storage.

One of the most popular storage policies employed by managers is class-based storage, which combines several of the methods mentioned above. Items are grouped into several categories based on a specific characteristic, such as COI or volume. Within each category, products are stored randomly. There are two distinct ways to arrange the product groups in a warehouse, within-aisle and across aisle (De Koster et al., 2007) (see Figure 7).

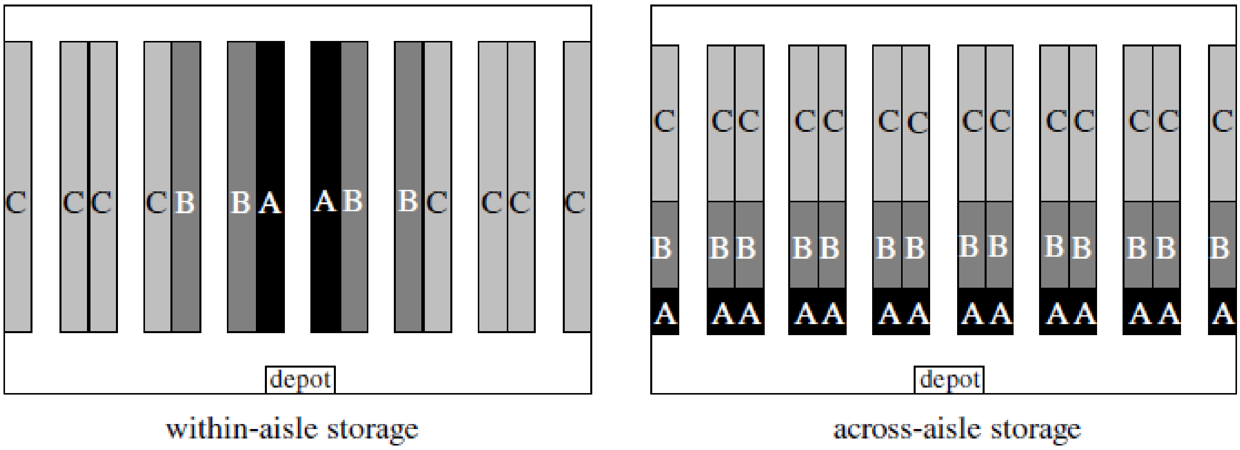


Figure 7 - Class based storage types (De Koster et al., 2007)

Jarvis and McDowell (1991) recommend that each aisle store only one class of products, and recommend within aisle storage rather than across aisle storage. Several studies support this. Petersen and Schmenner (1999) and Petersen (1999) found that within aisle has the strongest cut in travel time, resulting in 10-20% savings over across-aisle under various routing strategies. Petersen (2002) also finds that within aisle storage outperforms across aisle, both of which surpass random storage. Petersen et al. (2004) recommend using 2-4 classes. Le Duc and De Koster (2005) find that across aisle storage is better when combined with return routing. The contradictory results could be explained by Le Duc's (2005) study which finds that storage policy performance is highly dependent on the routing policy employed. For studies comparing within-aisle and across-aisle storage see Petersen (1999), Petersen (2000), Petersen and Aase (2004), Petersen et al. (2004) and Roodbergen (2005).

The above policies do not account for product complementarity and correlation. Family grouping storage takes this factor into account, pairing products that are often times ordered together in the same storage space. According to Rosenblatt and Roll (1984), this policy requires a larger storage space than random storage. A precursor to employing this strategy is being able to calculate the correlation between products.

2.4 ROUTING

Equally popular to the study of storage policies is the performance of different order picker routing policies, especially with the objective of travel distance minimization. Similar to the case of the Travelling Salesman Problem, an order picker has to travel to different points within the warehouse to pick items on his list. The itinerary followed is based on the routing policy selected. Route optimization methods are available for the Travelling Salesman Problem in the context of order picking for warehouses with one or two blocks (Cornuéjols et al., 1985; Ratliff and Rosenthal, 1983; Roodbergen and De Koster, 2001a, 2001b; De Koster and Van der Poort, 1998). However, more complex systems would require extensive computation to reach an optimal routing model. Consequently, several heuristic methods are employed in practice. The most common routing policies for single block warehouses are S-shape or traversal, return, midpoint method, largest gap and combined heuristic.

Each aisle containing an item to be picked is crossed fully with an S-shaped policy; the other aisles are not crossed. After picking the last item on the list, the picker returns to the depot. Return routing is similar, but instead of crossing the aisle entirely, the picker exits the aisle on the same side as he entered. Another routing policy is the midpoint heuristic. Hereby, the storage area is split into two and pickers follow a return policy within each half. Midpoint routing is preferred to S-shape when the average number of picks per aisle is one (Hall, 1993).

A similar policy to midpoint is largest gap. Although more complex, this largest gap routing is more efficient than midpoint routing (Hall, 1993). The final method is combined or composite heuristic and requires dynamic programming to establish the picking route (Roodbergen and De Koster, 2001a). Combined routing seems to be the best heuristic method available (Roodbergen, 2001; Roodbergen and De Koster, 2001a).

2.5. PERFORMANCE METRICS

The literature on warehouse performance assessment is rather limited. A large number of studies address single output systems, some considering only a single input. Tompkins et al. (2003) refer to the approach of assessing the effect of a single input on a single output as the ratio method. Narrowing the focus of research to this extent poses the danger of sub-optimization of the overall system. Goetschalckx and Ashayeri (1989) found service level maximization as the most frequent objective for order picking systems. Additionally, De Koster et al. (2007) stress the prevalence of travel distance optimization studies in more recent warehousing literature. The local optimization shortcoming of warehousing literature is captured by Rouwenhorst et al. (2000) and Gu et al. (2007).

Several researchers conduct multiple output studies. Collins et al. (2006), for example, evaluate warehouses on a set of four performance criteria: picking accuracy, inventory accuracy, storage speed, and order cycle time. In an international study of 65 warehouses, De Koster and Warffemuis (2005) compare performance differences between America, Asia and Europe, with no significant distinctions found. Revisiting the study, De Koster and Balk (2008) employ Data Envelopment Analysis (DEA) to discover that European warehouses outperform Asian and American equivalents, showcasing the strength of DEA in multiple input, multiple output comparisons. Hackman et al. (2001) also use DEA to compare efficiency among warehouses and find that the best performers are small and capital light warehouses.

2.6 DATA ENVELOPMENT ANALYSIS (DEA)

A popular method used to evaluate the relative efficiency of a particular Decision Making Unit (DMU) is Data Envelopment Analysis (DEA). The tool is most powerful in comparing models based on multiple inputs and multiple outputs, where the measurement units differ. Unlike other types of analysis, DEA requires only a minimum set of assumptions that allows DMUs, to be evaluated against one another on a set of performance measures (Chen et al., 2010).

Each DMU is able to produce a set of outputs with a specific amount of inputs. By comparing the ability of each DMU to transform inputs into outputs, DEA will establish the most efficient DMUs, which collectively form the efficiency frontier. For any DMU on the efficiency frontier, no combination of other DMUs could perform better. All DMUs that are not on the efficiency frontier are considered inefficient. DEA assigns a relative efficiency percentage to the inefficient DMUs, based on their position in relation to the efficiency frontier.

Due to its versatility, DEA is widely used in banking, agriculture, health care, transportation and education (Liu et al., 2013). It is also used in benchmarking warehouse operations (Hackman et al., 2001; McGinnis et al., 2005; De Koster and Balk, 2008; Chen et al., 2010).

The popularity of DEA lies in its many benefits. DEA requires no or few assumptions to compare DMUs against one another. Multiple inputs and outputs can be considered, and they can be measured using different units. Within the set of DMUs, DEA will assign an efficiency percentage relative to the most efficient unit in the DMU set.

However, DEA also has its limitations. As previously mentioned, DEA will compare each DMU with the rest of the DMUs in the set. While this means that it can rank them according to their efficiency, DEA is not able to measure the most efficient theoretical DMU. Therefore, it is a valuable tool in comparing a set of points, but not in finding an optimal solution. Additionally, DEA uses linear programming to calculate the relative efficiency of each DMU, which can cause computational issues when the set of DMUs is very large.

3. METHODOLOGY

This section describes the decision variables and performance indicators used for setting up the simulation. It first introduces the experimental parameters and the simulation setup. For each decision variable, a wide variety of parameters are tested. The policy sets resulting from the combination of the decision factors are modelled using the Zone Picking module of the Material Handling Simulation Package (MHSP) software. The MHSP software automatically calculates the system cost and the average throughput time based on the experimental setup. Finally, the last section of the chapter describes the Data Envelopment Analysis (DEA) framework, and the linear program used to determine the set of efficient models, based on the data provided by the simulation in MHSP.

3.1. SELECTION OF DECISION VARIABLES AND PERFORMANCE METRICS

One of the limitations of the order picking literature, as shown in the previous section, is that researchers focus on studying one design choice at a time, which can lead to local optimization. Rather than conducting a study on the effects of a particular design choice on a single performance indicator, the present study will address multiple decision factors considered in the design of an order picking system.

The system to be analyzed is a low level picker-to-parts zone order picking system with a basic process flow. The strategy for picking is pick-and-pass, whereby totes travel through the system and are filled sequentially along their path.

As mentioned throughout the literature review, a few elements are of particular interest and their interaction could have interesting outcomes for managers confronted with the design of a pick-and-pass system. One such decision factor is the optimal number of zones in a system given the assumption that all zones and aisles are identical in size. This, together with the grouping of zones in segments, has a strong effect on the order throughput time of the system. Additional zones will typically reduce congestion, meaning that totes spend less time waiting in the system before a picker will attend to it. However, the overall effect on throughput time cannot be anticipated as totes will have to visit more zones and travel longer distances to reach the zones in a system with more segments and zones/segment.

Also rarely studied in zone order picking literature is the effect of a block-and-recirculate protocol. As Van der Gaast et al. (2012) point out, allowing totes to temporarily skip a blocked segment and return to it at a later time is successful in tackling system congestion and spreading the amount of work throughout the system. Allowing totes to recirculate raises similar questions on the travel time trade-off as varying the number of zones and segments. The waiting time for a tote to be processed at a zone is reduced. However, the distance travelled is longer when a tote will have to return to a segment it bypasses on its first journey on the conveyor, which will increase the throughput time.

Next to recirculation, adding shortcuts in the system when possible should have a strong impact on the order throughput time, as totes will travel on average much less by avoiding parts of the warehouse they do not need to visit. Given its potential to reduce throughput time, the addition of shortcuts also warrants further investigation.

The elements selected so far determine the layout of the system. However, researchers agree on the strong interaction between layout and storage policy in determining the performance of a system (Caron et al., 1998; Roodbergen, 2001;Le Duc, 2005; Le Duc and De Koster, 2005). Therefore, the storage policy also has a large effect on the order time. To keep the study manageable, only two popular storage policies will be taken into account for further analysis: random and class-based. Although it would provide further insight to also include routing policy in the study as a decision variable, the addition of this element will be omitted to prevent the policy set from expanding too much.

These five input variables form the basis of the simulation test set: number of zones per segment, number of segments, recirculation, shortcuts and storage policy. With regard to the performance metrics, all systems will be analyzed in terms of costs, make span and average throughput time. Total costs include investment and operating cost and are a central point in deciding which system to employ. Similarly, average throughput time is an important performance metric used by managers and therefore will be examined in this thesis. Although only throughput time and cost will be used for Data Envelopment Analysis, models will be briefly compared on other metrics as well. Figure 8 depicts the sequence of the policy set modelling, the simulation and the data analysis.

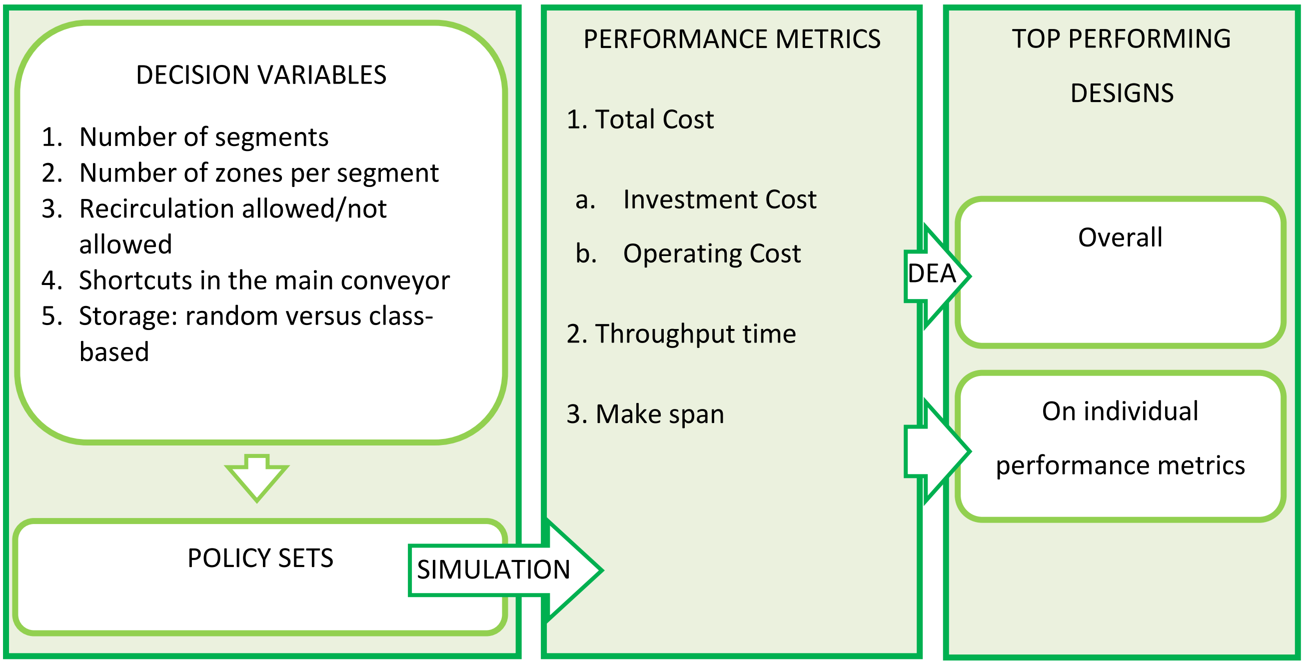


Figure 8 - Research design

3.2 SIMULATION SETUP AND EXPERIMENTAL PARAMETERS

In Figure 9, an example of a warehouse configuration is presented. At the beginning of the system, the totes enter the system via a source and travel on the conveyor belt. The layout of the warehouse is assumed to be U-shaped, such that the tote source and packing station are at the same side of the warehouse. The main conveyor belt is located in the middle of the system, meaning that segments expand outwards from the main conveyor.

All models have either four, six or eight segments, which are all connected to the main conveyor. The warehouse design is symmetrical across both directions of the main conveyor belt. Within each segment, there are two, four or six zones of equal storage capacity and size. The number of zones is the same in all segments in any given model. The total number of zones in a system varies across models from eight (in a configuration with four segments and two zones per segment) to forty-eight (in the configuration with eight segments and six zones per segment) There are in total nine combinations of segments and zones/segment:

(Segments, Zones/segment) = {(4, 2); (4, 4); (4, 6); (6, 2); (6, 4); (6, 6); (8, 2); (8, 4); (8,6)}.

When more totes try to enter the system, congestion gradually builds up. Implementing a block-and-recirculate protocol helps with this issue (Van der Gaast et al., 2012). To apply this protocol, the main conveyor belt U-shape is closed into a loop (see Figure 9). When a tote needs to visit a zone which is temporarily full, it will not enter the segment and instead will continue to travel on the main conveyor belt. In other words, when the tote arrives at the entrance to a segment (denoted by a decision point on the main conveyor in Figure 9), the system checks whether there is still space for the tote in the queuing area of the zone it needs to visit. If the queuing area of the zone is not yet full, the tote will leave the main conveyor and enter the segment. However, if the buffer space of the zone is full, the tote will not be allowed to enter the segment and instead continue to travel on the main conveyor belt towards the other zones it needs to visit. Prior to sending totes to the packaging station, the system checks if each tote still needs to pass through any zones. If the answer is yes, it will not allow the tote to exit the system and instead, it will redirect it back onto the main conveyor belt to travel through the system again. The models which allow totes to recirculate are setup so that totes in the system have priority over new totes released by the source, in order to prevent blocking.

Another decision variable is the addition of shortcuts in the system. The shortcuts connect the sides of the U created by the main conveyor (see Figure 9). As a tote travels towards the back of the warehouse, at the exit of each segment, the system checks whether the tote needs to visit zones further back in the warehouse. If that is the case, the tote continues travelling towards the back. However, if the tote does not need to visit zones further back into the warehouse, it will be redirected via a shortcut to the other side of the main conveyor and begin travelling towards the packaging station, visiting any remaining zones on the way out.

In order for a customer order to be filled, a tote is assigned the zones it must visit upon its release into the system. As it travels along the main conveyor, it will encounter specific decision points at the junction with segments. Here, the system will check if the tote must visit a zone in that segment. If it does, then the tote will be directed into the segment and off the main conveyor. Otherwise, it will continue to travel on the main conveyor. As stated above, an additional check is performed at these decision points in models with a block-and-recirculate protocol. Totes will only be allowed to enter the segment if the zone queue is less than a pre-determined threshold. For every five storage locations in the zone there is a queuing space on the conveyor. The threshold is equal to the number of queuing positions for each zone. The queuing area is connected with the number of storage locations in a zone for practical reasons: a large zone will also be visited my more totes than a small one.

Consequently, it is useful to accommodate a longer queue in large zones and a smaller queue in small zones. The purpose of setting a threshold is to avoid blocking the segment. If the number of queuing totes does not exceed the threshold, the tote is allowed to enter the segment. Within a segment, additional decision points direct the tote towards the zone(s) it must visit. At each of these decision points, the system checks if the tote needs to visit the closest upcoming zone and will direct the tote accordingly. Each zone has a buffer area, as described above.

Factors	Levels	Policies
Segments	3	(1) 4 (2) 6 (3) 8
Zones/ segment	3	(1) 2 (2) 4 (3) 6
Shortcuts	2	(1) None (2) Connecting main conveyor
Recirculation	2	(1) Not allowed (2) Allowed
Storage policy	2	(1) Random (2) Class-based

Table 1 - Experimental factors and levels

Once it reaches the zone, a picker will determine the route to collect the items from his zone in one trip. He will travel between locations using taxicab geometry and locate his next destination based on the nearest neighbor algorithm. The picker only returns to the depot when he has picked all items for the tote active in the zone. The total time spent retrieving items for a tote in one trip is calculated by adding the time spent walking and the time spent picking the items from a shelf. The picker walks with a speed of 2m/s. The actual item picking time is variable and picked from an exponential distribution with the rate of 0.2 picks per second.

Each warehouse has in total 432 locations. This number is selected to ensure that within each combination of zones and segments all zones have the same storage capacity. This is the case in all but one configuration. In the model with eight segments and four zones, the zones alternate between thirteen and fourteen shelves each. The storage area for each zone is five aisles deep and varies in length

Element	**Cost (€)**
Source	1,000
Packing station	3,000
Straight conveyor	1,000
Corner conveyor	1,500
Three-way conveyor	2,000
Four-way conveyor	2,500
Zone	2,000
Shelf	500
Picker	10 (per hour)
Travel parameters	
Walking	2 m/s
Picking time	EXP(0.2) picks/sec
Conveyor travel	1 m/s
Demand parameters	
Orders per simulation	1000 orders
Order generation rate	EXP (0.0167)
Order size	UNIF(1,5)
Simulation parameters	
Number of simulations	20 per model

Table 2 - Experimental setup

as needed (see Appendix 1). The shelves are positioned such that the depot is as close as possible to the center of the front aisle. Several researchers agree that this is the optimal location (Roodbergen, 2001; Roodbergen and Vis, 2006). In MHSP, the aisle configuration is not relevant. The pickers are allowed to travel through shelves, which they do according to taxicab geometry. Due to these built-in settings, the aisle configuration is irrelevant and does not affect the distance travelled by the picker.

By default, the storage policy is set as random. However, as previously mentioned it would be interesting to observe the interaction of a change in storage policy with the other variables previously described. Consequently, two storage policies will be compared: random and class-based storage. In the latter case, within-aisle class-based storage will be used, as academics seem to agree that within-aisle is more efficient that across-aisle storage (e.g. Jarvis and McDowell, 1991; Petersen 1999; Petersen & Schmenner, 1999). Petersen et al. (2004) recommend using between two and four classes. For this study, three classes will be used. The storage area is divided as follows: 10% of shelves are assigned to A-products, 20% to B-products and 70% to C-products. Of all ordered items, 54.54% are A-products, 27.27% are B-products and 18.18% are C-products.

Next to the layout and storage previously explained, there are other simulation parameters that affect the performance metrics resulting from simulation. Most of these are fixed by the program, such as the cost of the warehouse elements. These are listed in Table 2.

Three essential parameters make up the demand for products in the warehouse. These are the number of orders per simulation run (the number of totes launched in one simulation), the launching frequency (the rate at which orders arrive in the system) and the number of items in each customer order (the minimum and maximum order size). The number of orders is 1000 orders for each simulation run as the performance metrics seem to stabilize by this point. Totes are launched according to an exponential distribution with the average rate of 0.0167 totes/ second (or one tote every minute). In the policy sets that allow recirculation and shortcuts, the system has a tendency to block when the order arrival rate is too high. To solve this issue, one could set a maximum number of totes allowed in the system to avoid such a gridlock. However, this causes totes to wait in the system for a very long time, significantly increasing the time from receiving the order until order completion. Consequently, the rate is set at 0.0167 totes/ second, which is the highest rate where totes do not cause a gridlock. Order size is determined based on a uniform function with minimum of 1 item and a maximum of 5 items.

Finally, the number of simulations per model is determined by the point where the average performance is stable and the standard deviation is acceptable (see Tables 4 and 5 for a summary of the average throughput Confidence Intervals). For each model, 20 simulations will be run. Increasing the number of simulations past this point has a minor effect in reducing the standard deviation. It should be noted that the configuration with 4 segments and 2 zones per segment has very high standard deviation across the simulations regardless of how much the number of simulations is increased. The high variability in average throughput time is likely caused by the small number of total zones and segments, which cause a strong difference in processing customer orders with different numbers of items.

The MHSP software simulation output consists of several performance metrics. The ones relevant to this thesis are the average throughput time, the make span, the total cost, the investment cost, the operational cost, and utilization.

Throughput time is defined as the time elapsed between the customer order arrival (when it was generated by the system) until the customer order has been fulfilled and is ready for shipment (is has passed through the packing station). For a given model, the outcome of MHSP is the average throughput time for that model under the simulation parameters set. For every 1000 orders released into the system, MHSP calculates the average throughput time of the totes. Over 20 simulations of 1000 orders, MHSP then averages the individual simulation run throughput time values. Additionally, MHSP also outputs the variance of this set of values, which was used to calculate the confidence intervals. In this thesis, throughput time refers to the average of the 20 simulation average throughput times.

The make span is defined as the time elapsed between the first customer order arrival (when it was generated by the system), until there are no more customer orders in the system (all have been packed and the system is empty). The output of MHSP is the average make span of the 20 simulations.

The total cost of a system is calculated as the sum of investment and operational costs. The investment cost of a system is calculated by MHSP as a sum of the individual costs of the elements that make up that particular model. However, for the purpose of this analysis, the investment cost of the model is calculated as the proportion of the investment cost applicable to the make span timeframe, assuming five year straight depreciation with no residual value, 260 working days per year and 8 hours of work per day. The operational cost for each model is made up of labor cost only and is equal to the product of the number of pickers, the hourly wage, and the make span of the model. For the purpose of further analyses, the total cost will be equal to the sum of the pro-rated investment cost and the operational cost of each system.

Finally, utilization is also measured for the pickers. For each picker, the utilization is measured as the time totes are active in their zone divided by the make span of the simulation. These values are averaged over the 20 simulations to result in a single picker utilization for each model.

It is important to note that MHSP does not allow pickers to take breaks. Therefore, the operational cost, make span and throughput time are all influenced by the assumption that order pickers are always productive and present at their stations. A consequence of this is the lack of tote build-up due to pickers taking short breaks, which is a likely scenario in real situations. Additionally, utilization will never reach 100%, as the pickers are partly idle in the warm-up period and between the

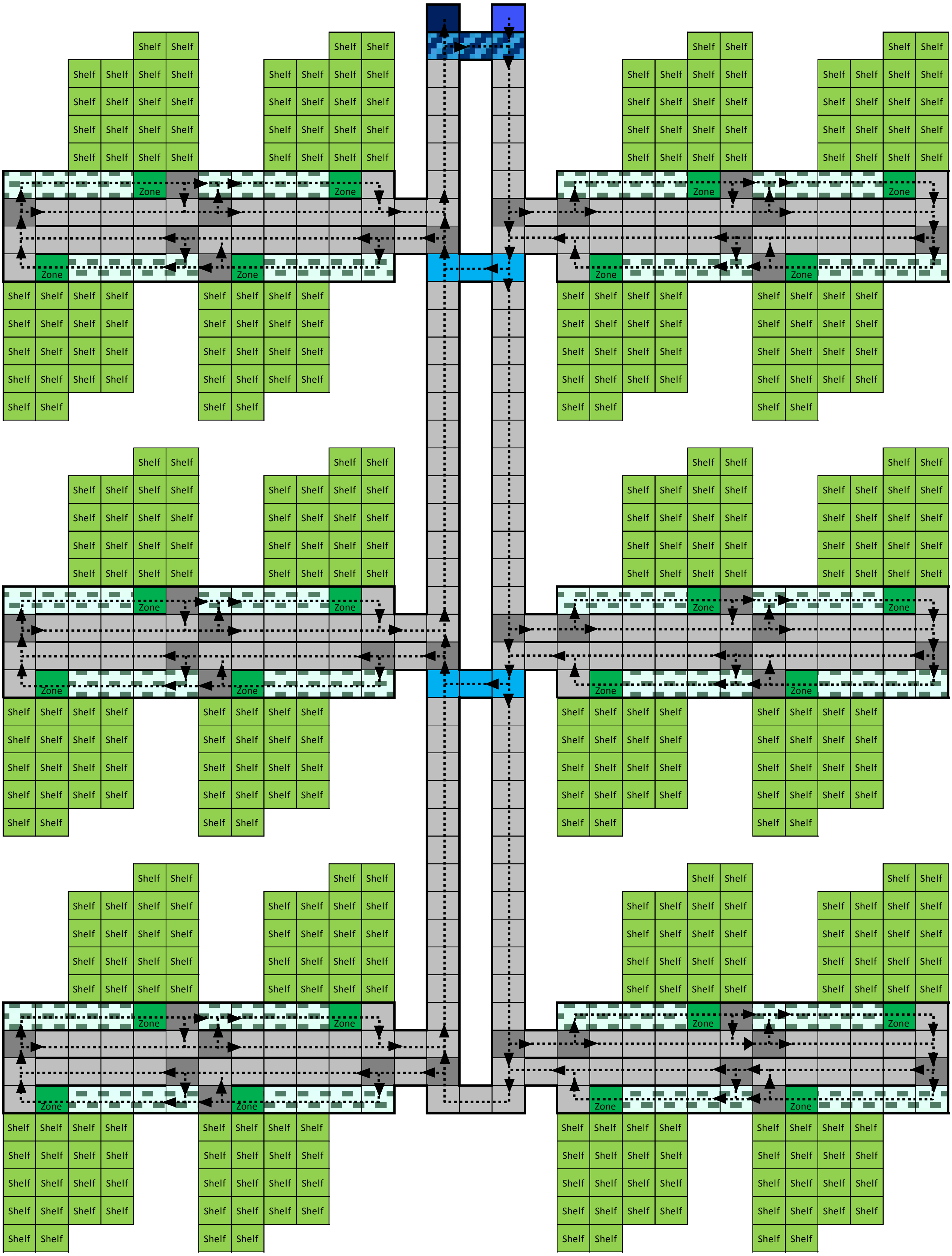
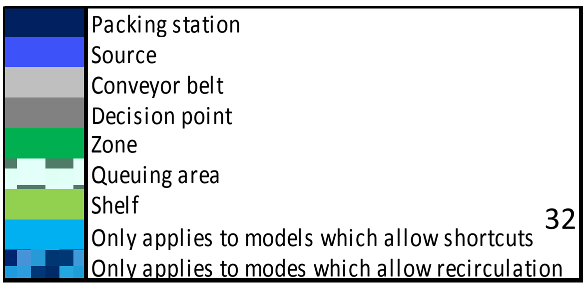


Figure 9 - Configuration of a model with 6 segments and 4 zones/ segment



3.3 DATA ENVELOPMENT ANALYSIS (DEA)

As mentioned before, DEA has several benefits which make it attractive in analyzing the models in this thesis. The need for only few assumptions and the ability to compare models across different unit measurements will enable DEA to rank models by their relative efficiency based on their performance in terms of total cost and average throughput time.

The previous two sub-chapters introduce the policy sets, or decision making units (DMUs) which are assessed using DEA. The data set generated through simulation in MHSP includes the total, investment, and operational costs, the make span and average throughput time for each DMU. The input for DEA is the total cost needed to operate the warehouse during the processing of 1,000 customer orders.

The output used in DEA is not as straight forward. The objective of DEA is to calculate the relative efficiency of the DMUs. To do so, it will find the benchmark by searching for the DMU that is able to create the highest output with the least input. However, the output to analyze in this case is average throughput time, for which the objective is minimization, rather than maximization.

To reverse this, the output data is calculated as follows. The maximum average throughput time is selected from the average throughput times of the 72 DMUs. The output measure for each DMU is equal to the difference between maximum average throughput time and the average throughput time of that DMU. Thus, the goal is to maximize this difference by minimizing the total cost of processing the orders. The linear program used for DEA is given by the following:

$$\min \theta_0$$

$$\text{s.t.} \ \sum_{i=1}^{m} \lambda_i * x_i \leq \ \theta_0 * x_0$$

$$\sum_{i=1}^{m} \lambda_i * y_i \geq \ y_0$$

$$\lambda_i \geq 0 \text{ for i } = \ 1,2, \dots, \text{m}$$

$where: x_i = operational\ cost\ of\ DMU_i$

$$y_i = \max avg\ throughput\ time\ of\ all\ DMUs \\ - avg\ throughput\ \ time\ \ of\ DMU_i\ being\ studied$$

$x_i = operational\ cost\ of\ the\ DMU\ being\ studied$

$$y_0 = \max avg\ throughput\ time\ of\ all\ DMUs \\ - avg\ throughput\ \ time\ \ ofthe\ DMU\ being\ studied$$

$\theta_0 = relative\ efficiency\ of\ DMU_0$

$\lambda_i = weight\ given\ to\ DMU_i\ to\ dominate\ DMU_0$

The linear program is run once for each of the DMUs, in total m = 72 times, to establish their relative efficiency (denoted by θ). However, there are several software alternatives available, which can perform this task automatically. Therefore, the inputs and outputs are analyzed using the DEA software called Efficiency Measurement System (EMS), version 1.3.0, developed by Holger Scheel. The results of the analysis are presented in the following chapter.

4. RESULTS

This chapter will present the results of the analysis conducted as described in the methodology. The results of the simulation in MHSP are briefly introduced. Following this, the outcome of the DEA is presented, followed by additional insights gathered from the data.

4.1 SIMULATION RESULTS

As previously mentioned, the policy sets are modelled in the Zone Picking module of the MHSP software. Using the experimental setup described in sections 3.1 and 3.2 a data set is created encompassing the performance parameters for each policy set. The output of the simulation includes average throughput time and throughput time variance, the make span of the system, the total, investment, and operational costs, and utilizations associated with each set. The results are presented in Tables 4 and 5. Here it is clearly visible that the variance and standard deviation of the policy sets with four segments and two zones per segment is very high. This happens regardless of how much the number of simulations is increased and could be accounted for by the small number of zones, which cause high variability in the processing times of different totes. Additionally, in models with only eight zones, totes could be queuing for long periods of time before reaching each zone they must visit.

The minimum, maximum and average values of the parameters across the 72 sets are presented in Table 3. It is noteworthy to mention the high difference between minimum and maximum average throughput times. This difference suggests that the interaction of the decision variables has a strong impact on the throughput time. There is high variability in the time that totes need to travel through the system, due to different customer order sizes and distances to cover. However, over the span of 1000 orders, this effect is partially suppressed. Therefore, while the make span varies as well, it fluctuates less than the average throughput time.

As expected, the total costs vary considerably across policy sets. There are two components to the total cost: investment cost and operational cost. The addition of segments and zones to a model will generate large expenses. Although it also affects costs, implementing shortcuts and recirculation policies in a model is much less expensive and causes only small increases in the investment costs, which results in the clusters visible in Figure 10. Operational costs tend to follow the same pattern as investment costs: the more complex the system layout, the higher the costs.

The effect is amplified by the increasing number of pickers in systems with more zones as well as by an increase in the distance travelled which occurs when totes have to visit more segments across a larger warehouse.

	Time in system (sec)	Make span (h)	Total cost	Investment cost	Operational cost
Minimum	561,61	3,50	€ 490,98	€ 207,30	€ 283,68
Maximum	765,83	3,62	€ 2.079,17	€ 341,37	€ 1.738,56
Average	644,43	3,56	€ 1.112,85	€ 257,59	€ 855,26

Table 3 - Summary of policy set performance

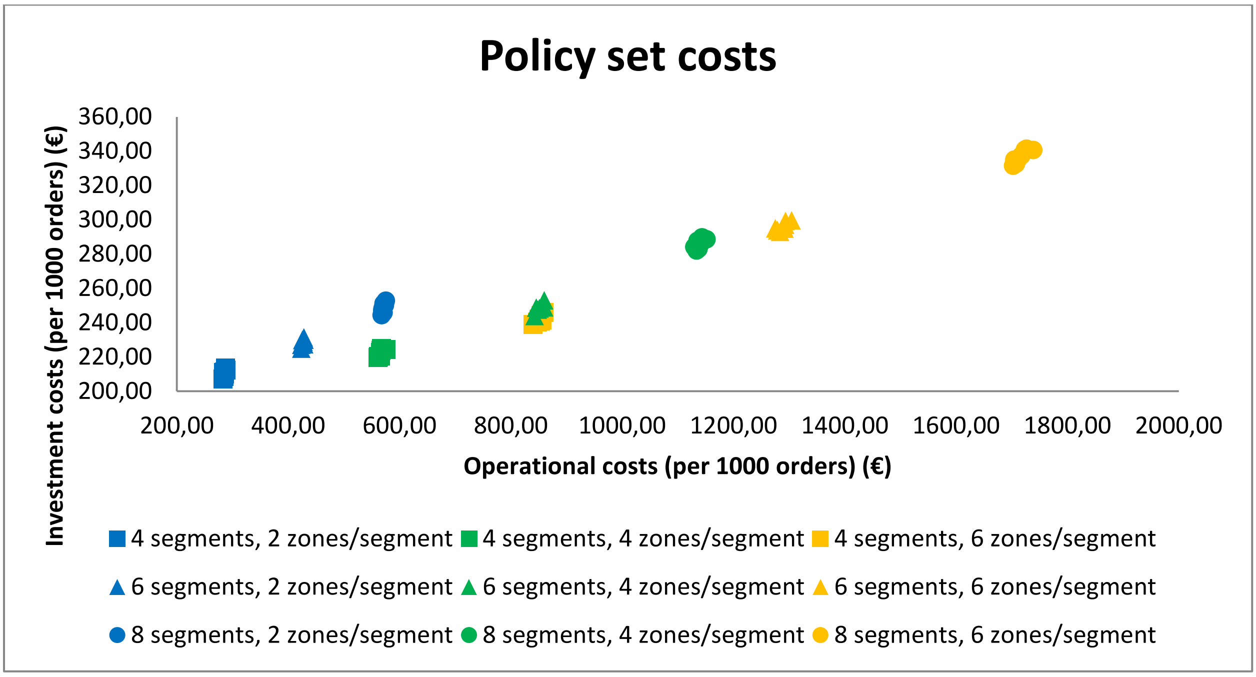


Figure 10 - Policy set costs based on number of segments and zones/segment

The high variability of throughput time and costs across the policy sets warrants further investigation in order to establish the best performing models. To accomplish this, the simulation results will form the basis for DEA. The setup and results of DEA are described in the following sub-section.

DMU	Segments	Zones/ segment	Recirculate	Shortcut	Storage	Average throughput time (seconds)	Throughput time std. dev. (seconds)	LCL	UCL	Make span (hours)	Operational costs (per 1000 orders)	Investment costs (per 1000 orders)	Total costs (per 1000 orders)	Average picker utilization
1	4	2			random	765,71	59,73	739,53	791,89	3,57	€ 285,36	€ 208,53	€ 493,89	70%
2	4	2			ABC	702,90	22,60	693,00	712,80	3,55	€ 283,68	€ 207,30	€ 490,98	66%
3	4	2	R		random	745,16	25,44	734,01	756,31	3,58	€ 286,00	€ 211,06	€ 497,06	70%
4	4	2	R		ABC	700,08	20,17	691,24	708,92	3,60	€ 288,00	€ 212,54	€ 500,54	65%
5	4	2	R	S	random	721,68	25,29	710,60	732,76	3,60	€ 287,76	€ 213,40	€ 501,16	70%
6	4	2	R	S	ABC	669,92	19,40	661,42	678,42	3,55	€ 284,32	€ 210,85	€ 495,17	65%
7	4	2		S	random	726,56	44,87	706,89	746,23	3,57	€ 285,92	€ 209,97	€ 495,89	70%
8	4	2		S	ABC	661,35	21,31	652,01	670,69	3,58	€ 286,00	€ 210,03	€ 496,03	65%
9	4	4			random	598,38	6,03	595,73	601,02	3,60	€ 575,68	€ 224,18	€ 799,86	29%
10	4	4			ABC	590,32	5,96	587,71	592,94	3,54	€ 566,08	€ 220,44	€ 786,52	27%
11	4	4	R		random	605,56	4,78	603,46	607,66	3,54	€ 566,24	€ 222,55	€ 788,79	29%
12	4	4	R		ABC	595,93	4,95	593,76	598,10	3,56	€ 570,24	€ 224,12	€ 794,36	26%
13	4	4	R	S	random	576,00	4,89	573,86	578,15	3,54	€ 566,88	€ 223,82	€ 790,70	29%
14	4	4	R	S	ABC	567,75	6,18	565,05	570,46	3,56	€ 567,84	€ 224,96	€ 792,80	26%
15	4	4		S	random	571,97	5,24	569,68	574,27	3,52	€ 562,56	€ 220,09	€ 782,65	29%
16	4	4		S	ABC	565,60	5,35	563,25	567,94	3,51	€ 561,12	€ 219,52	€ 780,64	27%
17	4	6			random	603,39	4,40	601,46	605,32	3,56	€ 853,92	€ 240,85	€ 1.094,77	18%
18	4	6			ABC	594,65	5,46	592,26	597,04	3,57	€ 855,84	€ 241,39	€ 1.097,23	16%
19	4	6	R		random	607,91	4,62	605,89	609,94	3,50	€ 840,00	€ 238,94	€ 1.078,94	18%
20	4	6	R		ABC	600,15	4,45	598,20	602,10	3,55	€ 851,04	€ 242,08	€ 1.093,12	16%
21	4	6	R	S	random	579,31	4,90	577,17	581,46	3,59	€ 860,40	€ 245,78	€ 1.106,18	18%
22	4	6	R	S	ABC	574,94	5,75	572,42	577,46	3,56	€ 854,64	€ 244,13	€ 1.098,77	16%
23	4	6		S	random	574,97	6,11	572,29	577,65	3,55	€ 851,52	€ 241,20	€ 1.092,72	18%
24	4	6		S	ABC	568,55	6,12	565,87	571,23	3,53	€ 847,92	€ 240,18	€ 1.088,10	16%
25	6	2			random	661,98	6,37	659,18	664,77	3,57	€ 428,76	€ 227,44	€ 656,20	41%
26	6	2			ABC	651,74	6,15	649,05	654,44	3,53	€ 423,72	€ 224,76	€ 648,48	39%
27	6	2	R		random	666,07	7,03	662,99	669,15	3,58	€ 429,60	€ 229,95	€ 659,55	41%
28	6	2	R		ABC	658,14	5,40	655,77	660,50	3,54	€ 424,68	€ 227,31	€ 651,99	39%
29	6	2	R	S	random	606,82	8,58	603,06	610,58	3,57	€ 428,16	€ 231,23	€ 659,39	42%
30	6	2	R	S	ABC	595,23	7,44	591,97	598,49	3,55	€ 425,40	€ 229,74	€ 655,14	39%
31	6	2		S	random	599,70	8,10	596,16	603,25	3,56	€ 427,56	€ 228,85	€ 656,41	42%
32	6	2		S	ABC	589,93	5,78	587,40	592,46	3,53	€ 423,96	€ 226,93	€ 650,89	39%
33	6	4			random	630,08	4,24	628,22	631,93	3,51	€ 842,64	€ 243,74	€ 1.086,38	18%
34	6	4			ABC	623,74	3,96	622,00	625,47	3,59	€ 860,40	€ 248,88	€ 1.109,28	16%
35	6	4	R		random	635,96	4,04	634,19	637,73	3,55	€ 851,52	€ 248,36	€ 1.099,88	18%
36	6	4	R		ABC	629,46	2,51	628,36	630,56	3,54	€ 848,40	€ 247,45	€ 1.095,85	16%

Table 4 - MHSP simulation outcome (DMUs 1-36)

DMU	Segments	Zones/ segment	Recirculate	Shortcut	Storage	Average throughput time (seconds)	Throughput time std. dev. (seconds)	LCL	UCL	Make span (hours)	Operational costs (per 1000 orders)	Investment costs (per 1000 orders)	Total costs (per 1000 orders)	Average picker utilization
37	6	4	R	S	random	578,15	7,40	574,91	581,39	3,58	€ 859,92	€ 252,88	€ 1.112,80	18%
38	6	4	R	S	ABC	567,03	4,74	564,96	569,11	3,52	€ 845,52	€ 248,64	€ 1.094,16	16%
39	6	4		S	random	568,24	4,42	566,30	570,18	3,55	€ 851,28	€ 248,29	€ 1.099,57	18%
40	6	4		S	ABC	561,61	4,52	559,63	563,59	3,57	€ 857,52	€ 250,11	€ 1.107,63	16%
41	6	6			random	672,78	5,16	670,52	675,04	3,57	€ 1.283,76	€ 292,82	€ 1.576,58	11%
42	6	6			ABC	668,87	4,41	666,94	670,81	3,59	€ 1.292,04	€ 294,71	€ 1.586,75	10%
43	6	6	R		random	679,18	4,73	677,11	681,26	3,59	€ 1.293,12	€ 297,03	€ 1.590,15	11%
44	6	6	R		ABC	673,55	4,16	671,72	675,37	3,62	€ 1.304,28	€ 299,59	€ 1.603,87	9%
45	6	6	R	S	random	617,18	6,76	614,22	620,14	3,54	€ 1.275,12	€ 294,94	€ 1.570,06	11%
46	6	6	R	S	ABC	611,87	5,85	609,31	614,44	3,59	€ 1.293,48	€ 299,19	€ 1.592,67	10%
47	6	6		S	random	611,58	5,46	609,19	613,97	3,55	€ 1.279,44	€ 293,89	€ 1.573,33	11%
48	6	6		S	ABC	603,70	7,76	600,30	607,10	3,55	€ 1.278,72	€ 293,72	€ 1.572,44	10%
49	8	2			random	718,03	3,32	716,58	719,49	3,57	€ 571,52	€ 245,92	€ 817,44	28%
50	8	2			ABC	713,30	4,34	711,40	715,20	3,55	€ 567,84	€ 244,34	€ 812,18	27%
51	8	2	R		random	724,80	4,52	722,82	726,78	3,57	€ 570,40	€ 247,49	€ 817,89	29%
52	8	2	R		ABC	716,97	4,23	715,11	718,82	3,56	€ 569,44	€ 247,08	€ 816,52	26%
53	8	2	R	S	random	629,72	8,66	625,92	633,51	3,60	€ 575,52	€ 252,83	€ 828,35	29%
54	8	2	R	S	ABC	619,00	5,48	616,60	621,40	3,57	€ 571,36	€ 251,00	€ 822,36	26%
55	8	2		S	random	619,78	7,69	616,42	623,15	3,56	€ 569,92	€ 248,31	€ 818,23	29%
56	8	2		S	ABC	614,96	6,81	611,98	617,95	3,59	€ 573,92	€ 250,06	€ 823,98	26%
57	8	4			random	720,08	3,78	718,42	721,73	3,54	€ 1.133,76	€ 282,08	€ 1.415,84	13%
58	8	4			ABC	714,04	3,97	712,29	715,78	3,55	€ 1.137,28	€ 282,95	€ 1.420,23	11%
59	8	4	R		random	727,23	5,67	724,75	729,72	3,56	€ 1.139,84	€ 285,65	€ 1.425,49	13%
60	8	4	R		ABC	719,58	3,81	717,91	721,25	3,60	€ 1.151,36	€ 288,53	€ 1.439,89	11%
61	8	4	R	S	random	628,80	5,07	626,58	631,03	3,57	€ 1.143,36	€ 289,62	€ 1.432,98	13%
62	8	4	R	S	ABC	624,11	6,31	621,35	626,88	3,55	€ 1.135,68	€ 287,67	€ 1.423,35	11%
63	8	4		S	random	620,45	6,66	617,54	623,37	3,55	€ 1.136,64	€ 285,87	€ 1.422,51	13%
64	8	4		S	ABC	615,00	4,28	613,13	616,88	3,53	€ 1.129,92	€ 284,18	€ 1.414,10	11%
65	8	6			random	751,24	5,65	748,77	753,72	3,56	€ 1.707,84	€ 332,54	€ 2.040,38	8%
66	8	6			ABC	745,08	4,11	743,28	746,88	3,55	€ 1.702,56	€ 331,51	€ 2.034,07	7%
67	8	6	R		random	765,83	5,57	763,39	768,27	3,62	€ 1.738,56	€ 340,61	€ 2.079,17	8%
68	8	6	R		ABC	762,08	5,97	759,46	764,69	3,57	€ 1.711,68	€ 335,34	€ 2.047,02	7%
69	8	6	R	S	random	664,60	7,41	661,35	667,84	3,59	€ 1.723,68	€ 340,80	€ 2.064,48	8%
70	8	6	R	S	ABC	655,30	7,32	652,09	658,50	3,60	€ 1.726,56	€ 341,37	€ 2.067,93	7%
71	8	6		S	random	653,20	5,17	650,94	655,47	3,55	€ 1.704,48	€ 334,95	€ 2.039,43	8%
72	8	6		S	ABC	644,47	6,72	641,52	647,41	3,58	€ 1.717,44	€ 337,50	€ 2.054,94	7%

Table 5 - MHSP simulation outcome (DMUs 37-72)

4.2. DEA

Of the data set previously mentioned, two performance metrics will form the input and output for DEA. The input is given by the total costs of processing the customer orders. As DEA checks the most efficient DMUs based on the amount of output they can product with a specific input, an additional step was required in generating the output data. The objective of DEA is to maximize the output. However, the goal for this design is to minimize the average throughput time. Therefore, the output data is given by the difference between the maximum average throughput time from all DMUs and the average throughput time of the DMU under analysis. Thus, DEA will find the most efficient sets based on the minimum average throughput time achievable at a specific total cost level.

After entering the data into EMS v1.3.0, the software automatically establishes the most efficient DMU(s) and assigns the others a percentage indicating their relative efficiency. The results of the analysis are available in Table 6.

The efficiency frontier is established by a single most efficient policy set, Model 32, which has 6 segments, 2 zones/ segment, allows totes to travel via shortcuts and employs ABC class-based storage. The DMUs with a relative efficiency above 90% have either 6 segments and 2 zones/segment or 4 segments and 4 zones/segment. The ten most efficient designs have a maximum of 16 zones in total. On average, the most efficient designs have 16 zones. However, when comparing otherwise identical DMUs, the one with fewer zones generally performs better. Figure 11 depicts the relative efficiency of different number of total zones. While 16 zones seem to lead to the highest average efficiency, it is also important to note that DMUs with 12 zones can become more efficient under specific experiment parameters. The lagging DMUs seem to confirm that fewer zones are more efficient, as the worst performing DMUs have a total of 48, 32, and 36 zones respectively. This result supports the finding of Van der Gaast et al. (2012), who also state that minimizing the number of segments and zones that a tote has to visit increases the efficiency of a system.

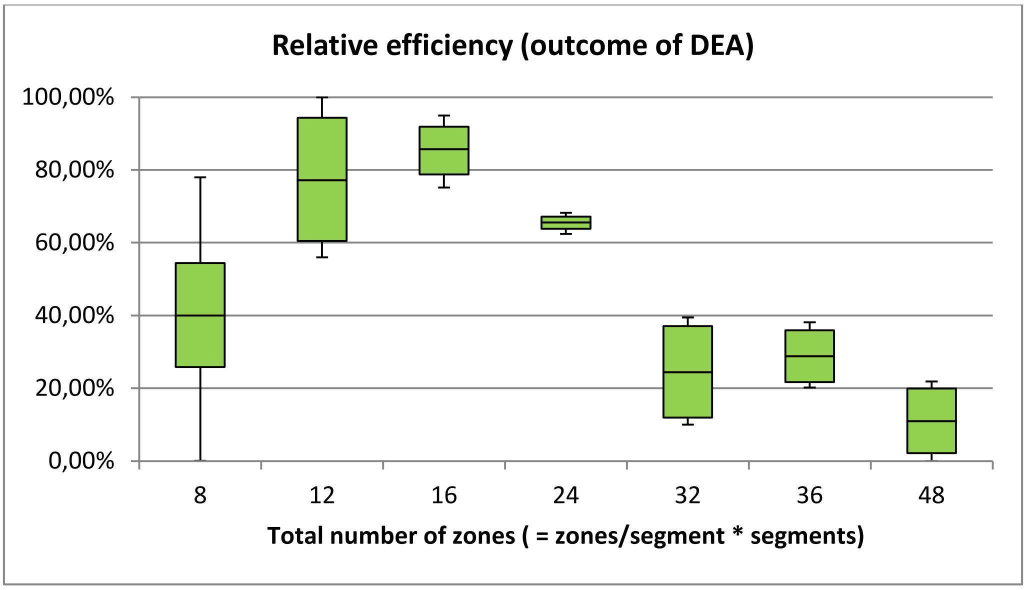


Figure 11 - Relative efficiency of DMUs based on the total number of zones

It is also noteworthy that the nine most efficient DMUs allow totes to use shortcuts. This is an interesting finding, which warrants additional analyses. Moreover, it appears that random storage is less efficient than class-based storage for otherwise identical DMUs. Numerous studies in academic literature support this finding. The following section will provide more details on the performance of DMUs based on these and other variables.

Figure 12 plots the DMUs according to their average throughput time and the operational cost. The eight most efficient policy sets are highlighted. This visualization helps to grasp the results of DEA. Here it becomes even clearer how inefficient certain DMUs are. The further away a DMU is from the origin, the less efficient it is. Therefore, Models 65-68 should never be employed for a similar demand rate as the one used in this thesis.

DMU	Segments	Zones/ segment	Recirculate	Shortcut	Storage	Score	DMU	Segments	Zones/ segment	Recirculate	Shortcut	Storage	Score
32	6	2		S	ABC	100,00%	34	6	4			ABC	47,40%
30	6	2	R	S	ABC	96,36%	33	6	4			random	46,24%
16	4	4		S	ABC	94,91%	36	6	4	R		ABC	46,05%
31	6	2		S	random	93,65%	35	6	4	R		random	43,69%
14	4	4	R	S	ABC	92,45%	64	8	4		S	ABC	39,47%
15	4	4		S	random	91,65%	48	6	6		S	ABC	38,15%
29	6	2	R	S	random	89,23%	63	8	4		S	random	37,82%
13	4	4	R	S	random	88,84%	62	8	4	R	S	ABC	36,84%
10	4	4			ABC	82,57%	47	6	6		S	random	36,28%
12	4	4	R		ABC	79,15%	46	6	6	R	S	ABC	35,77%
8	4	2		S	ABC	77,94%	61	8	4	R	S	random	35,38%
9	4	4			random	77,47%	45	6	6	R	S	random	35,03%
11	4	4	R		random	75,18%	5	4	2	R	S	random	32,60%
6	4	2	R	S	ABC	71,67%	7	4	2		S	random	29,30%
40	6	4		S	ABC	68,22%	50	8	2			ABC	23,93%
56	8	2		S	ABC	67,75%	42	6	6			ABC	22,61%
38	6	4	R	S	ABC	67,23%	52	8	2	R		ABC	22,14%
24	4	6		S	ABC	67,09%	72	8	6		S	ABC	21,85%
39	6	4		S	random	66,49%	41	6	6			random	21,84%
54	8	2	R	S	ABC	66,07%	49	8	2			random	21,64%
55	8	2		S	random	66,05%	44	6	6	R		ABC	21,29%
26	6	2			ABC	65,10%	71	8	6		S	random	20,43%
23	4	6		S	random	64,63%	43	6	6	R		random	20,16%
22	4	6	R	S	ABC	64,29%	70	8	6	R	S	ABC	19,78%
37	6	4	R	S	random	62,41%	51	8	2	R		random	18,56%
21	4	6	R	S	random	62,39%	69	8	6	R	S	random	18,14%
28	6	2	R		ABC	61,12%	3	4	2	R		random	15,39%
53	8	2	R	S	random	60,80%	58	8	4			ABC	13,49%
25	6	2			random	58,56%	57	8	4			random	11,96%
18	4	6			ABC	57,73%	60	8	4	R		ABC	11,88%
20	4	6	R		ABC	56,08%	59	8	4	R		random	10,02%
27	6	2	R		random	55,97%	66	8	6			ABC	3,77%
17	4	6			random	54,91%	65	8	6			random	2,64%
19	4	6	R		random	54,16%	68	8	6	R		ABC	0,68%
4	4	2	R		ABC	48,60%	1	4	2			random	0,09%
2	4	2			ABC	47,43%	67	8	6	R		random	0,00%

Table 6 - DEA outcome

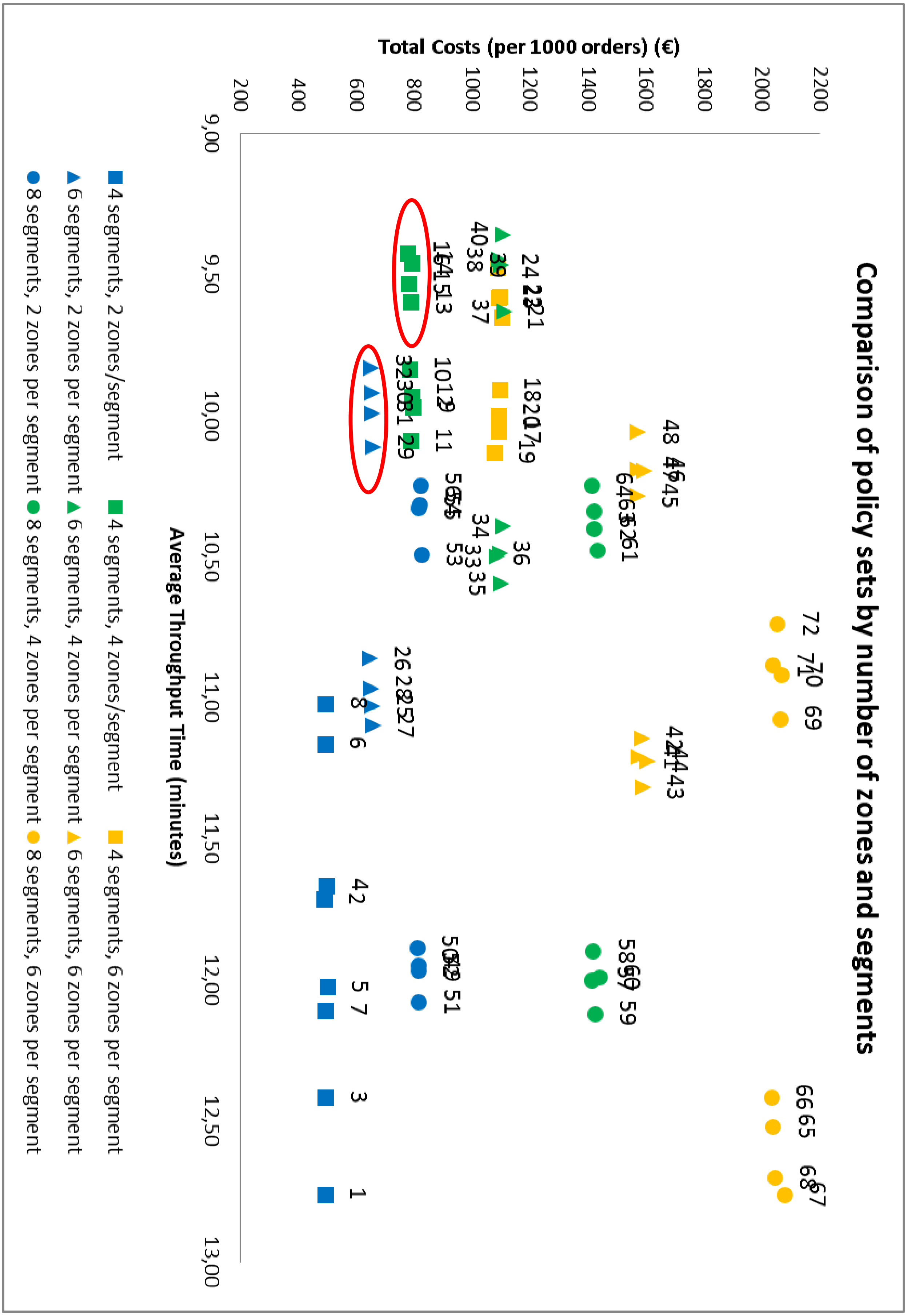


Figure 12 - Policy set performance by number of segments and zones/segment

4.3 ADDITIONAL INSIGHTS

The visualization of the DMUs according to their throughput rate and operational cost highlights an interesting observation. For each combination of segments and zones/segment, there are two clusters on the scatter plot, approximately at the same total cost level, but at different average throughput times. This indicates that at least one variable included in the study has a strong effect in speeding up order processing. Finding out which variable(s) are responsible for this could have a significant impact on increasing pick-and-pass system efficiency.

4.3.1 RECIRCULATION

According to the current state of research, recirculation of the totes should improve throughput time and lower congestion in the system. The results in this study conflict with this statement, as the average throughput rate of policy sets with recirculation is in fact slightly higher than that of policy sets without recirculation. However, the difference is only 0.9%. Overall, DMUs which follow a block-and-recirculate protocol are slightly less efficient in terms of throughput time, cost and make span.

However, this could be explained by the demand rate set in the simulation. As the totes leave the source according to an exponential distribution with a rate of 0.0167 totes/ second, it is likely that only few totes will actually make use of a block-and-recirculate protocol. Given that the systems will likely not become congested at this launch rate, the few occasions in which a tote will have to travel along the main conveyor belt and return to the system once again will cause the average throughput time to increase. Therefore, this result would suggest that recirculation should only be employed in systems where demand is high and totes are launched in the system with a high frequency. In such a system, the block-and-recirculate protocol would likely have a more significant – and positive – impact, as Van der Gaast et al. (2012) found. The statistics of the models with and without recirculation are presented in Table 7 and Figure 13.

	Average Throughput Time (sec)	Average Make Span (h)	Average Total Cost	Average Investment Cost	Average Operational Cost
Policy sets with recirculation	647,25	3,57	€ 1.116,35	€ 259,13	€ 857,22
Policy sets without recirculation	641,61	3,56	€ 1.109,35	€ 256,06	€ 853,29
% change	0,88%	0,36%	0,63%	1,20%	0,46%

Table 7 - Performance summary under different recirculation policies

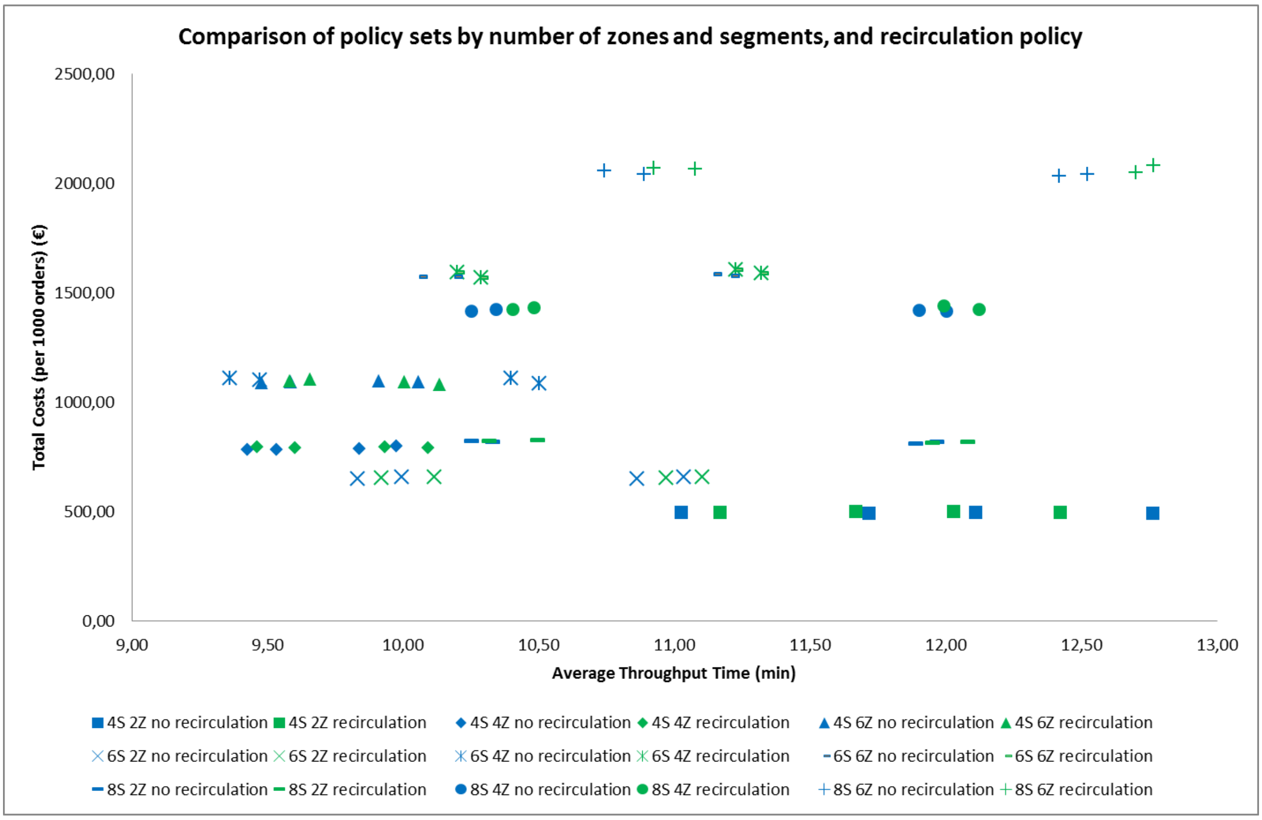


Figure 13 - Policy set performance by segments, zones/ segment and recirculation policy

4.3.2 SHORTCUTS

As recirculation was not accountable for the clusters formed by segment/zone combinations, this section will analyze the effect of shortcuts on the DMUs. Intuitively, allowing totes to skip areas of the warehouse which they do not need to visit should lower throughput time. Figure 14, which visualizes the effect of shortcuts on each segment/zone combination, confirms that this is the case and provides an explanation for the grouping of the DMUs in clusters. For each segment/zone combination, the difference in performance with and without shortcuts is large. Table 8 provides the percentage change that occurs when implementing shortcuts to a system. On average, there is a 7.39% improvement in average throughput time, which is achieved with almost no changes in total costs. Operational costs, that are the product of number of pickers, wage/hour and make span, will decrease slightly. This is caused by the throughput time change, which affects the make span positively. These results explain the high presence of DMUs with shortcuts in the high efficiency set delivered by DEA.

	Average Throughput Time (sec)	Average Make Span (h)	Average Total Cost	Average Investment Cost	Average Operational Cost
Policy set with shortcuts	612,75	3,56	€ 1.113,28	€ 258,51	€ 854,76
Policy sets without shortcuts	661,68	3,57	€ 1.114,78	€ 257,98	€ 856,80
% change	-7,39%	-0,18%	-0,13%	0,21%	-0,24%

Table 8 - Performance summary under different shortcut policies

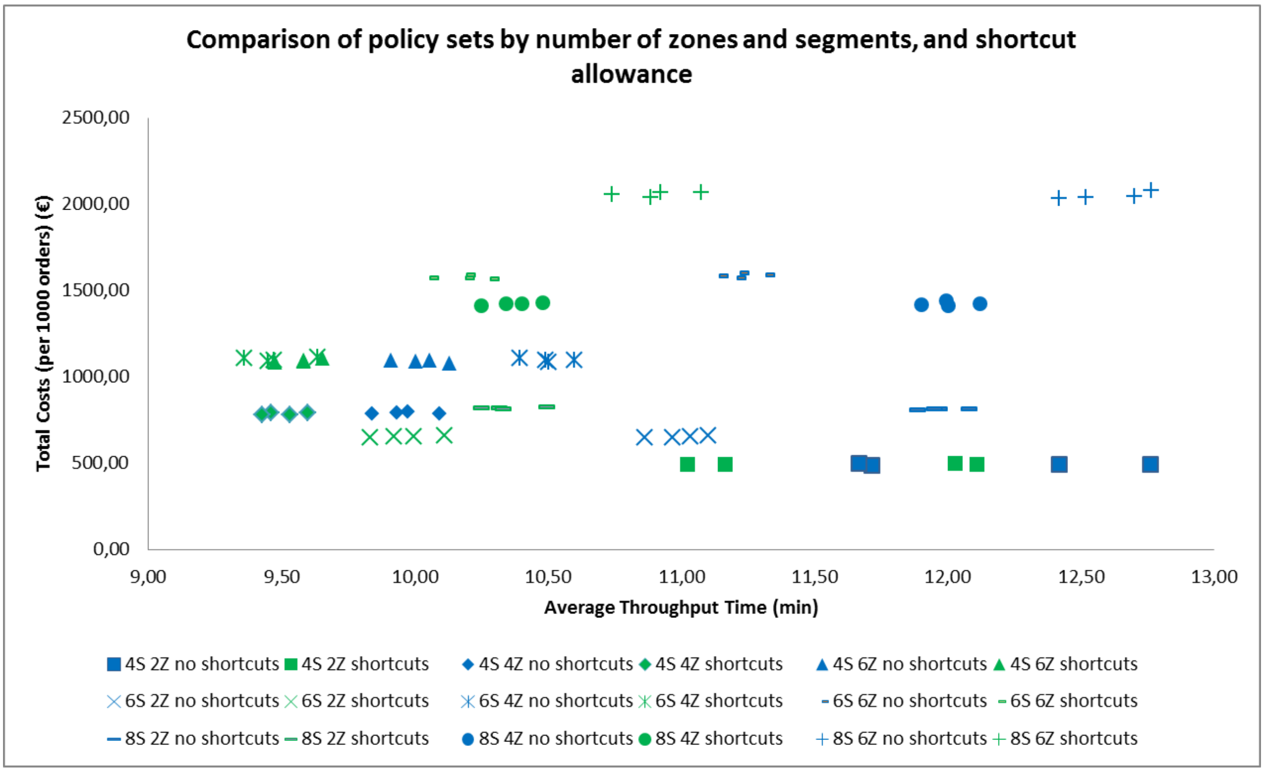


Figure 14- Policy set performance by segments, zones/ segment and shortcuts

4.3.3 STORAGE POLICY

The final decision variable of the policy sets is the storage policy employed. Researchers agree that class-based storage outperforms random storage in a given system (e.g. Petersen, 2002; Le Duc and De Koster, 2005; De Koster et al., 2007). Additionally, a brief overview of the DEA results also suggests that for the policy sets assessed in this thesis, class-based storage is preferred over random storage.

The performance comparison between random and class-based storage is presented in Table 9 and Figure 15. Although the effect is not very strong, there is a slight decrease in throughput time and make span under a class-based policy, supporting the outcome of previous studies.

	Average Throughput Time (sec)	Average Make Span (h)	Average Total Cost	Average Investment Cost	Average Operational Cost
Policy sets with class-based storage	640,05	3,56	€ 1.147,91	€ 260,24	€ 887,67
Policy sets with random storage	642,25	3,56	€ 1.130,43	€ 258,98	€ 871,46
% change	-0,34%	-0,03%	1,55%	0,49%	1,86%

Table 9 - Performance summary under different storage policies

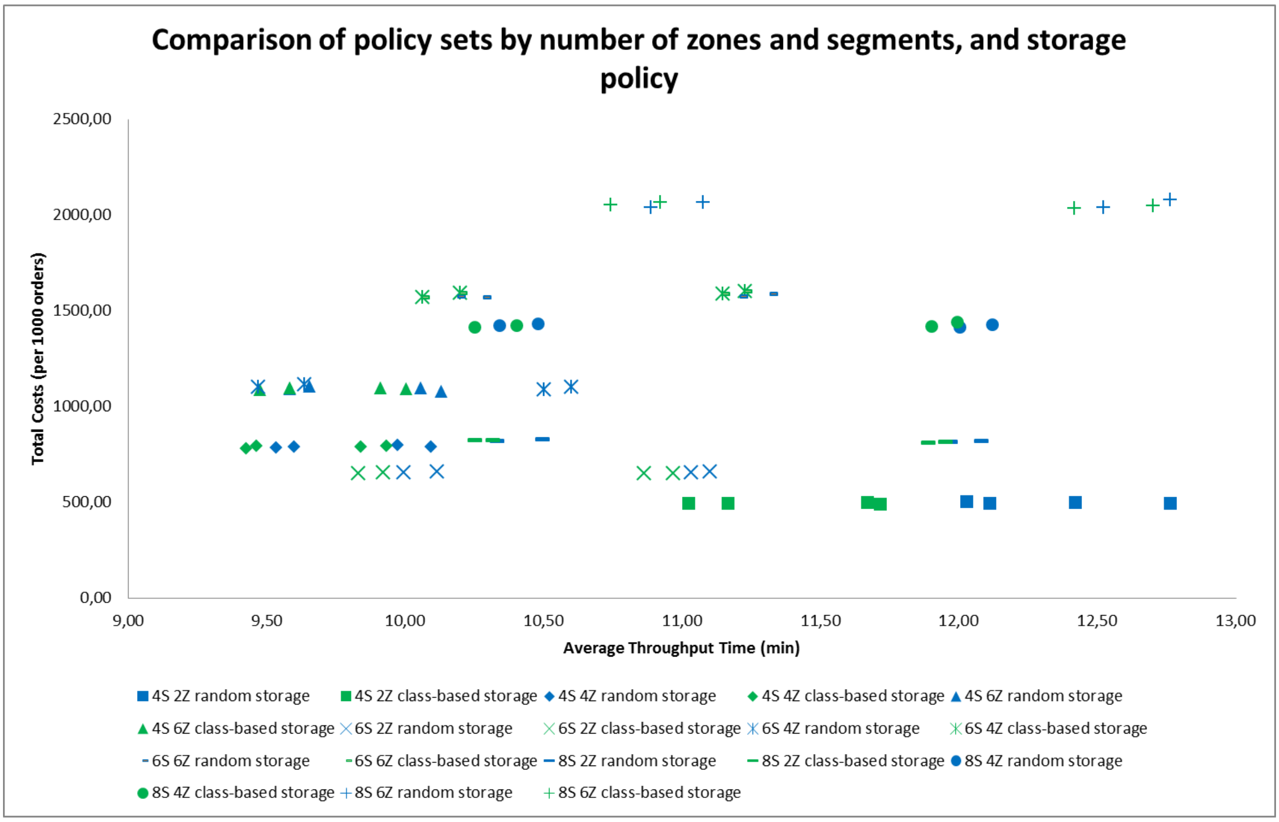


Figure 15 - Policy set performance by segments, zones/ segment and storage policy

4.4 ORDER PICKER UTILIZATION

As mentioned previously, one of the limitations of the study is that the launch rate of the customer orders is set very low. Consequently, the utilization of the pickers is rather low in most models (see Tables 4 and 5). It is interesting to study what happens in the same policy sets when the launch rate is increased after selecting a smaller set of models to test from the original 72, and eliminating the restricting models, which allow both recirculation and shortcuts. Consequently, a selection of the models were run again for the same simulation set up as before, but with a higher launch rate, exp(0.03 totes/second) (see Table 10).

The new rate is the highest rate which allows totes to leave the source almost immediately after being generated, as it does not cause blocking in the system. Any rate higher than this causes congestion and therefore will cause the average throughput time to increase to almost twice its current level. Even at this launch rate a gridlock tends to appear in the models which allow recirculation. Therefore, a maximum number of customer that orders can be in the model at any given time needs to be implemented. This maximum is set at 100 customer orders for models with recirculation. The table below presents the new picker utilizations, average throughput time, and make span. It is very interesting to observe that increasing the launch rate will generally lead to higher average throughput time, but lower make span. As totes are sent into the system much faster compared to the original scenario, pickers will be idle less, resulting in shorter make spans. However, totes wait longer to be served by a picker, as queues tend to form due to the higher launch rate. Therefore, the average throughput time is in fact higher than in the original scenario. This means that the system should have a higher launch rate for cases in which orders need to be processed in batches, but a lower launch rate is preferable when customer orders need to be processed and shipped individually.

For DMUs with 4 segments and 2 zones/segment, both the average throughput time and the make span are very different compared to the rest of the DMUs. This could be caused by the high variance of the metrics when using such a small number of zones. As previously observed, the confidence intervals for these models are very large as the models cannot seem to handle the given demand pattern. Therefore, these models are considered unrepresentative for each scenario.

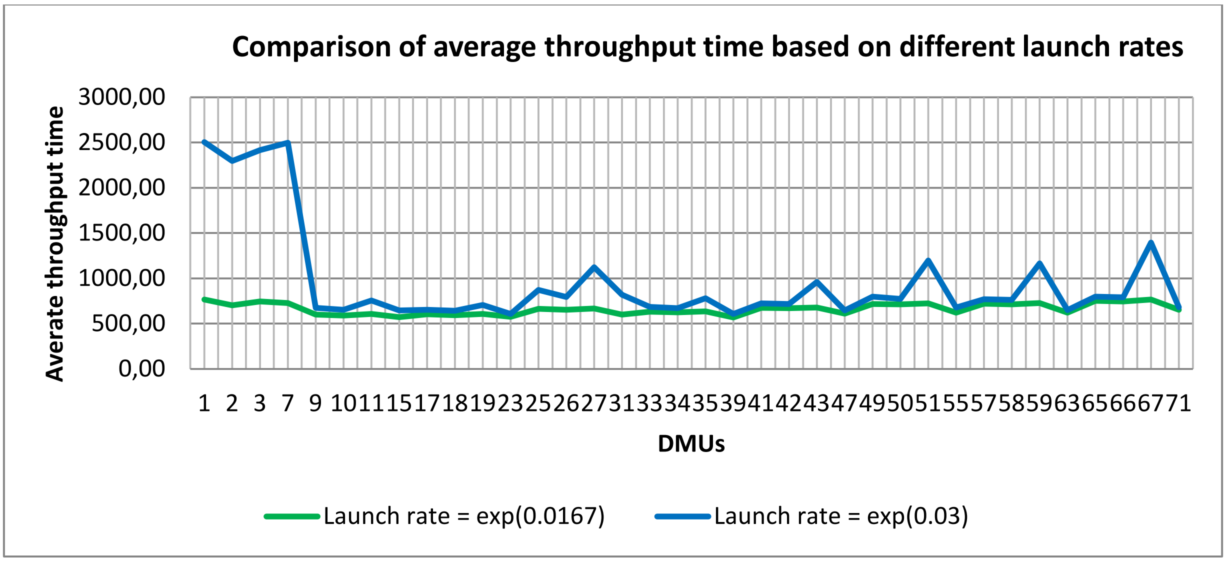


Figure 16 - Comparison of average throughput time based on different launch rates

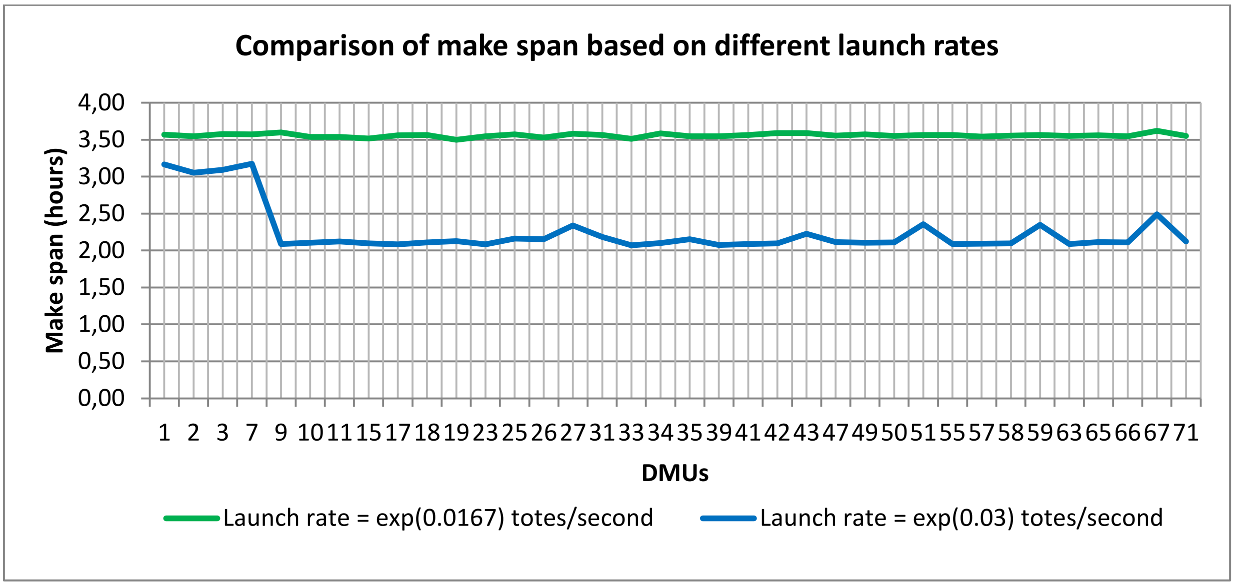


Figure 17 - Comparison of make span based on different launch rates

DMU	Segments	Zones/ segment	Recirculate	Shortcut	Storage	Average throughput time (seconds)	Total costs (per 1000 orders)	Investment costs (per 1000 orders)	Operational costs (per 1000 orders)	Simulation make span	Average picker utilization
1	4	2			random	2504,502	438,09	184,97	253,12	3,164	79,04%
2	4	2			ABC	2296,37	422,58	178,42	244,16	3,052	76,96%
3	4	2	R		random	2415,721	429,77	182,49	247,28	3,091	80,74%
7	4	2		S	random	2496,292	440,53	186,53	254	3,175	78,46%
9	4	4			random	673,951	463,96	130,04	333,92	2,087	49,25%
10	4	4			ABC	652,803	467,74	131,10	336,64	2,104	44,69%
11	4	4	R		random	756,269	472,96	133,44	339,52	2,122	48,29%
15	4	4		S	random	646,13	467,23	131,39	335,84	2,099	48,92%
17	4	6			random	652,692	641,23	141,07	500,16	2,084	30,12%
18	4	6			ABC	643,632	648,92	142,76	506,16	2,109	26,90%
19	4	6	R		random	705,593	656,31	145,35	510,96	2,129	29,49%
23	4	6		S	random	605,802	646,66	146,02	500,64	2,086	30,11%
25	6	2			random	870,466	397,24	137,68	259,56	2,163	67,65%
26	6	2			ABC	793,801	395,77	137,17	258,6	2,155	63,33%
27	6	2	R		random	1121,11	431,10	150,30	280,8	2,34	62,96%
31	6	2		S	random	818,938	402,18	140,22	261,96	2,183	67,57%
33	6	4			random	685,883	640,82	143,78	497,04	2,071	30,31%
34	6	4			ABC	672,189	650,10	145,86	504,24	2,101	27,01%
35	6	4	R		random	778,68	666,81	150,57	516,24	2,151	29,60%
39	6	4		S	random	605,844	643,87	145,39	498,48	2,077	30,32%
41	6	6			random	724,002	923,58	171,54	752,04	2,089	18,33%
42	6	6			ABC	718,161	926,23	172,03	754,2	2,095	16,38%
43	6	6	R		random	959,929	986,32	184,24	802,08	2,228	17,14%
47	6	6		S	random	645,469	936,74	174,98	761,76	2,116	18,16%
49	8	2			random	796,083	481,72	144,92	336,8	2,105	48,72%
50	8	2			ABC	772,603	482,87	145,27	337,6	2,11	44,56%
51	8	2	R		random	1198,208	540,52	163,56	376,96	2,356	43,44%
55	8	2		S	random	676,461	479,64	145,56	334,08	2,088	49,31%
57	8	4			random	768,495	836,00	166,56	669,44	2,092	21,34%
58	8	4			ABC	761,392	838,79	167,11	671,68	2,099	19,22%
59	8	4	R		random	1165,772	938,85	188,13	750,72	2,346	19,11%
63	8	4		S	random	651,074	835,80	167,96	667,84	2,087	21,48%
65	8	6			random	799,42	1212,30	197,58	1014,72	2,114	13,48%
66	8	6			ABC	789,038	1208,86	197,02	1011,84	2,108	11,94%
67	8	6	R		random	1396,216	234,18	234,06	11,38%	1194,72	0,00%
71	8	6		S	random	679,927	200,30	200,16	13,40%	1018,56	0,02%

Table 10 - MHSP Output based on launch rate = exp (0.03)

4.5 CONCLUSION AND FINAL REMARKS

This chapter presented the findings of the study. A short introduction of the data set which resulted from the MHSP software simulations reveals that total, investment and operational costs are minimized for those systems with the least number of zones. The results of DEA were described and analyzed thereafter. The best performing DMUs were the ones with the lowest number of zones, in line with the results of Van der Gaast et al. (2012). The data presented a peculiar grouping in clusters for each segment/zone combination, which required additional analyses. Therefore, each of the other three decision variables was analyzed individually. The clusters were caused by the effect of shortcuts, which have a high potential of throughput time reduction, estimated at approximately 7.39%, at only a small increase in investment costs. In the analysis performed on storage policies, class-based storage appears to perform slightly better than random storage. This is in line with the academic research to date. Finally, the effects of implementing a block-and-recirculate protocol were counterintuitive, contradicting the literature on the topic. The reason for this conflict is most likely explained by the low launch rate of the totes into the system, which deems the protocol unnecessary. To assess the effects of increasing the launch rate, part of the policy set performance was assessed under a different launch rate. The results are similar and recirculation does not seem to add value in this set of models either. However, it should also be noted that the launch rate used in the simulations is far lower than a realistic launch rate for a pick-and-pass system, which could explain the contradiction. Compared to the original scenario, increasing the launch rate results in lower make span, but longer average throughput time. This means that when batches of products should be delivered together to a customer the system should launch the totes as quickly as possible. This causes pickers to remain busy a larger proportion of the time, lowering the make span compared to a scenario with a low launch rate.

Overall, both throughput time and make span are minimized in those policy sets with a minimal number of zones, which employ a class-based storage policy, and which allow totes to use shortcuts to bypass areas of the warehouse they do not need to visit.

5. CONCLUSIONS AND RECOMMENDATIONS

This thesis set out to identify the most efficient pick-and-pass design based on DEA, in terms of several decision factors. The decision factors were selected based on the expected effect on performance metrics as they are outlined in academic literature as well as based on the current limitations of the research regarding pick-and-pass. Ultimately, the selected decision variables which made up the policy set were the number of segments, the number of zones per segment, allowing totes to recirculate, allowing totes to skip areas of the warehouse that they do not need to visit and storage policy. These five variables were modelled into 72 pick-and-pass policy sets using the Zone Picking module of the MHSP software. A data set was generated through simulation of customer orders. This provides the basis for Data Envelopment Analysis (DEA).

The most efficient policy set is defined as the one that is able to minimize the throughput time with the lowest cost possible. By employing DEA, the most efficient design is found to have six segments, two zones per segment, to allow totes to make use of shortcuts and to store products based on an ABC class-based storage policy. Although this describes the most efficient system, against which the others are benchmarked, it is also important to evaluate what attributes characterize the top performing sets, as opposed to focusing on a single DMU. Efficiency appears to be most significantly related to the number of zones in a system. This number should be as small as possible to accommodate the demand levels required by the warehouse operations. This finding is supported by Van der Gaast et al. (2012). Secondly, totes should be allowed to avoid areas of the warehouse they do not need to visit. This topic is only briefly touched upon in pick-and-pass literature. However, the throughput time reduction associated with this variable is significant, at 7.39%. Therefore, this topic should be further explored by researchers in the context of pick-and-pass systems. Storage policy is found to have a small effect on the performance of the policy sets. In agreement with most research regarding storage policy, this study also confirms that class-based storage is more efficient than random storage. The performance difference between random and class-based storage is small. However, the effect of increasing the skewness of the ABC curve should be studied further. Finally, a surprising finding was that under the current setup, a block-and-recirculate protocol would reduce performance. The effect does not change when the launch rate is set higher. However, this result is most likely attributable to the low launch rate of the source, which was constrained to avoid blocking of the system in specific policy sets. Additional research is needed to identify the effect of various demand rates on the effectiveness of recirculation in increasing system performance. In addition to the original design, a part of the models were simulated using a higher launch rate. Although DMUs with recirculation still have higher average throughput times, the higher launch rate will result in a higher average throughput time, as totes wait longer to be served by a picker, but in a lower make span, as pickers are idle less of the time and more totes are served in parallel than in the original scenario. Thus, higher launch rates should be used in situations where a batch of orders should be shipped out together.

The policy sets which minimize total cost are the same as those that minimize investment and operating cost. Again, policy sets with fewer zones are less costly. Each additional segment will increase the investment cost. Moreover, as the pick-and-pass system expands with more zones and segments, the operational costs rise as totes travel longer through the system and more pickers are required to cover additional zones. Adding shortcuts and recirculation to a system will increase the investment costs slightly. However, depending on the demand for products, they could significantly lower the operational costs, meaning that with sufficient time, the total cost would be smaller than in equivalent warehouses. Throughput time and make span are both minimized in systems with a low number of zones, which allow totes to travel via shortcuts and which store products according to a class-based policy.

Consistently throughout the study, a smaller number of zones results in the highest performance across all indicators. Consequently, managers should consider minimizing the number of zones and segments that make up the design of the pick-and-pass system. Additionally, if the layout of the main conveyor loop permits the addition of shortcuts, these should be implemented to lower the throughput rate and the make span of the system. Implementing a class based storage policy should result in a marginal increase in performance metrics. However, managers should be wary of the costs needed to set up such a system, as these may not be cancelled out by performance increase. Finally, allowing totes to recirculate is not indicated for low demand rates, as this study shows, recirculation will increase the average throughput time unnecessarily and on average result in lower performance.

5.1 LIMITATIONS AND DIRECTIONS FOR FURTHER RESEARCH

Several additions to the study would provide significantly more insight. One such addition would be the comparison of the systems under different demand rates and patterns. The current system assumes a fairly low demand to prevent specific policy sets from blocking. However, it would be interesting to test the performance of the policy sets against higher and/or fluctuating demand. This could provide an explanation to the current finding on the block-and-recirculate protocol. Additionally, an order picking decision variable which strongly interacts with storage policy is routing. Due to the dependencies that exist between these two variables, the addition of routing policy to the set of decision variables would complete the topics most often addressed in literature and which appear to have strong correlations among each other. Next to expanding the decision variables set, is the addition of a widely used performance metric, namely service level. Managers often look towards the service level as a measure of customer satisfaction, which gives it great importance as a key performance indicator in practice. Therefore, to incorporate the customer aspect into the study, service level maximization should be added as an objective of the study.

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APPENDIX

APPENDIX 1 – EXAMPLE OF SEGMENTS IN THE SEGMENT/ZONE COMBINATION (6,2)

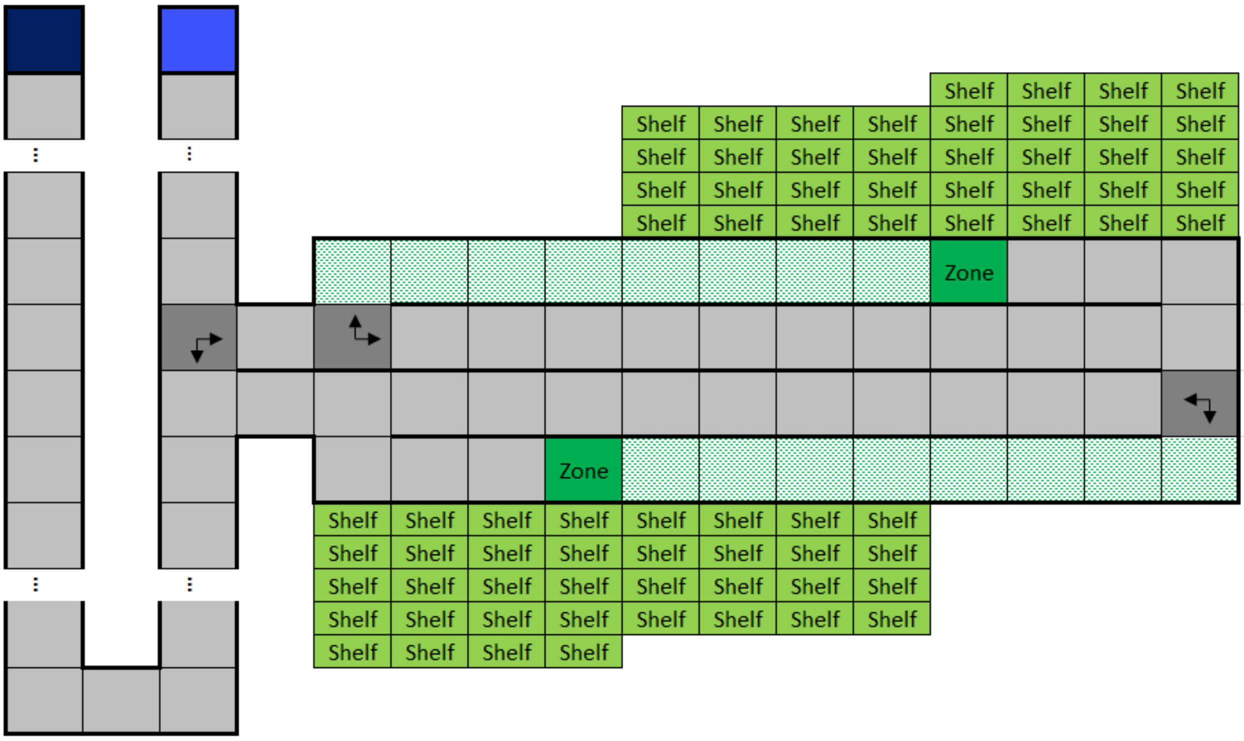


Figure 12 – Illustration of segment in (S,Z) = (6,2)

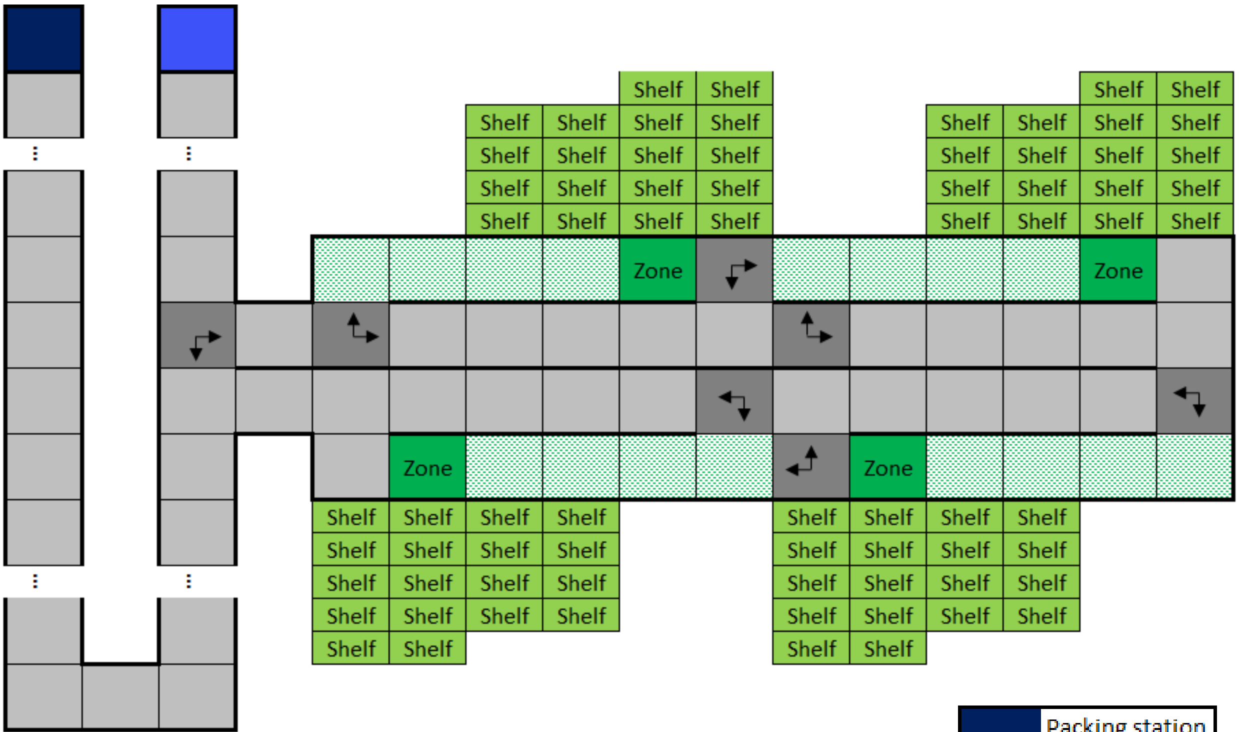
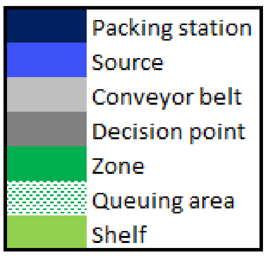


Figure 13 – Illustration of segment in (S,Z) = (6,4)



APPENDIX 2 – THE POLICY SET / DECISION MAKING UNITS

Model	Segments	Zones/ segment	Recirculate	Shortcut	Storage
1	4	2			random
2	4	2			ABC
3	4	2	R		random
4	4	2	R		ABC
5	4	2	R	S	random
6	4	2	R	S	ABC
7	4	2		S	random
8	4	2		S	ABC
9	4	4			random
10	4	4			ABC
11	4	4	R		random
12	4	4	R		ABC
13	4	4	R	S	random
14	4	4	R	S	ABC
15	4	4		S	random
16	4	4		S	ABC
17	4	6			random
18	4	6			ABC
19	4	6	R		random
20	4	6	R		ABC
21	4	6	R	S	random
22	4	6	R	S	ABC
23	4	6		S	random
24	4	6		S	ABC
25	6	2			random
26	6	2			ABC
27	6	2	R		random
28	6	2	R		ABC
29	6	2	R	S	random
30	6	2	R	S	ABC
31	6	2		S	random
32	6	2		S	ABC
33	6	4			random
34	6	4			ABC
35	6	4	R		random
36	6	4	R		ABC

Model	Segments	Zones/ segment	Recirculate	Shortcut	Storage
37	6	4	R	S	random
38	6	4	R	S	ABC
39	6	4		S	random
40	6	4		S	ABC
41	6	6			random
42	6	6			ABC
43	6	6	R		random
44	6	6	R		ABC
45	6	6	R	S	random
46	6	6	R	S	ABC
47	6	6		S	random
48	6	6		S	ABC
49	8	2			random
50	8	2			ABC
51	8	2	R		random
52	8	2	R		ABC
53	8	2	R	S	random
54	8	2	R	S	ABC
55	8	2		S	random
56	8	2		S	ABC
57	8	4			random
58	8	4			ABC
59	8	4	R		random
60	8	4	R		ABC
61	8	4	R	S	random
62	8	4	R	S	ABC
63	8	4		S	random
64	8	4		S	ABC
65	8	6			random
66	8	6			ABC
67	8	6	R		random
68	8	6	R		ABC
69	8	6	R	S	random
70	8	6	R	S	ABC
71	8	6		S	random
72	8	6		S	ABC