Development of a warehouse slotting model to improve picking performance

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ABSTRACT

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Congestion during picking operations in warehouse with mixed aisles (narrow aisles and wide aisles) has rarely been studied in current literature in the context of warehouse slotting (i.e. arrangement of inventory in warehouse). This study aims at improving the picking efficiency of the Asmodee Canada Inc. warehouse. Using a combination of clustering slotting heuristics and popularity-based slotting heuristics, a re-slotting policy was developed. Furthermore, to provide a robust re-slotting with limited number of items moves, a healing technique based on urgency score was developed. Use of a process control chart to monitor the picking performance of Asmodee's warehouse and hence to signal healing was suggested. Using picking simulation, we find that when the re-slotting heuristics is used, there is substantial reduction in distance travelled of up to 29% and waiting times due to congestion can be reduced by as much as 85%. The healing technique also decreased distance travelled and waiting times. However, as the number of items moved in healing constitute on average less than 5% of the items, such improvements are limited. The distance traveled was reduced by as high as 9.4% in some aggregated orders and waiting time reduction was as high as 29.1%. The techniques developed in this paper will help Asmodee Canada Inc. in improving their picking operations. It will also help to build better strategies for warehouses having mixed aisles, where in aisle congestion is an issue to consider while re-slotting.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1: Introduction

Warehouse is a facility that is designed to store materials in bulk for future distribution or sales. Warehouses are crucial building blocks of supply chains. They ensure smooth running of operations along the supply chain. One of the most important function of warehousing is to help adapt to the variability in supply and demand caused by seasonality of products, change in product pricing, promotions etc. Warehouse operations involve four major activities: i) receiving, ii) storage, iii) order picking and iv) shipping. In the current business environment of globalization and e-business, managing warehouse operations is becoming even more challenging because of higher service expectations from customers. Warehouses must store higher number of stock keeping units (SKUs), the orders have high variations (i.e. more customizations, rather than having limited SKUs and bulk orders the SKU variety in the orders are more varied now), and need to be processed faster to meet the customer expectations. One of the major performance metrics for warehouses is the number of picks per unit of time, a metrics to gauge the order pick performance (Mantel et al., 2007). For more effective warehouse operations, order picking needs to be more efficient. In this regard, the travel time required to pick an order is found to constitute 50% or more of the total picking time (Tompkins et al., 1996). As travel time constitutes a large part of the picking time, the performance metrics is highly dependent on the sequence in which an order is picked and the distance a picker must travel to fulfil the order. Storage policies in the warehouse play a key role in influencing the picking time as these policies impact the distance and hence the time needed to pick an order.

A way to reduce the travel time is to do an efficient and effective warehouse slotting. Warehouse slotting is the process of optimizing the SKUs' location in the warehouse based on various factor such as demand volatility, warehouse layout, picking method with the objective of making picking operations more efficient. In general, there are two storage policies used in warehousing: random and dedicated storage. SKUs are assigned randomly to a location based on wherever the space is available or placed on dedicated locations based on slotting methods such as turnover, popularity, volume, pick density, and cube-per-order index (COI). Amazon (the biggest ecommerce retailer) uses random slotting to place its incoming orders (Kofler et al. (2015)). Another category of storage policy that combines random and dedicated policy is zone based storage policy, where a group of products is placed randomly in a zone. Based on SKU's slotting method, SKUs are placed near or away from the pickup / drop off point or input / output (I/O) point. Some warehouses use random storage policy is easier to use and equally distributes the products in the warehouse. However, the biggest disadvantage of the random storage policy is the longer distance travelled by the pickers leading to longer picking time.

Many of the slotting techniques to arrange SKUs in a warehouse are adapted from the fundamental slotting technique based on SKU turnover or picking frequency / popularity. In this slotting technique, the most popular or frequently picked product is placed closest to the I/O point and, in the decreasing order of frequency, the SKUs are placed with increasing distance from the I/O point. Cube per Order Index (COI) is one of the earliest metrics developed and it is widely used as a slotting technique for dedicated storage systems (Heskett, 1963). COI is the ratio of an item's volume to the number of trips required to fulfill the item's order demand per period, not taking into consideration the order pick structure measures (Trevino et al., 2009). The study by Petersen (1999), confirmed that volume-based storage provides improved performance as compared to random storage. The findings of Petersen, et al. (2005), show that the popularity, turnover, and COI slotting measures provide less picker travel distance and fulfillment time than volume and pick density slotting among the popular storage strategies considered. As COI is based on picking just one SKU in each trip it becomes infeasible for many of the warehouses as many of them use multiple SKU picks in a single order. Thus, not only does the turnover or frequency become a popular factor but also how SKUs are to be arranged based on their combination in an order also becomes essential with multiple picks in each trip. For this issue, affinity-based clustering and correlation based slotting techniques have been developed that take into account how SKU demand is linked to each other based on the orders received. Another policy that tries to combine product affinity and product frequency slotting strategy is order oriented slotting. These techniques have found to provide good results but some of them, especially order oriented slotting are hard to implement in warehouses as this strategy requires large number of iterations to provide a solution as it is a type of quadratic assignment problem (NP-hard combinatorial optimization problem). One of the basic clustering slotting strategies that have been studied is A-B-C classification of products where each product category based on classification is stored together (Yu et al., 2015).

Although using the turnover or affinity based slotting strategies has the potential to reduce the travel distance, however for narrow aisles, there is a potential to have congestions in these aisles that can negate the time saved by covering less distance by increasing the waiting time of pickers. Congestion can reduce the picking efficiency improvements attributed to a slotting technique. In narrow aisle warehouses, using turnover based slotting strategies or clustering strategies can amplify the congestion issue as some locations will see high picker traffic that will cause blocking in the aisle (Pan and

Shih (2008)).

Another issue that warehouses need to look at is that how to do periodic slotting specially in warehouses that have constant changes in demand and products. It is very unlikely that a warehouse will do slotting / re-warehousing periodically as it is a time and resource intensive activity. Thus, a new concept of healing has been looked at where limited number of moves are done periodically to relocate some products rather than re-slotting the whole warehouse Kofler et al. (2011). This technique eases the pressure on the warehouse operations while simultaneously maintaining the picking efficiency.

Every order picking strategy needs to assess the environment in which the warehouse is operating in. Some of the questions that need to be asked in this respect are: Is the picking automated or manual? Is the SKU heavy or light? How many tiers are there in the racks? Are there single item bulk orders or multi-item small orders? Is there demand seasonality for some products? There are many factors that can impact the slotting. However, only the major factors the management prioritize need to be accounted for while developing a solution.

In our case, where the warehouse currently is arranging the SKUs randomly, the overall objective of the warehouse operations is to maximize the number of billable orders per day.

In this study, we look at two problems:

a. The first problem is the warehouse slotting problem in mixed aisles (wide and narrow). We will develop a policy for the assignment of SKUs to storage locations, while reducing picker travel distance and congestion in narrow aisles.
b. The second problem is to create a periodic re-slotting policy (healing) with a limited number of SKUs being rearranged so as to maintain a good picking

performance.

These two problems are essential to deal with, as a slotted warehouse improves the warehouse efficiency but it is also important in dynamic warehouses that the efficiency is maintained over a period of time rather than seeing a decrease in efficiency as demand for SKUs vary. A model will be developed to build an improved slotting approach for SKUs based on various factors and compare it with the current practice to highlight the improvement. A dashboard will be built to periodically examine the performance of slotting for each SKU and to trigger healing re-slotting accordingly. Another model will be developed for healing re-slotting. A detailed analysis of findings and managerial insights based on the findings will be reported to the company.

In the upcoming sections from 1.1. to 1.4. we will give an overview of the company studied, its warehouse operations, and the challenges it is facing. In Chapter 2, we will review the research that has been done in the area of warehouse slotting and how we integrate different techniques based on the advantages they provide for the challenges the company is facing. Chapter 3 will explain the basis of the proposed solution and details on the heuristics that have been used in our solution. In Chapter 4, we will discuss the results based on the heuristics implemented and showcase the improvements. Chapter 5 will summarize the implications of our research and how it will benefit the company. Future potential extensions of this study are also argued in this last chapter.

1.1. Asmodee Background

Asmodee is a French publisher of board games, role-playing games and card games with operations spread across the world. Asmodee was founded in 1995, and since then it has acquired several publishers. In 2018, Asmodee became the second largest publisher of board games, following Hasbro. The company sell its products B2B (business to business) and B2C (business to customer). A part of Asmodee's strategy statement is as follows: From games to entertainment… infinite possibilities.

One of Asmodee's warehouses is located in Rigaud, Quebec from which it supplies games to Canadian customers. The current study aims at improving the slotting operations of this warehouse. The warehouse is described in the next section.

1.2. Warehouse

Asmodee Canada Inc.'s Riguad warehouse ships B2B and B2C orders. It has two warehouse buildings, one of the building is used to receive the products in bulk from where the pallets are transported to the main warehouse where picking operations for the customer orders are done. Product sales peak in the last quarter of the year generally in the month of October, November and December. The warehouse handles up to 2,000 SKUs, with approximately 50 SKUs being the best sellers and constituting a high proportion of the annual sales.

The main warehouse (as shown in Figure 1) is divided into two areas with majority of the area allocated to the storage of SKUs for order picking of B2B orders. A small area is reserved for storage of SKUs used for picking B2C orders. The warehouse has 12 employees (excluding the warehouse manager and the logistics manager). Up to 6 temporary employees are hired in the peak sales months. These employees mostly handle order picking activities.

Figure 1: Warehouse Layout (Lane Type: Green indicates wide aisle, Red indicates Narrow/ Congested aisle; Rack Type: Blue: 1-Tier, Yellow: 2-Tiers, Orange: 3-Tiers, Purple: 4-Tiers)

In our case, we have an asymmetric warehouse with seven aisles parallel to each other and an eighth aisle that is on the left bottom corner of the warehouse. Top and middle right area is a separate area reserved for storing products for B2C orders. The start point and end point of picking operations are two different locations placed in the middle of the warehouse in front of the packaging area. The aisle widths are different with the first, third and sixth aisle starting from the right are wide, the other aisle are narrow. The last aisle on the right bottom is considered as a narrow aisle for slotting purposes because of safety concerns as there is a constant movement of forklift in that area. The length, breadth, height, and the number of shelves in the rack vary. However, most of the racks have two shelves where products are picked from. The packaging area is located at lower end of the warehouse, just behind the picking start and end point. The packaging area contains 5 stations for boxing the picked items. The stations are equipped with desktop computers to print out the delivery labels. On the right side of the packaging area is the pallet area where the orders are put together on pallets. The pallets are picked up from the packaging area every evening at the end of shift by delivery partners for shipping.

1.3. Picking Process

The number of pickers varies throughout the year. During the peak season i.e. the last three months of the year, the number of pickers is 8-9, whereas during other periods, on average, 4 pickers work in the warehouse. The order completion process is as follows:

1) The picker picks up the order slip at the start point, the order slip contains all the items that need to be picked with their location and quantity. Each picker is given an individual cart to pick the orders and they, at any moment, are allowed to fulfil one order only.

2) The picker passes through all the aisles as necessary according to the routing policy of the company. The picker scans the items and enters the quantity of the item picked in the hand-held bar scanner and also ticks off the item on the order slip.

3) After completing the order list, the picker returns back and enters the packaging area from the end point and packs all the items in the boxes at the packaging station.

4) After sealing the boxes, the picker enters the details of the order on the online delivery system and prints out the courier labels from the system.

5) After printing the labels, one delivery address label is sticked on every box and also label of ‘mixed games’ is also sticked on boxes containing different games. A pouch in which list of all games is present has to be pasted on one of the boxes.

6) The labelled boxes are then stacked on the pallets placed near the packing areas, completing the order fulfilment by the picker.

1.4. Routing Policy

The routing policy in the warehouse is based on the location and the aisle type (narrow or wide). The picker l follows an S-shaped routing policy in general. The picker will skip the aisle where there is no picking. In cases where the middle cross aisle can be used rather than going to the end of the aisle to pass to the next aisle where picking needs to be done, the picker uses the cross aisle. The picker can only walk in one direction in narrow aisle and cannot change direction within the narrow aisle. Thus, if a picker is moving to a narrow aisle using the middle cross aisle, s/he has to see whether there are some picks in the narrow aisle from racks that are in the lower end of the narrow aisle and whether some picks are in the upper end of the narrow aisle. If this is the case, then the picker will not use the cross aisle but would rather travel to the upper or lower end of the aisle in which s/he is and then move to the narrow aisle from one end. Thus, the picker can pick all the items without requiring any change in direction. After all the picks are done, the picker enters the packaging area by returning to the end point.

1.5. Problem Description

As the Asmodee warehouse is using random slotting they wanted to improve the efficiency of their picking operations. Thus, we need to look into reducing the travel distance of the pickers. Also, during the peak months of sales there are significant congestion issues that reduce the efficiency of operations. The challenge is that there is a mix of narrow and wide aisle thus, congestion needs to be taken into consideration rather than just looking at reducing at travel distance as congestion can significantly increase the waiting time. Due to volatility in demand we have to propose a method of regular but limited number of swaps to slot the warehouse in order to maintain efficiency as re-slotting the whole warehouse is not practical on a monthly or quarterly basis.

Chapter 2: Literature Review

There are generally two kinds of picking systems in warehouses (Henn et al. 2012): Picker-to-Parts system and Parts-to-Picker system. In Picker-to-Parts system the picker goes to the location where the item has been placed in the warehouse to pick the quantity of items in the order. The picker generally uses a cart or a fork lift to do the picking. In Parts-to-Picker system the automated storage and retrieval system (AS/ RS) retrieves the pallet or bin from the racks and transfers it to the front, where picker takes out the required item units and the system then places back the pallet or the bin. De Koster et al. (2007) stated that more than 80% of order picking in Western Europe are using picker-to-parts system. In our case we are dealing with a picker-to-parts system.

The research on slotting techniques has been very diverse. One of the earliest and most common slotting technique is the Cube per Order (COI) Index. The ratio of the cubic volume of the SKU to the turnover of SKU is used to arrange the SKUs in increasing order of COI. Some of the other commonly used measures for slotting heuristics are popularity, pick density, turnover, and volume (Petersen et al. (2005)). In all these slotting measures the products are ranked based on the measure and assigned a location based on the distance of location from I/O point. As the rank gets lower the distance of location of the item increases from the I/O point. Some of storage assignment strategies used are: within-aisle, across-aisle, golden zone within-aisle and golden zone across-aisle. Within-aisle places the products first in the aisle closest to the I/O point and when the aisle is full then we move to the next closest aisle to fill the items in that aisle. Across-aisle fills the products in the bin that is closest to the I/O point in all the aisle first and then it fills the next closest bins in all the aisle. Golden zone is the area on the racks between a picker's waist and shoulders. In both cases i.e. within-aisle and across-aisle the items should be first placed in golden zone for the golden zone within-aisle and golden zone across-aisle strategies. The study by Venkatadri and Kubasad (2012), used within-aisle, across-aisle storage assignment strategies and Nearest-Location heuristic to compare the results and it found that Nearest-Location heuristic provided the best results but other strategies also provided very good results in terms of total distance travelled with little difference among all the strategies that were test. Most of the research on slotting policies assumes, that the picker returns to the I/O point after picking an SKU. This is not valid for cases where, to fulfil an order, the picker must pick more than one SKU. For such cases item correlation, affinity based strategy, clustering or an order oriented slotting strategy needs to be implemented where the total distance / time for picking all the SKUs for an order is minimized. In order-oriented slotting, the SKUs that are ordered together are placed close to each other to minimize total travelled distance / time. The study by Trevino et al. (2009), show that the binary mixed integer linear programming model (BMILP) developed to take into account the sequence of order picking for slotting model provides better results than the previous models / heuristics that considered minimizing individual SKU distance from I/O point. This strategy results in substantial improvement over the COI based slotting strategy when the number of SKUs to be picked are moderate to high. Mantel et al. (2007) found that small number of SKUs in an order does not provide substantial improvements in comparison to COI based slotting. Research by Li et al. (2016) found that a product-based affinity and class based simultaneous slotting strategy where the objective is to maximize the total affinity and product of zone indicators and order frequency on the basis of ABC classification provide better order picking time reductions than only ABC classification methods. Another approach that is being studied is order batching along with slotting. The study by Yang et al. (2020) considered order batching with different storage policies and found that storing multiple SKUs at same picking location can improve picking efficiency. Zhang (2016) used sum-seed and the static-seed clustering algorithms that use correlation among the items to find clusters. Our algorithm is inspired from this algorithm as these algorithms take into account both factors: correlation and frequency of products while doing slotting. The results of the clustering algorithms performed better than turnover based storage strategy.

After the initial slotting is done, SKU's demand might change over time. New SKUs might be added or current ones dropped. The demand for a given SKU also changes over time. Hence, combined with other factors, the picking performance drops gradually. Study by Kofler et al. (2014) showed that rearranging/ re-slotting in case of a dynamic warehouse should take into consideration the efforts required to do rearranging while planning the slotting policy since in a dynamic warehouse the picking time improvements due to slotting can decrease rapidly and regular re-slotting efforts need to be in place. It may not be possible to re-slot the whole warehouse periodically. In such a case, 'healing' needs to be carried out where only a limited number of SKUs are re-located on a daily basis. Healing can be done easily and periodically. Study by Kofler et al. (2011) found that changing a limited number of storage locations on a daily basis in warehouse (healing) can result in efficient warehouse operations combined with an initial re-warehousing that will provide an optimal solution. But even when healing is performed with moves that provide the highest picking efficiency, the robustness of the moves is not considered. There could be some products that need to be moved every day without having a huge impact, while other products might have less variation, but they could have huge impact on picking efficiency. Without considering the robustness of the priority of moves, it could be costly and time consuming to do healing daily. In another extended study, Kofler et al. (2015) took robustness of moves into account and found that for limited daily slotting a robust slotting approach that takes into account urgency, stability, importance measures performs better than a greedy re-location approach. The authors found that considering urgency of product (it counts how many periods the item has been stored in the wrong aisle when compared to the aisle proposed by the slotting policy) to do healing provides the best results. In our case, as slotting the whole warehouse after short periods is not practical, we intend to use healing in the warehouse after the initial slotting based on the warehouse performance that will be monitored using process control chart. When the performance will drop below a certain threshold healing will be used to improve the performance. Thus, we will use the urgency of moves of products as our criterion to prompt healing.

Another attribute that impacts the picking time is the order picking routing. Generally, the aim of routing policies is to sequence the picking items in the order so as to minimize the total travel distance. There are algorithms that try to find the optimized travel distance. However, in practical scenarios, heuristic routing policies are generally used as they are easy to implement and easy for pickers to remember. Some of the routing heuristic policies implemented in warehouse operations are: i) transversal (S-shape), ii) return, iii) midpoint and iv) largest gap (Ruijter, 2007 & Bataineh, 2017).

i)Transversal (S-shape): For this strategy a picker enters the aisle from one side and leaves the aisle from other side. Thus, covering the distance of the aisle and the picker can only travel in one direction an aisle. The picker can only skip an aisle if there is no pick from that aisle.

ii) Return: In this routing policy, the picker will enter and exit an aisle from the same location. The picker will only enter those aisles where an item needs to be picked.

iii) Midpoint: In this routing strategy the picker only travels to the middle of each aisle from one side and return thus covering only half part of the aisle. For the other half, the picker goes to the other side of warehouse and covers the other half of each aisle in which item needs to be picked. Thus, picker only transverse fully the first or last full aisle.

iv) Largest Gap: The largest gap policy is same as the midpoint policy with the only difference being that picker enters an aisle and pick till the point where there is the largest gap (distance between two adjacent picks) between the next pick. The largest gap is defined as the maximum distance between two consecutive picks within the same aisle. Thus, when the largest gap is reached the picker will return back and move to the next aisle while picking the rest of the items when the pickers transverses from the other side of the aisle. In our case, the warehouse uses S-shape routing in general that has been discussed in section 1.4.

Although analyzing the efficiency based on the distance travelled by the picker for deciding warehouse slotting policy can be a good key performance indicator (KPI). However, this KPI does not take into account the congestion that some of the slotting policies can cause. Congestion is a factor that needs to be considered while implementing storage policies as placing highly frequent products together might lead to higher picking time due to waiting period in congested aisles in multi-picker situations. The study by Lee et al. (2020) looked at clustering the products and then storage assignment of products while considering congestion. The authors found that congestion can be a major cause of high picking time. Congestion in warehouse can result in slower picking operations. This is specially the case in warehouses with narrow aisles where the pickers can't pass through. Congestion can be of different types: in-the-aisle blocking, pick-face blocking, in-the-aisle interferences, total aisle blocking, cross aisle blocking and depot blocking (Huber, 2014). In our case, the major contributor to drop in efficiency is in-the-aisle blocking in narrow aisles. In-the-aisle blocking, if a picker is present at any location in the aisle, then another picker does not have enough space to pass through and thus will have to wait either behind the other picker or at the entry of the aisle for the first picker to exit the aisle.

There are numerous articles that have studied the impact of congestion but none of them have taken into account the impact of the cross aisle. An S-shape routing policy in a symmetric warehouse is considered in these articles. The S-shape routing policy results in a queuing problem. Gue et al. 2006 used the concept of Markov chains to study congestion in narrow aisle preparing a stochastic model. The study found that for a reasonable number of pickers and picking density, blocking can cause significant congestion. When the number of pickers is low (2-3 pickers) the congestion can go up to approximately 2% of the total picking time whereas for higher number of pickers the study found that for 10 pickers the congestion could go upto 10-15% of the total picking time. The study also found that if the picking density is very high, then, even with busier aisle, the congestion will not have a huge impact on total picking time as with very busy aisles waiting will be less because pickers will spend more time picking the items and have less travel time in aisle. With low picking density, the blocking was found to be very low as there is not much stoppage in the aisle. Klodawski et al. (2018) found that with an increase in the number of pickers, the picking efficiency increases in narrow aisles warehouse but the increase in picking efficiency is reduced due to higher congestion.

AlHalawani and Mitra (2015) tried to analyze the traffic in the warehouse and used simulated annealing method to attain two objectives: reduce congestion and increase order picking speed. They used the redundant path usage to calculate the congestion rate on each path. Bataineh and Khasawneh (2016) analyzed that congestion can have a significant effect on picking time, and concluded that with an increase in number of pickers and items to be picked, the congestion increases. Venkatadri et al. (2015) analyzed the congestion in forward pick area in a fast-picking tunnel based on product placement and found that using probability low-high strategy (i.e. SKUs with low probability of picking are placed at the start of aisle and SKUs with high probability of picking are placed at the end of the aisle) reduced congestion substantially. A major constraint with this kind of study is that it takes into assumption the picker movement is unidirectional, which might not be the case in warehouses with multiple aisles also there isn't a consideration of cross aisle. Pan and Shih (2008) compared the assignment policy of Jarvis and Mcdowell (1991) (policy where the least picked item is placed farthest from the start point) and random assignment policy to compare the congestion. The authors found that an organized warehouse has a higher congestion compared to randomly assigned warehouse. Pan et al. (2012) used a heuristic to balance workload in the last 'n' aisle calculated using difference between total aisle and total pickers, that improved performance. If there are N pickers and m aisles then n = (m – N), the other aisles will follow turnover slotting strategy but in the last 'n' aisle workload will be balanced using heuristic developed in the study so as to reduce congestion. One can conclude that higher picking density can lead to significant in-aisle congestions in narrow aisles. Thus, one should aim to balance the picking density in narrow aisles by trying to equally distribute the products so that all aisles will have the similar picking density.

The goal of the field company Asmodee Canada Inc., is to maximize the number of billable orders per day that are ready to be shipped. At present, the warehouse has arranged all the SKUs randomly without considering any specific SKU characteristic such as turnover, order volume etc. The management has observed that the current slotting strategy is resulting in high picking times that lowers the number of orders fulfilled. Our study will tackle the issues of regular changes in SKUs (as some SKUs are added / deleted on a monthly basis), resulting in periodic re-slotting. Also, as the aisle width varies there is a challenge to look at congestion in narrow lanes. The literature review has not dealt with the congestion and re-slotting issue simultaneously. We will have to take into consideration the congestion to do the initial slotting (with rack sizes also varying in the warehouse). Furthermore, we will tackle how to heal the warehouse with limited re-slotting.

Chapter 3: Methodology

3.1. Overview of the Methodology

In this study, the improvement of warehouse operations is conducted in two stages. In the first stage, re-slotting is done. For slotting, we use a combination of static seed clustering heuristics for wide aisles and a popularity across aisles heuristics (Petersen et al., 2005) for narrow aisles to allocate each item in the warehouse to a slot in order to improve the picking efficiency. The re-slotting approach improve the efficiency by reducing the travel distance and the wait time due to congestion in narrow aisles. In the second stage, healing is performed. Healing aims to continue maintaining a good picking efficiency with limited re-slotting of SKUs in the long run. The picking efficiency could drop with changes in demand and some end-of -life SKUs might be taken off the racks and new SKUs need to be slotted.

3.2. Stage 1: Overview of clustering slotting and popularity across aisle slotting heuristics

Our first step was to analyze the historical order data and the layout of the warehouse. From the warehouse layout, it became clear that we had three wide aisles and four narrow aisles, where the eighth aisle is considered as a narrow aisle for slotting purposes due to safety reasons resulting from the frequent movement of the forklift in that area. The average number of items picked in an order was approximately seven. Approximately 20-25% of SKUs made 75% of the sales. From the analysis of the warehouse layout and sales pattern, it became evident that different slotting techniques have to be used in wide aisles and narrow aisles as implementing only frequency based or items demand affinity based technique across all aisles would increase congestion in the narrow aisles. Also, we wanted to use a technique that uses a combination of both turnover and affinity characteristic of an item for slotting in wide aisles. As a first step to slotting, we use the existing item locations in warehouse and swap items between narrow and wide aisle based on the picking frequency. High pick frequency items are swapped to wide aisle and low pick frequency items are swapped to narrow aisle. For each shift of item from wide to narrow aisle, an item is shifted from narrow to wide aisle.

To maintain a balance between slotting based on turnover and affinity, the clustering slotting heuristics for wide aisles was used to cover most of the high demand products in wide aisles and the popularity across aisle slotting heuristics for narrow aisles was then used to slot the remaining low demand products in the narrow aisles. For the clustering slotting heuristics, the following steps are followed:

1. Order the aisles based on distance from the I/O point.
2. Create a list of the picking frequency of the items in wide aisles and order them in decreasing order of frequency.
3. Select the first item on the list, say ‘i’, and then find the closely associated item, say ‘j’, (an item which is ordered most frequently with this item). A closely associated item must have an association factor greater than ‘α’ (α = critical association, between 0 to 1, defined by user), association factor is the ratio of the total orders in which both item ‘i’ and item ‘j’ were ordered together to the total orders in which item ‘i’ was ordered. Place the first item in the rack according to the order in which they need to be filled starting from the lowest shelf in the rack. Association frequency for a pair of items ‘i' and ‘j’ is calculated as the sum of all the orders containing both item ‘i’ and item ‘j’.

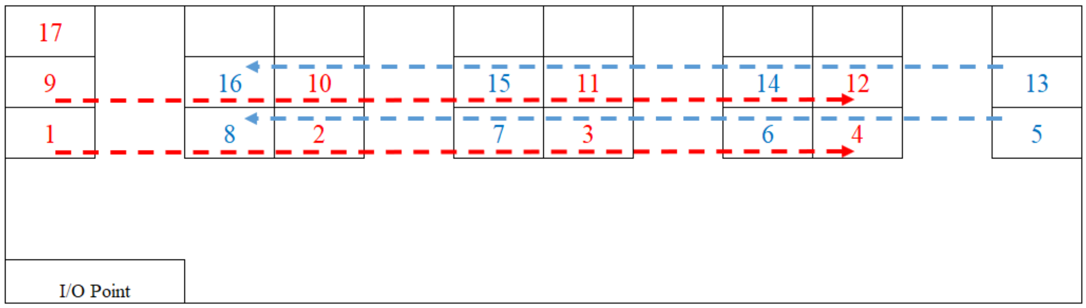
3.1. Order the association frequency of the item pairs in decreasing order of the correlation frequency.

4. Select the item that is most associated with item ‘i’ and place it along with item ‘i’.
5. Verify if item ‘j’ requires more space than available to store the items in that shelf. If it requires more space, move to the next shelf in the rack or, if all shelfs are occupied, move to the next rack and then repeat steps (1-4) after removing the items that have been slotted from the list.
6. Update the list. If there is still space left in the shelf, repeat step (3-4).
7. Continue until all items in wide aisles are slotted.

For the remaining products in the narrow aisles, we use popularity across aisle slotting heuristics. In this heuristic, the items in the narrow aisles are slotted as follows:

1. Order the aisles based on the distance or priority.
2. Arrange the item list in the decreasing order of frequency.
3. We arrange SKU in S-shaped order. We start from the first aisle and move to last aisle and from the last aisle to first aisle, covering all the aisle in between (both way). This arrangement is demonstrated in Figure 2. We always start from bottom tier and go to the top tier.
4. As a rack gets full, move to the next rack in the aisle.

Figure 2: Illustration of S-shaped popularity across aisles heuristics slotting (where each number represents an item placed in a bin)



The steps for warehouse slotting are given in the pseudo code below:

Following formulas are used in pseudo code:

1. $Volume\_of\_bin_{rw,tier} = Volume\_of\_shelf_{rw,tier}/Total\_bins_{rw,tier}$ (where *rw* is rack and *tier* is the shelf tier)
2. $SKU\_volume\_stored_i = SKU\_volume_i *$ $Avg\_Number\_of\_SKU\_sold\_per\_period_i$ (where *i* is the SKU)
3. $SKU\_bins\_required_i = roundup(SKU\_volume\_stored_i / Volume\_of\_bin_{rw,tier})$
4. $association\_factor_{Seed\_SKU,y} = SKU\_pairs\_wide\_aisle\_count_{Seed\_SKU,y} /$ $total\_picks_{Seed\_SKU}$ (where *Seed_SKU* is the Seed SKU and *y* is the other SKU ordered with Seed SKU)

Pseudo Code for slotting of warehouse

Input: The SKU, order, rack, and facility data.

Output: Slotting of the warehouse.

1.0. Read the SKU, order, rack, and facility data.

1.1. Read the labeling of datasets in following steps:

1.1.1. *f(o)* = List of Orders

1.1.2. *rw* = List of racks in wide aisle. We assume all racks are arranged in increasing order of distance from packaging area.

1.1.3. *rn* = List of racks in narrow aisle. We assume all racks are arranged in increasing order of distance from packaging area.

1.1.4. *tier* = List of tiers in all racks *rw* and *rn*.

1.1.5. *wide_list* -> list of SKU currently in the wide aisles

1.1.6. *narrow_list* -> list of SKU currently in the narrow aisles

1.1.7. Define *Max_bin_limit* (Limit in terms of how much bins can be given to one SKU in a rack)

1.1.8. Define *association_list (i)* (List of all items 'j' associated with the item 'i' arranged in decreasing order of association with item 'i' ranked one)

1.1.9. Define *critical_association*

2.0. Compute total picks for each SKU. $total\_picks_s$ = sum (pick frequency for *s* in all *f(o))*

3.0. Arrange all *wide_list* SKU in increasing order and *narrow_list* in decreasing order of their $total\_picks$

4.0. For all SKUs in *wide_list*

4.1. For all SKUs in *narrow_list*

4.1.1. If $total\_picks_{sn}$ - $total\_picks_{sw} > 0$ (or an integer parameter set by user) *sn belongs to narrow_list and sw belongs to wide_list*

4.1.1. Swap the pair between *wide_list* and *narrow_list*

5.0. For all racks in *rw*

5.1. For all tiers *tier* in rack *rw*

5.1.1. While all SKUs s in *wide_list* not slotted

5.1.1.1. Pick the SKU s with the max $total\_picks_s$ (we call it 'Seed_SKU') then create *association_list (Seed_SKU)*

5.1.1.2. For SKU s in list *association_list*

5.1.1.2.1. If $Bins\_empty_{rw,tier}$ >= *min (SKU_bin_required, Max_bin_limit)* **and** $association\_factor_i$ >= *critical_association*

5.1.1.2.1.1. $Bins\_empty_{rw,tier}$ = $Bins\_empty_{rw,tier}$ - *min (SKU_bin_required, Max_bin_limit)*

5.1.1.2.1.2. Assign SKU *i* the rack *rw* and tier *tier*

5.1.1.2.1.3. Remove SKU *i* slotted from *wide_list*

6.0. Distribute the SKUs in decreasing order of $total\_picks_s$ across narrow aisle. Each consecutive SKU should go in next consecutive aisle and when SKU is placed in last aisle repeat the process starting from last aisle to first aisle.

7.0. For all racks *rn*

7.1. For all tiers *tier* in rack *rn*

7.1.2. While all SKUs s in *narrow_list* in an aisle not slotted

7.1.2.1. Pick the SKU s with the max $total\_picks_s$

7.1.2.2. If $Bins\_empty_{rn,tier}$ >= *min (SKU_bin_required, Max_bin_limit)*

7.1.2.2.1. $Bins\_empty_{rn,tier}$ = $Bins\_empty_{rn,tier}$ -*min (SKU_bin_required, Max_bin_limit)*

7.1.2.2.2. Assign SKU *i* the rack *rn* and tier *tier*

7.1.2.2.3. Remove SKU *i* slotted from *narrow_list*

3.3. Stage 2: Overview of healing

The aim of healing is to maintain good picking efficiency with limited item moves in the warehouse. When healing, we use the urgency score of items. The urgency score indicates the total periods in which the item has already been in wrong aisle compared to the one suggested by the slotting heuristics. In this case, we do the slotting as explained in the last section for each week individually for all the weeks that we want the healing period to cover and compare the aisle in which the item is located in each period after slotting with the current aisle location of the item. We calculate urgency score using the rule that if the re-slotted location of an item in a week is different than the current location of item, we add one point. However, if the slotted location in that week after the re-slotting is different than the slotted location in previous week, we first reset the score to zero. After calculating the score, we divide the score by number of periods for which the comparison was done, one week being equal to one period. The urgency score obtained will be between 0 and 1. Higher the urgency score higher the priority of moving the item to the right aisle. Once the urgency score is calculated, we make a list of all the feasible two-swap moves. To make this list we arrange all the products in decreasing order of the urgency score and pick frequency. Swapping starts from the top rank product in list. The Urgency score of the top rank product should be greater than zero. We then find the next product down the list with the highest Urgency score that can be swapped with the first product. The condition for finding the product with which the top rank product can be swapped with is that, for two products to be swapped their current aisle location should be equal to the slotted aisle location of the other product. The above process is repeated till no more potential swaps can be found. The swaps are limited to 50 two-swaps in each healing period in line with the discussions held with the management in this respect. The steps for healing are provided in the pseudo code below:

Pseudo code for healing of warehouse

Input: The SKU, order, rack, and facility data.

Output: Healed slotting of the warehouse.

1.0. Read the SKU, order, rack, and facility data.

1.1. Define *SKU_ Urgency_Score_list*

1.2. Define *SKU_healing_list*

2.0 For all periods *p* in range (period = 1 to *total periods*)

2.1. Repeat all steps of *Pseudo Code for slotting of warehouse* (detailed in last section 3.2.) taking order list of period *p*

2.2. Store the aisle location of all SKUs in period *p* in *SKU_healing_list*

3.0. For SKU *SKU* in *SKU_healing_list*

3.1. For periods *p* in range (*p* = 1 to total periods)

3.1.1. If $SKU\_slotted\_aisle\_location_{SKU,p}$!= $SKU\_current\_aisle\_location_{SKU}$ **and** $SKU\_slotted\_aisle\_location_{SKU,p} == SKU\_slotted\_aisle\_location_{SKU,p+1}$

3.1.1.1. $Score_{SKU} = Score_{SKU} + 1$

3.1.2. ElseIf $SKU\_slotted\_aisle\_location_{SKU,p}$!=

$SKU\_slotted\_aisle\_location_{SKU,p+1}$ **and**

$SKU\_slotted\_aisle\_location_{SKU,p}$!= $SKU\_current\_aisle\_location_{SKU}$

3.1.2.1. $Score_{\ SKU} = 1$

3.1.3. ElseIf $SKU\_slotted\_aisle\_location_{SKU,p}$!=

$SKU\_slotted\_aisle\_location_{SKU,p+1}$ **and**

$SKU\_slotted\_aisle\_location_{SKU,p}$ == $SKU\_current\_aisle\_location_{SKU}$

3.1.3.1. $Score_{\ SKU} = 0$

4.0. Calculate Urgency Score for all SKUs *SKU* in *SKU_healing_list* using

$Urgency\_score_{\ SKU}$ = $Score_{\ SKU}$/ *total periods*

5.0. Arrange SKUs in decreasing order of Urgency Score in *SKU_ Urgency_Score_list*

6.0. For SKU *a* in *SKU_ Urgency_Score_list*

6.1. For SKU *b* in *SKU_ Urgency_Score_list* with rank lower than SKU *a*

(last_p = last period under analysis i.e. *p* = total periods*)*

6.1.1. If $SKU\_slotted\_aisle\_location_{SKU\_a,last\_p}$ ==

$SKU\_current\_aisle\_location_{SKU\_b}$

and $SKU\_slotted\_aisle\_location_{SKU\_b,last\_p}$ ==

$SKU\_current\_aisle\_location_{SKU\_a}$

and $Urgency\_score_{\ SKU\_a}\ != 0$ **and** *number_of_swaps <=50*

6.1.1.1. Swap SKU *a* and SKU *b* rack locations

6.1.1.2. Remove SKU *a* and SKU *b* from *SKU_ Urgency_Score_list*

6.1.1.3. *number_of_swaps = number_of_swaps +1*

3.4. Point of Healing

In order to decide when the company should perform healing, we adopted a methodology based on Statistical Process Control (SPC). We use the control charts to monitor the picking efficiency. Average 'picking time per pick' in a warehouse is a KPI that will be used in measuring the picking. The picking time per pick is defined as:

$$\frac{\text{Total picking time for an order}}{\text{Number of picks in an order}}$$

In our case as we use picking time per pick as the performance measure. X-bar chart and R-bar chart were created. For X-bar chart, the control limits were determined using the following relationships:

$$UCL = \overline{X} + A_2 \overline{R} \quad (1)$$

$$LCL = \overline{X} - A_2 \overline{R} \quad (2)$$

Where: UCL = upper control limit, LCL = lower control limit, X = average performance value, R = average range of sample data, and A_2 = a standard constant based on the sample size.

For the R-bar chart, control limits were determined for the range of performance:

$$UCL = D_4 \overline{R} \quad (3)$$

$$LCL = D_3 \overline{R} \quad (4)$$

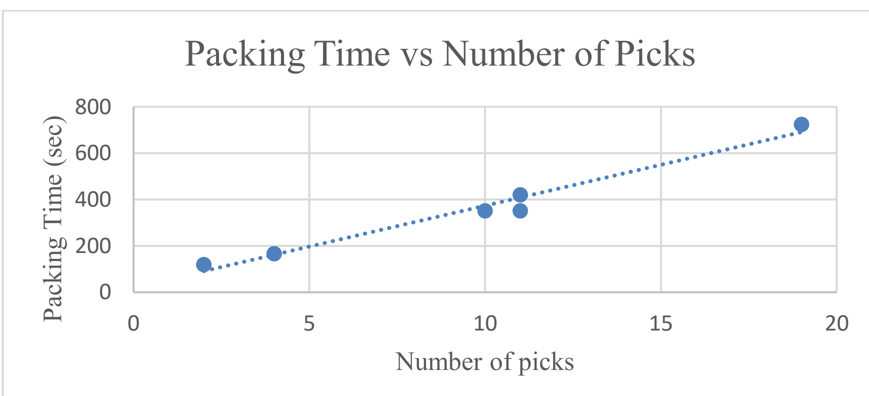
Where: UCL = upper control limit, LCL = lower control limit, $\overline{R}$ = average range of values of samples of the performance measure, D_3 and D_4 = standard factors

3.5. Simulation of the Picking Activity

To evaluate the effectiveness of re-slotting, we conducted simulation using Python, considering in-aisle congestion only in narrow aisles. Congestion is considered only in narrow aisles as pickers in narrow aisles do not have enough space to pass one another thus causing blockages. In wide aisles, however, the pickers can easily pass through the aisle. Hence, congestion is assumed non-existing in wide aisles. Sample order data can be seen in Table 1 (in section 4.1.). The order data is organized by arranging the orders based on the date of order posting and in increasing sequence of order identification number (i.e., Sales Order Processing (SOP) number). In the first step, we randomly distribute the orders among the pickers, starting from first order that is assigned to first picker, each order is assigned to the next consecutive picker and this process is repeated till all orders have been assigned. The second step is to define the routing rules according to the routing policy as discussed in section 1.4 for each order, and calculate the distance travelled for each. Each rack was given x, y coordinates. The picker can either move in x or y direction but a diagonal movement, from one rack to another rack, within an aisle is permitted. The simulation determines the location of each picker, the time being spent in picking the items associated with an order, and waiting time in narrow aisles due to congestion. Walking speed of pickers was taken to be 33 inch/sec (as measured in the warehouse during previous observations). Nine pickers are considered in simulation, picking simultaneously. The congestion time is calculated based on picker blocking situation. A picker has to wait at the aisle entrance if at least one picker is present in the aisle, and it is travelling towards the picker waiting at the entrance, else the picker has to wait behind the picker present in aisle if both are moving in the same direction. The time spent in waiting at each instance is added to calculate the total congestion time. For calculating the pick time (time a picker takes after s/he has reach the rack location to search and place the items from rack into the cart), we sampled pick times using four pickers in warehouse over two days. As the pick times did not follow any standard probability distribution, we use empirical distribution. Average/ constant pick time (that is based on normal distribution) was not used for picking times as commonly used in various other studies in the literature (Gue et al. 2006; Bataineh, 2017; Klodawski et al. 2018). The orders were randomly selected for observing the pick time. Some of the picks were slow as sometimes it took more time for a picker to find the item or because the picker had to open the cartons to take out the items. A set of 46 pick times were used.

For packing time estimation, we used a sample of six different orders of varied sizes packed by four different pickers. As depicted in Figure 3, we found a linear trend between the number of picks made and packing time. We calibrated a function that is the sum of linear function (based on the trend line equation: $y = 35.275x + 20.716$, where y = Packing time and x = Number of picks in an order) and a normal distribution randomness function based on packing time error. The normally distributed packing time error function had a mean zero and a standard deviation of 31.

Figure 3: Plot of order packing time vs the number of picks in an order



Chapter 4: Case Study

4.1. Case Study Data

Different datasets were used for slotting and healing. We were provided with the order data from October to December 2020. As shown in Table 1, the order dataset contains the list of items (shown by Item Number) that were ordered in each order (each order number is represented by SOP Number) along with the date, quantity (indicated by QTY) and other details about the order. The product dataset contained the dimensions of the items. The location dataset contained location of each item in the warehouse i.e. which rack and tier the item was placed in. A dataset of all rack locations i.e. xy coordinates and rack dimensions was also created for slotting and for conducting the simulation.

Table 1: Sample order data set

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1	GL Posting Date	SOP Type	Customer Number	Customer Name	SOP Number	Item Number	Item Description	Item Class	Season	Studio	QTY	U Of M	Salesperson ID	Month	Year	Province
2	2020-09-25	Invoice	6576	Etailz Inc.	3002077	CN3072	CATAN EXP: !	BGE	REGULAR	CATAN	12	EA	TBEA001	9	2020	ON
3	2020-09-25	Invoice	6576	Etailz Inc.	3002077	DW7301	MEMOIR'44	BG	REGULAR	DAYS OF W	18	EA	TBEA001	9	2020	ON
4	2020-10-06	Invoice	6576	Etailz Inc.	3002949	DW7208	TICKET TO RI	BG	REGULAR	DAYS OF W	30	EA	TBEA001	10	2020	ON
5	2020-11-05	Invoice	6576	Etailz Inc.	3003791	CN3072	CATAN EXP: !	BGE	KEYSTONE	CATAN	12	EA	TBEA001	11	2020	ON
6	2020-11-10	Invoice	6576	Etailz Inc.	3003789	CN3072	CATAN EXP: !	BGE	KEYSTONE	CATAN	12	EA	TBEA001	11	2020	ON
7	2020-11-27	Invoice	6576	Etailz Inc.	3004343	CN3072	CATAN EXP: !	BGE	KEYSTONE	CATAN	6	EA	TBEA001	11	2020	ON
8	2020-11-10	Invoice	6576	Etailz Inc.	3003789	CN3078	CATAN EXP: (	BGE	REGULAR	CATAN	24	EA	TBEA001	11	2020	ON
9	2020-11-23	Invoice	6576	Etailz Inc.	3004346	CN3078	CATAN EXP: (	BGE	REGULAR	CATAN	30	EA	TBEA001	11	2020	ON
10	2020-11-27	Invoice	6576	Etailz Inc.	3004343	CN3078	CATAN EXP: (	BGE	REGULAR	CATAN	24	EA	TBEA001	11	2020	ON
11	2020-11-10	Invoice	6576	Etailz Inc.	3003260	CN3103	CATAN - TRA	BG	REGULAR	CATAN	8	EA	TBEA001	11	2020	ON
12	2020-11-10	Invoice	6576	Etailz Inc.	3003260	CN3205	CATAN HIST(	BG	REGULAR	CATAN	15	EA	TBEA001	11	2020	ON
13	2020-11-23	Invoice	6576	Etailz Inc.	3004346	DW7202	TICKET TO RI	BG	KEYSTONE	DAYS OF W	60	EA	TBEA001	11	2020	ON
14	2020-11-10	Invoice	6576	Etailz Inc.	3003789	DW7227	TICKET TO RI	BG	REGULAR	DAYS OF W	48	EA	TBEA001	11	2020	ON
15	2020-11-05	Invoice	6576	Etailz Inc.	3003791	DW7301	MEMOIR'44	BG	REGULAR	DAYS OF W	36	EA	TBEA001	11	2020	ON

4.2. Picking Simulation Validation

To validate the simulation, we shadowed different pickers for six real life orders to validate the results with our prepared simulation in Python using three different random seeds. Reliability of simulation findings was measured using Absolute Percentage Error (APE). Randomness was changed by changing the seed in each simulation run. Orders used for validation varied in sizes from average daily orders in terms of picks to a very high order with high picks and a very low order with low number of picks, ranging from 2 to 19 picks in the six orders considered. The simulation covers the total time taken from the start point to the time the picker puts packaged order on the pallet and is ready to start the next order. The picking simulation is found to provide reliable results as seen in Table 2 with 5 of the 6 picks having APE less than 15% for all the randomness seeds. The variation persists in real packaging time and picking time as in some cases during picking, boxes have to be opened to pick items causing increase in picking time. For packaging time, the pickers use their own judgement to do boxing that can result in high variations in time because of the variation in boxing decisions they make. Even considering these high variations, the simulation is performing rather reliably.

Table 2: Picking simulation validation results

Pick	Real Picking time (sec)	Simulated Picking Time (sec) (Randomness Seed =500)	APE	Simulated Picking Time (sec) (Randomness Seed =600)	APE	Simulated Picking Time (sec) (Randomness Seed =700)	APE
1	847.0	878.0	3.7%	837.0	1.2%	804.0	5.1%
2	736.0	888.0	20.7%	851.0	15.6%	782.0	6.3%
3	896.0	855.0	4.6%	855.0	4.6%	860.0	4.0%
4	198.0	203.0	2.5%	204.0	3.0%	220.0	11.1%
5	327.0	410.0	25.4%	393.0	20.2%	403.0	23.2%
6	1511.0	1313.0	13.1%	1339.0	11.4%	1323.0	12.4%

4.3. Findings of Stage 1: Clustering slotting heuristic and popularity across aisle heuristic

In this stage, we conducted experiments generating slotting using the stage 1: clustering slotting heuristics and popularity across aisle heuristics. To generate the slotting, we used three months of order data (order sample shown in Table 1). Randomness seed 500 was used to run simulation. The seed was randomly selected. As the order data is different for different periods, and order lengths are also different, there is enough randomness in the simulation. Total distance travelled by a picker for slotted item locations was calculated and compared with existing warehouse item locations taking three different order sizes to analyze the reduction in distance travelled. Similar comparison was done to analyze congestion by running simulation for a 4-hour time and comparing the total waiting time when 9 pickers were involved in the picking. The reduction (in %) for the two performance measures of 'distance travelled' and 'waiting time' are calculated using the formulas below.

Reduction in distance travelled (%) =

$$\frac{(\text{Distance travelled in the existing slotting} - \text{Distance travelled in the proposed slotting}) * 100}{\text{Distance travelled in the existing slotting}}$$

Reduction in waiting time (%) =

$$\frac{(\text{Waiting time in the existing slotting} - \text{Waiting time in the proposed slotting}) * 100}{\text{Waiting time in the existing slotting}}$$

The reduction percentage provides the improvement (i.e. reduction) due to the slotting method proposed compared to existing slotting. We randomly selected total distance traveled for three different aggregated orders to analyze the performance. As shown in Table 3 there is an average reduction of 26% in distance travelled when the slotting heuristic discussed in Stage 1 was implemented. The significant reduction in distance can be attributed to the proximity of affinity items re-slotted as the result of the heuristics used and assignment of high frequent pick items to the aisle closer to the packaging area.

Table 3: Results of the distance travelled (in inches) clustering slotting and popularity across aisle heuristics

Number of Orders	Distance travelled (inch) Existing slotting	Slotting heuristic	Reduction (%)
25	175273.5	127945.2	27.0
15	60076.0	46501.9	22.6
10	68888.4	48614.4	29.4

The use of pick frequency and item affinity in tandem takes into consideration the case of multiple picks in every trip. Thus, this heuristics leads to reduction in distance travelled. For case of waiting time, there is a significant reduction as seen from Table 4. As expected, the shifting of most high frequency pick items to wide aisles drastically reduces the load on narrow aisles. Furthermore, by balancing the picking load in all narrow aisles by using popularity across aisle heuristics further leads to a reduction in congestion in narrow aisles. Keeping narrow aisles for items with low picking frequency drastically improves the performance as the number of items that make up most of the sales (around 75-80%) get shifted to wide aisles. Thus, the probability of a picker being in a narrow aisle falls considerably.

Table 4: Results of the waiting time (in seconds) for clustering slotting heuristics and popularity across aisle heuristics

Sr. No.	Waiting time(sec) Existing slotting	Slotting heuristic	Reduction (%)
1	3273	731	77.7
2	3721	560	85.0
3	5274	1691	67.9

4.4. Findings of Stage 2: Healing

In this stage we conducted experiments generating slotting using the urgency score (discussed in Section 3.3.) to carry out a maximum of 50 two-item swaps. In the first healing stage, healing was performed on the SKUs as slotted by the company (where random slotting was used). In each consecutive month all the order data from first period till period in question was used. For all consecutive healings, that we have done monthly, the performance was compared of the healed slotting with the slotting that was there at the start of the month. One we can see in Table 5 that healing a limited number of items results in a reduction in the distance travelled. The limited reduction in distance travelled can be attributed to the small number of items being moved compared to total items in the warehouse. Furthermore, within the aisle in which the item is swapped, the healing technique does not take into account as to whether the item should be placed close to the packaging area or not. Also, with the cross aisle in the warehouse the improvement is reduced due to the greater flexibility that picker gets in transitioning from one aisle to the other aisle. The number of potential healing moves decrease as the months passed because of diminishing rate of return due to improved slotting as healing is repeated.

Table 5: Results of the distance travelled (in inches) for 3 months of healing

Healing done at the end of September			
	Distance travelled (inch)		
Number of Orders	Existing Slotting	Healed Slotting	Reduction (%)
10	68842.7	66212.5	3.8
15	103187.0	97965.3	5.1
25	121309.2	119636.8	1.4

Healing done at the end of October			
	Distance travelled (inch)		
Number of Orders	1st Healed Slotting	2nd Healed Slotting	Reduction (%)
10	53751.4	56010.6	-4.2
15	69665.2	70390.4	-1.0
25	92626.1	91188.3	1.6

Healing done at the end of November			
	Distance travelled (inch)		
Number of Orders	2nd Healed Slotting	3rd Healed Slotting	Reduction (%)
10	28738.0	26578.0	7.5
15	35197.9	31904.3	9.4
25	111976.1	108383.6	3.2

As presented in Table 6, there is a substantial reduction of on average, approximately 25% in waiting time in the first period. The improvement decreases as the healing is conducted in consecutive months. Hence, the solution can be argued to be robust as for each consecutive month, rate of improvement decreases which shows that the healing done in previous months is not fragile, resulting in long term viability of the healing. Also, the number of potential swaps that can be done decrease drastically for every month in which healing is done, showing that there are lesser items that need to be swapped as time progresses.

Table 6: Results of the waiting time (in seconds) for 3 months of healing

Healing done at the end of September			
	Waiting time (sec)		
Sr. No.	Existing Slotting	Healed Slotting	Reduction (%)
1	3527	2616	25.8
2	6059	4872	19.6
3	5464	3875	29.1

Healing done at the end of October			
	Waiting time (sec)		
Sr. No.	1st Healed Slotting	2nd Healed Slotting	Reduction (%)
1	4201	3317	21.0
2	5041	4369	13.3
3	3442	3220	6.4

Healing done at the end of November			
	Waiting time (sec)		
Sr. No.	2nd Healed Slotting	3rd Healed Slotting	Reduction (%)
1	3972	3519	11.4
2	4566	4383	4.0
3	2304	2214	3.9

4.5. Point of Healing/ Slotting

Statistical control chart technique was used to determine when a new healing is to be triggered. The re-slotted warehouse data were used to calibrate the control charts. Orders with picks in the range from 3 to 10 picks, were used as most of the orders have picks within this range. Orders outside this range with lower picks than three and order with picks higher than ten did not have representative picking time per pick. The picking time per pick is high for orders with too few picks and is low for orders with too many picks. For each observation, to calculate mean and range readings were used. To calculate UCL and LCL for X-bar chart and R-bar chart we use equation 1,2,3 and 4.

Figure 4 and Figure 5 show the X-bar chart and R-bar chart that have been developed using eighteen different reading to capture six observations with each observation using three readings. When comparing picking performance with the current warehouse slotting, most of the picking time per pick observation in X-bar chart were outside the UCL. Thus, the chart is a good indicator of the deviation in performance. As can be seen in Figure 5, the variability can be as high as 22 seconds, including all the order (i.e. order with picks less than three and orders with picks greater than 10) will cause such a high variability that the range chart might become obsolete in terms of indicating any deviation.

Figure 4: X-bar chart for monitoring the picking performance

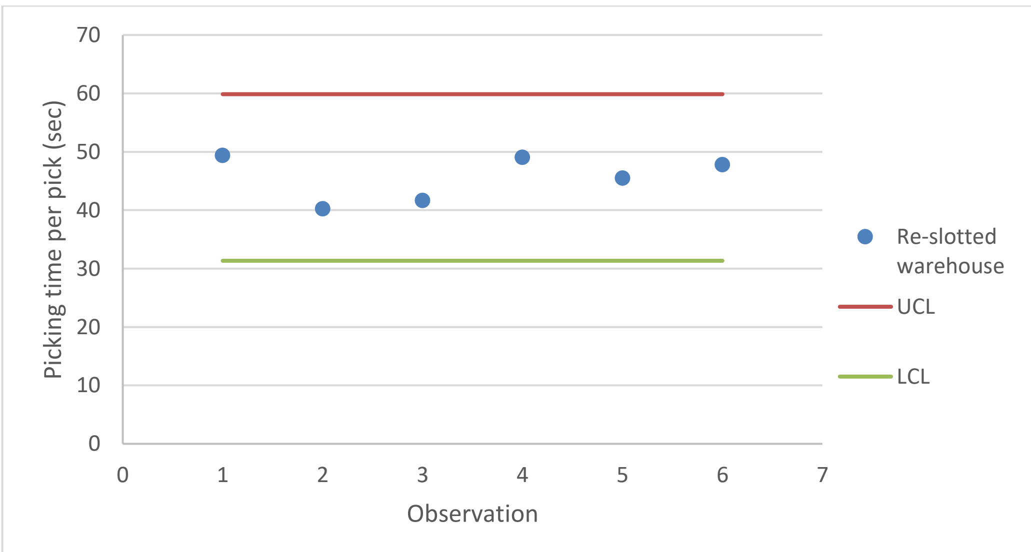
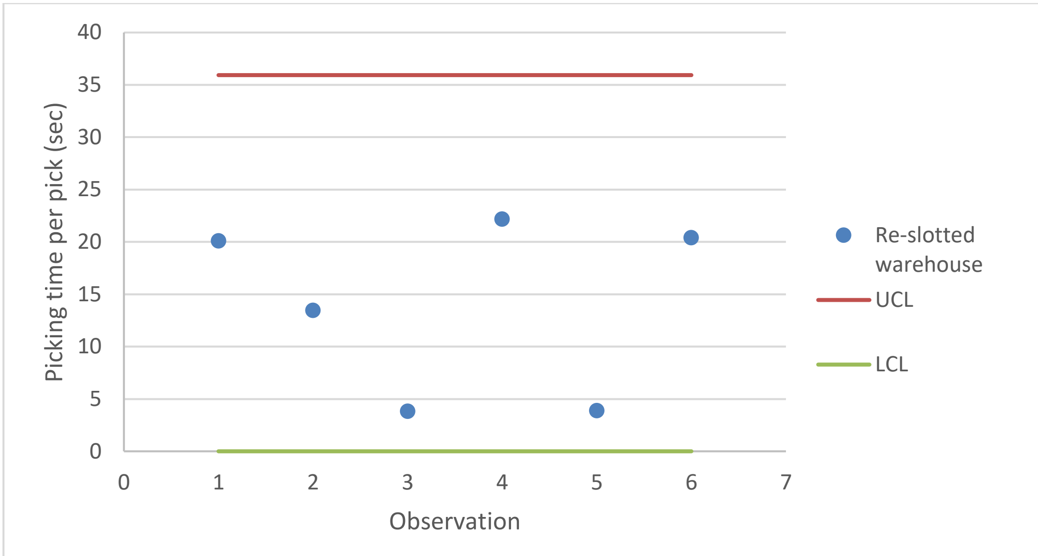


Figure 5: R-bar chart for monitoring the picking performance



In general, if there are data points being consistently out of the range (specifically beyond the UCL limit) there is an indication that the picking performance has degraded and needs to be investigated whether it is due to an unchanged slotting for a long period that is not up to date with the changing order pattern. If this is the case, the company can either do healing or perform re-slotting based on how much effort and time they can potentially dedicate to rearrangement.

Chapter 5: Discussion

This study examines two aspects that influence the picking performance. We aimed to reduce both the travel distance for picking and the congestion that is caused due to in aisle blockage in narrow aisles. To improve these two-picking performance parameters, we used a combination of two slotting techniques that have been traditionally studied individually in the literature. Incorporating a mixture of narrow and wide aisles is another novelty of our study. Our results show that by using a combination of clustering heuristics for wide aisles and popularity across aisles heuristics there can result in significant reductions in travel distance and congestion simultaneously. As many articles focus just on the picking distance reduction using slotting, these articles ignore the congestion effect that can be exacerbated in warehouses that also have narrow aisles.

After re-slotting the warehouse, we found that distance travelled by pickers reduced by up to 29% as compared to the current warehouse slotting (which was mostly random slotting). This reduction is due to placing the more frequently demanded products in aisles closer to the packaging area. Such products were also placed in up-front direction of the aisle. In terms of waiting time, the reduction was as high as 85% compared to current waiting times. The significant reduction was the result of the removal of all frequently demanded products from the narrow aisles. Furthermore, the picking density was balanced between the narrow aisles by means of popularity across aisle heuristics. The reductions in waiting time and distance travelled will increase the efficiency of picking operations and lead to more orders being fulfilled per day. The above results clearly indicate that although random slotting is easier to implement and require practically no analysis or monitoring, it can result in slower picking operations due to more distance travelled by pickers and / or higher waiting time due to congestion in narrow aisles. Specially in case of waiting time, the results indicate that for random slotting with mixed aisles, there is significant potential for improving congestion using slotting heuristics.

Results associated with healing also showed reduction in distance travelled and waiting times. With limited number of swaps each month, the reduction in distance traveled was as high as 9.4% and waiting time reduction was as high as 29.1%. Our findings show that when healing is conducted, the resulting distance and time reductions are less significant. In the three healings conducted, we only move less than 5% of the products. This small fraction of moves results in limited improvement. Furthermore, as the products are moved across different aisles, healing does not consider what location the product should go to within the new aisle (i.e. should the product be placed on a rack closer to packaging area or on a rack that is distant from the packaging area). As healing is done to achieve a robust slotting rather than creating a fragile temporary improvement, it only moves products that will have a long-term impact on performance. Considering that only limited number of products are moved, the improvement should be considered as relatively significant versus re-slotting all the items in the warehouse would prove to be extremely labor and time intensive.

This study is intended to assist Asmodee Canada Inc. by examining its current product slotting and improving it using the re-slotting and healing techniques developed. Furthermore, the process control chart will help the management to monitor the performance of their picking operations. Thus, they will be able to initiate healing to improve product slotting whenever necessary. Our study provides the company with a comprehensive solution right from providing a re-slotting policy to a healing policy supported by a performance monitoring system. Hence, an integrated, wholistic approach to the slotting problem is provided rather than a siloed solution.

To implement slotting, the company needs to initiate the process during the off-season period so that the slotting does not cause unnecessary stress in the warehouse operations. Slotting should preferably be done during the latter end of the day as the new location would have to be updated in the system. The organization should start with slotting the frequent pick products to wide aisles. These products make up the bulk of total sales and picking efforts. During slotting, a daily target should be set in terms of how many racks in an aisle should be re-slotted. After the wide aisles are fully slotted, the narrow aisles should then be slotted. The warehouse should start monitoring the picking performance as the warehouse gets re-slotted so that it is possible to track the progress. Healing should be initiated when after re-slotting, the performance drops beyond the set point in process control charts and consistently remains outside the control limits.

Chapter 6: Conclusion

Few articles have dealt with congestion in picking operations, whereas most articles assume that congestion will not play a key role in degrading the picking performance. Even fewer articles have considered mixed aisles (narrow and wide aisles) warehouses. In this study, we tackled both the issues of congestion and mixed aisles while slotting the warehouse using clustering slotting heuristic and popularity across aisle heuristic. We have provided a robust healing strategy based on urgency score to improve the picking performance without putting a lot of pressure on the warehouse resources. Using a process control chart, we developed a method to monitor the performance and investigate the picking process should the performance is continually degrading. Performance degradation below the allowable limit triggers healing.

6.1. Limitations

There are several limitations to this study. The slotting and healing model developed is tested with the order and layout data of only one company. The results are based on order data of a single company. There might be variation in effectiveness if tested with order data and layout data of several companies in different industries such as defense, automobile etc. The slotting is done based on the order data available. Thus, one cannot base the slotting on future forecast sales of a product that might see a sudden drop or rise in sales due to events such as promotions by a retailer, release of a game in a particular category by competitor, etc. As most of the racks had 1 or 2 tiers for picking, the impact of vertical storage on picking has not been considered in the slotting heuristics used. The pick time from the racks increases as we move away of the golden zone on a rack. Only in-aisle congestion has been considered in our study without considering the impact of other types of congestion on performance such as pick-face blocking, cross aisle blocking and depot blocking. The impact of restocking the racks during the picking operations (that might cause blockage of the area due to a forklift) has not been considered in estimating the waiting time. Although we used a single randomness seed in our simulation for getting the results but use of multiple randomness seeds will help better capture the variability of results in each seed.

6.2. Future Research

Estimating the reallocation costs will result in better understanding of the overall cost savings due to re-slotting. Using the reallocation costs and saving due to slotting will help in determining the number of optimum number of swaps that should be done during a given healing. We will be able to maximize the total savings by considering the reallocation cost of the swaps. Other industries / company data should be tested with the model developed. The model developed needs to be applied using different order data and warehouse layouts to understand the model's robustness and effectiveness. One could also explore how the proportion of narrow aisles and wide aisles can impact the congestion. There might be a preset ratio of number of narrow and wide aisle below which in-aisle congestion has a significant impact on the picking performance. A simulation model where we consider the restocking activities during picking will help in understanding the congestion due to restocking activities. For warehouses that have vertical storage, it would be interesting to see if filling the golden zone first in all racks and then filling shelves outside the golden zone improves the overall picking performance in a warehouse with both narrow and wide aisles. Using a combination of multiple types of congestion in a warehouse such as in-aisle blocking and pick-face blocking will help in understanding how each blocking type is contributing to waiting times.

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