A Simulation-Optimization Approach to the Storage Location Assignment Problem: A Case Study of a Distribution Warehouse in Automotive Manufacturing

by

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and have found that it is complete and satisfactory in all respects,
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Dedicated to my family and grandparents,

ABSTRACT

Warehouses play a central role in any supply chain. Warehousing operations constitute around 25% of a company's overall expenses for logistics. About 55% of the warehouse operating cost is generated by travel activities during order-picking operations. Therefore, the total travel distance directly affects the cost of order-picking and put-away operations. The total travel distance can be reduced by designing an effective storage policy and by systematic allocation of storage spaces to products. In this thesis, we focus on the allocation of storage spaces to different products with various characteristics for unit-load, single-command, picker-to-part warehouses with multiple input/output ports. We propose a simulation-optimization based approach to solve the storage location assignment problem. In the proposed methodology, the simulation model is used for generating certain input parameters for the optimization model. Then, the optimization model returns the best storage space allocations for each product so as to minimize the total expected travel distance. We test our approach with a real data set obtained from a major automotive manufacturer in Turkey. Our results reveal that the proposed method may reduce the total travel distance by up to 12%.

ÖZETÇE

Depolama sistemleri tüm tedarik zincirlerinde kilit rol oynamaktadır. Depolama operasyonlarının bir şirketin lojistik giderlerinin yaklaşık %25'ini oluşturduğu bilinmektedir. Depolama sistemlerinin işletme maliyetinin yaklaşık %55'i de sipariş toplama sırasında kat edilen mesafeden kaynaklanmaktadır. Bu nedenle, kat edilen toplam mesafenin sipariş toplama ve yerleştirme maliyetleri üzerinde doğrudan etkisi bulunmaktadır. Etkili bir depolama politikası ve ürünlerin depolama alanlarına sistematik bir şekilde atanması ile kat edilecek toplam mesafe azaltılabilir. Bu tez çalışmasında, farklı özelliklere sahip ürünlerin birim yük, tek çevrim, toplayıcıdan parçalara sipariş toplama sistemi kullanan, birden fazla giriş/çıkış kapısına sahip depolarda, depolama alanlarına atanmasına odaklanılmıştır. Stok ataması problemini çözmek için benzetim-eniyileme tabanlı bir yaklaşım tasarlanmıştır. Önerilen yöntemde benzetim modeli, eniyileme modeline girdi parametresi üretmek için kullanılmaktadır. Eniyileme modeli ise her ürün için beklenen toplam kat edilen mesafeyi enküçükleyecek depolama atamasını yapmaktadır. Bu çözüm yaklaşımımız, Türkiye'nin önde gelen otomotiv üreticilerinin birinden aldığımız gerçek veri ile test edilmiştir. Sonuçlar, önerilen metot ile sipariş yerleştirme ve toplama esnasında kat edilen mesafenin %12'ye kadar azaltılabileceğini göstermektedir.

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NOMENCLATURE

SLAP	:	Storage Location Assignment Problem
I/O	:	Input / Output
COI	:	Cube-per-Order-Index
MIP	:	Mixed Integer Programming
DSS	:	Decision Support System
CPU	:	Central Processing Unit
3PL	:	Third Party Logistics Provider
DM	:	Decision Maker
PC	:	Personal Car
MCV	:	Medium Commercial Vehicle
SUV	:	Sports Utility Vehicle

Chapter 1

INTRODUCTION

Warehouses are fundamental elements of a supply chain. They play critical roles in balancing supply-demand mismatch and consolidating the products from different suppliers for combined delivery to customers [2]. Despite the fact that the lean principles and Just-In-Time production have gained interest, the supply and demand uncertainties in most markets still hold. Moreover, customers demand high variety of products within shorter time periods. Satisfying the customer demand in a timely manner with an enlarged product range increases the importance of inventory and therefore warehouses. The new concepts have disseminated the practice of make-to-order policy especially in the automotive industry; however, to maintain customer satisfaction companies allow changes in the orders. This may require keeping inventory of more products and in variable amounts, which have direct implications on warehousing management. At this point, the role of the warehouses becomes more pronounced in managing the demand variability. Therefore efficient management of warehouse operations is a significant issue for companies to cut down costs.

Warehouse operations involve movement of the goods within the facility and can be classified as receiving, put-away, storage, order-picking, and shipping. Receiving covers unloading activities upon product arrival and put-away includes moving the products to predetermined storage locations. After an order request is received, certain products are picked from their storage locations by travelling, searching, and extracting the products [3]. Finally, the orders are shipped. Performing these activities in an accurate way requires a tremendous cost for labor expenses, land, materials handling equipment and information systems. Cost of land, equipment, and information systems generally require an initial investment, which is unavoidable; however labor activities are repetitive and can be enhanced to reduce the total cost. Sharma et al. [4] report that the overall cost of a warehouse constitutes 22-25% of a company's total expenses for logistics. Among the operational activities, order-picking comprises the highest cost by accounting for 55% of warehouse operating costs. Travelling consumes 55% of the time spent during the order picking [3]. Therefore, improvements on travel time or distance lead to significant contributions to the warehouse operating activities. The literature shows a consensus on the opportunities of reducing travel time as it does not add any value but costs labor hours ([5], [6], and [3]).

Reducing travel time/distance can be achieved by the placement of frequently moving products closer to the input/output (I/O) points, which will also shorten the order-picking time. In light of this idea, the question that arises for the warehouse managers is where to place each product type such that the total travel distance is minimized while placing and picking the products. This problem is referred to as the Storage Location Assignment Problem (SLAP) in the literature and is widely discussed. When complete information on product arrival and departure times is not available, products are grouped into classes and these classes are assigned to storage locations. Three different storage policies are implemented depending on the number of product groups: Dedicated Storage, Random Storage and Class-Based Storage [2]. The problem in practice is which products to group in a class and which locations to assign to each group. Further details on the problem are provided in Section 2.

Our thesis is inspired by one of the largest automotive manufacturers in Turkey. The finished goods warehouse of the company operates as a distribution warehouse. The vehicles manufactured within the factory and the vehicles imported from the company's international production plants to be distributed in the domestic market are stored in this warehouse. The company owns the warehouse, however, due to capacity problems they have the option to lease external parking places. The vehicles are dispatched to domestic dealers and other international manufacturing plants for distribution. Distribution to overseas is done via ships, therefore these vehicles are directly shipped to a nearby harbor. Furthermore, such vehicles do not occupy any place in the warehouse except the reserved loading area for exportation; therefore, the path they traverse within the warehouse is predetermined and there is no opportunity for improvement. The possible reductions for the travel distance can only be done for the vehicles dispatched to the domestic market. There are several limitations while deciding on the storage locations of vehicles. There are three types of vehicles according to their physical characteristics each requiring a different sized location. Moreover, the warehouse is composed of several regions and there are certain storage restrictions for each region. Since the products consist of automobiles, batching and multiple orders per pick are not possible. The final products are actually driven to and from their storage locations by employees of the company. As a storage policy the warehouse management uses closest-open-location policy. An arriving vehicle is placed to an open lot closest to the exit port. Additionally, the restrictions defined for each region generates a preferred selection set for each vehicle type. Therefore, the policy is implemented under the restrictions of the preferred set and physical requirements. This procedure may cause the vehicles with slow turnover frequency to occupy the lots closer to ports and force the frequently moving vehicles to be assigned to remote locations. This means traveling extra distances repetitively, and preventing this by proposing a new policy is the motivation of our study.

Although we are inspired by the case of the manufacturer, we design our solution approach for a generalized version of this problem. The warehouse studied operates under a unit-load, single-command, picker-to-parts system and has multiple I/O ports. The products stored in the warehouse show variability in type and size. The warehouse consists of different regions and different products have different priorities for using each region.

Our major goal in this thesis is to develop a decision support system that returns warehouse storage locations for each product group so as to optimize a certain performance measure. Moreover, we aim to solve the problem under uncertainty, where the only available information on arrivals and departures is production and sales forecasts.

Our performance measure is the total travel distance, i.e., we aim to determine storage locations in an attempt to minimize the total distance traversed during put-away and order-picking. Different physical space requirements of products, variable capacities of storage regions and prioritized zones add originality to the problem. We propose a simulation-optimization based approach as a solution methodology. The output of the simulation model provides certain input parameters to the optimization model, which is then solved to determine storage locations for each product. Finally, we use the simulation model to assess the output of the optimization model. We investigate the possible improvements that could have been made for the real data set if our approach was used. The simulation with the real data is repeated with the obtained assignment policy and the change of the total travel distance from the existing case is analyzed. Our results on the real data reveal that, the policy we propose provides a reduction in travel distance between 4% and 12%.

1.1 Outline of the Thesis

The thesis is organized as follows: In chapter 2, we review the literature on warehousing operations and Storage Location Assignment Problem. In Chapter 3, we give a formal definition of the problem and introduce our solution methodology by presenting the simulation and optimization models developed. In Chapter 4, we make a detailed description of the case study, introduce the scenarios to be analyzed and present the computational results. Finally, we conclude by giving the final remarks and identifying the future research directions in Chapter 5.

Chapter 2

LITERATURE REVIEW

The warehousing management and Storage Location Assignment Problem (SLAP) are both widely discussed in the literature. As van den Berg [7] states, research activity on warehousing management increased after the focus of the management shifted from productivity to inventory reduction in the 1970's. In this chapter, we review the warehousing literature in three sections. In Section 2.1, we introduce the warehouse types and classifications presented in the literature. Then, in Section 2.2, we present warehousing operations and their reflections on the total cost. In Section 2.3, we review the literature on SLAP, covering the proposed storage policies and methods used to solve the problem. Later, we present the alternative objectives and performance measures. Finally, studies on SLAP are briefly summarized reporting the storage policies, objectives and the solution methods used.

2.1 Warehouse Types and Classification

Warehouses can be named and classified according to different measures. Bartholdi et al. [3] classify warehouses according to the customer group they serve, e.g., retail distribution centers, service parts distribution centers, etc. In a survey conducted by van den Berg [7], the classification is made both according to warehouse functions and source of supply points. Along with refering to distribution warehouses (DC) and production warehouses, van den Berg gives two classifications according to order-picking systems and product retrieval. With respect to order-picking there are three categories: Picker-to-product, product-to-picker and picker-less systems. In the first category, the picker accesses the product with a vehicle. In the second one, the product is delivered to the picker with automated equipment. In the third category, the system is fully automated so there is no need for pickers. In terms of product retrieval, van den Berg [7] again divides the warehousing systems into two: unit-load retrieval systems and order-picking systems. Unit-load warehouses are systems where in a load, all of the items can be combined as a single entity and moved with the same materials handling equipment. In such systems unit-loads are placed or retrieved at once, while in order-picking systems items are picked in less-than-unit-load quantities. Another classification criterion proposed by Goetschalckx [8] is the command cycle. A warehouse operates under a single-command if only one activity is done (either put-away or retrieval) per an order-picking trip. A dual-command cycle indicates that a put-away and a retrieval activity are performed per trip. If the system does not operate under a unit-load policy, then multiple items are stored and retrieved individually during the trip, which is called a multi-command cycle.

2.2 Warehouse Operations

Movements of the items within the warehouse are classified into five main groups in the literature: receiving, put-away, storage, order-picking, and shipping. After the arrival, products are unloaded and transferred to put-away operations. Bartholdi et al. [3] emphasize that the storage addresses of the products should be determined beforehand to facilitate the order-picking process. Therefore, the management should keep track of the storage locations; this shows the need for information systems. They state that the travel during the put-away constitutes 15% of the operating cost [3]. The products are stored in assigned locations until an order is received. Storage policies are discussed in detail in Section 2.4.1. During the order-picking, certain products are retrieved from their storage locations. Two important points are the determination of the product location and the physical retrieval operation. With the use of information systems or certain storage policies, the storage location can be tracked. However, during the retrieval certain amounts of distances are needed to be travelled. Travel occurs for each item demanded so, this is a repetitive operation. Bartholdi et al [3] emphasize that order-picking corresponds to 55% of warehouse operating expenses, and among the order-picking activities, travel consumes the largest proportion (see Figure 2.1). Consequently, travel is perceived as the first candidate to improve among the warehouse operations ([5], [6], [1], and [3]). Chuang et al. [5] also state that travel is the most common objective for improvement both in academia and in practice.

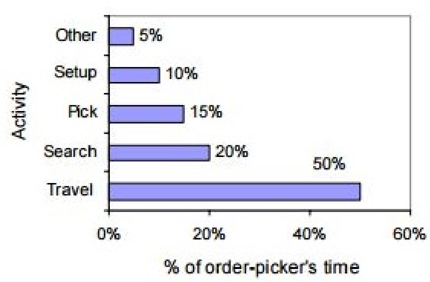

Figure 2.1: Order Picking Activities [1]

Chen et al. [9] state that there are four alternatives to reduce the travel distance during the order-picking: finding good order-picking routes, zoning the warehouse, assigning orders to batches, and assigning products to correct storage locations. Order-picking routes determine the sequence for items to be picked, while zoning divides the warehouse into smaller groups where certain pickers are assigned to certain zones and operate only within that zone. Batching means combining a set of orders in a picker tour. Apart from these three alternatives, assigning products to storage locations (SLAP) is one of the most commonly studied subjects in the warehousing literature. Since our thesis problem focuses on SLAP, it will be reviewed in detail (For order-picking, zoning and batching problems see, [1]).

2.3 The Storage Location Assignment Problem (SLAP)

SLAP is concerned with the assignment of products to storage locations such that a performance measure is optimized. Travel distance is highly dependent on the storage location; therefore, one popular approach is to solve the SLAP with the objective of minimizing the total distance. Gu et al. [2] give a formal definition of the problem by specifying the information present, the decision variables and possible constraints. They state that the objective is to determine storage locations for each product group so as to minimize the total distance traveled. The input parameters are given by the layout of the storage area, physical features of storage locations and products, and demand information. They also list the possible constraints as storage capacity/efficiency, picker capacity/efficiency, response time, compatibility between products and storage locations, and item retrieval policy.

2.3.1 Storage Policies

Before solving the SLAP, a general strategy for storage allocation needs to be determined. Then under a particular strategy, products are assigned to some classes according to their attributes. Certain product types are aggregated in a class to reduce uncertainty, provide higher utilization of storage spaces, and also to reduce the problem size. The most common storage policies are random, dedicated and class-based storage. In random storage, the number of product classes is one and each product is randomly assigned to an available storage location, i.e., any storage location can be used for any product. In dedicated storage, the number of classes equals the number of products, and certain spaces are reserved for each class. If the number of classes changes between the two, the policy is named class-based storage. The class-based storage is a combination of the random and dedicated storage: Each product group is assigned to a dedicated zone, but within each zone the products are assigned randomly to storage spaces. For the three policies there is a trade-off between storage utilization, required storage space and retrieval efficiency. Random storage requires the least storage space and has the highest utilization rate; however, computer-aided systems are needed to track the location of the products. At the other extreme, dedicated storage facilitates the order-picking process through fixed locations, yet it requires the maximum number of storage spaces and incurs the lowest space utilization. Class-based storage may provide both utilization and location identification advantages, depending on the number of the classes. Class formation can be done based on different measures. Sharma et al. [4] summarize these criteria as order rate, turnover rate, moving speed and physical characteristics/attributes of the products. Grouping items according to Pareto's method (or ABC classification) is also common ([1], [4], [10], and [11]). Some authors also used clustering techniques to specify product classes for each product, with respect to products' occurrence rate in the same order or various criteria defined (see [9] and [7]). Apart from the three policies, there is another strategy applied in practice. When no information is available on arriving products or when companies do not use the available information, the arriving items are assigned to Closest-Open-Location. Gu et al. [2] also list similar approaches as Farthest-Open-Location, Longest-Open-Location and Random-Location.

The next decision is to determine which locations to allocate for each product class. There is a range of assignment criteria used in the literature. The commonly used criteria are volume and popularity based methods. The idea is to place the fastest moving products closer to the ports. These methods include assignments based on turnover rate or moving speed, cube-per-order-index (COI), order frequencies and picker travel times. COI is the ratio of the maximum required storage space to the number of storage operations per unit time, meaning that it utilizes the information on popularity and storage space requirement. Usually the product classes with lower COI values are assigned close to input/output (I/O) ports. The approach with the turnover rate and order frequency is the same. Fast moving items are placed in the most desirable or closest locations. The assignment methods have some assumptions on the warehousing systems under which the method will work best (see [2]). Therefore, determining the storage policy and assignment criteria depend on the system characteristics, requirements and capabilities.

2.3.2 Objectives and Performance Measures

Another crucial point in SLAP is to select the performance measure or objective that the optimal policy will be designed around. In their survey on warehouse performance measures, Staudt et al. [12] classify the performance indicators in terms of time, quality, cost and productivity. Travelling cost constitutes 55% of the warehousing expenses and has direct implications on material handling operations. Therefore, in the literature the most frequently observed objective is the minimization of the travel distance or travel time. On the other hand, some attention is also paid to the warehouse utilization levels. For instance, in [6], Fontana et al. simultaneously minimized the total order-picking distance and total space required. For a detailed study on all warehouse performance measures please see Staudt et al. [12].

2.3.3 Studies Conducted on SLAP

This section reviews selected studies from the literature in terms of the adopted objective function/performance measure, storage policy and solution methods.

Chuang et al. [5] developed an approach called the Clustering-Assignment-Problem. For the classification selection they analyzed the between-item associations and made the clustering accordingly. Then they used the class-based storage policy to locate the classes formed, based on frequency. They developed an mixed integer programming (MIP) model to solve the SLAP with the objective of minimizing the order-picking distance. They also provided comparisons between other policies in terms of the improvement in the objective function.

Sharma et al. [4] used class based storage policy, where classes are formed by a clustering approach. The clustering is based on the quality of produced items. The objective of the mathematical model is to minimize traveling time and distance. They also proposed a new design for layout by introducing zoning. An implementation of their model is applied to an instance of a manufacturing firm.

Some studies compare different storage policies. Hausman et al. [13] compared random storage policy and turnover-based class based storage. They showed that turnover rate is more efficient in terms of reducing travel time. Malmborg [11] analyzed the assignment policy trade-offs between random and dedicated storage. The performance indicators are minimum space requirements and item retrieval efficiency. Classes are formed based on ABC classification and storage space assignment is made by solving an MIP model. Also in [8], different storage policies are examined in detail for unit load systems.

In some studies the problem is solved with an alternative objective or with multiple objectives, one of which is travel time. Fontana et al. [6] simultaneously minimized the storage space required and total order-picking distance. They used the class based policy and COI criteria. They solved the problem adopting the Pareto-optimal (efficient frontier) solution approach. They generated non-dominated solutions and let the decision maker choose among a small number of alternatives. However, they stated that for large instances heuristics should be developed. A similar problem implementing class-based storage with COI policy is studied by Muppani et al. [14]. They developed an MIP model which minimizes the sum of the storage space cost and order-picking cost. Because of the nonlinear objective they solved it via simulated annealing. They tested their approach on an instance of a distribution warehouse.

A storage allocation model with a different objective is studied by Montulet et al. [15]. They developed an assignment model minimizing the peak load, i.e., the maximum average daily capacity requirement. They utilized dedicated policy and turn-over based criteria.

An example to the development of a decision support system (DSS) is presented by [16]. They designed a system which makes a detailed analysis of different configurations. DSS includes modules for layout design, comparing storage allocation strategies and assignment policy. For assignment they used cluster-based analysis. The objective is to minimize total traveling distance and cost. The DSS enables the decision maker to compare different scenarios. They applied the tool in an automotive spare parts warehouse.

2.4 Our Contributions

We study the SLAP in unit-load, single-command, picker-to-part warehouses with multiple I/O ports, under class-based storage policy. In the literature the common approach for solving the SLAP is the development of heuristics and generally they do not account for the uncertainty in production and demand structures. Most of the studies assume that demand rate is constant over the planning horizon and the replenishment (in our model, production) is done based on the EOQ formula. However, in practice both of production and demand have seasonal changes, which should be considered while planning for a storage assignment. Considering this fact, we aim to propose a decision support system to aid the decision maker on the tactical level decisions where the demand uncertainty is not resolved. Therefore, we design a simulation-optimization based method to provide the storage location assignments under a class-based policy, where exact information on demand and production is not available. For solving the optimization model that returns the best storage location assignments for each product group, the maximum number of products that is expected to be stored in the warehouse should be known. Since we consider the plans for the upcoming period, we need an estimate for the expected maximum number of products for each class. Therefore, we developed a simulation model which approximates arrivals and departures with probabilistic distributions using the information on production and sales forecasts. The simulation model also accounts for the change in the demand patterns of products that are grouped under the same class. Monthly production and sales forecasts are used for smaller product groups within the same class, therefore the seasonal changes are better reflected. As an outcome of the simulation, we obtained the maximum storage space requirements per product class which are used as parameters for optimization model. The optimization model makes the storage space assignments for each product class so as to minimize the total distance traveled. The total distance measured includes the distance traveled during put-away and order-picking. In the literature, most of the studies only focused on the distance during the order-picking, however, consideration of the put-away will provide more realistic results.

In the considered problem structure, there are various products variable in required storage space size and type. Some products are preferred to be stored primarily in certain warehouse regions, i.e., some products have priority for using specific storage spaces. Therefore, we defined a set of constraints named as 'Priority Constraints'.

They can be added to the optimization model if the usage restriction is considered as a hard constraint. In the simulation, we modeled the priorities in all cases which add originality to our problem.

We tested our approach with real data, and showed that the suggested class based storage improves the existing system. Then, we solved the model both with exact data and with an approximated arrival and departure distribution. The results turned out to be similar, which indicates that usage of the simulation model is acceptable for future planning. It should be noted that, to use this method for different warehouses, the goodness of the fitted or approximated distributions should be evaluated as we did in the case study. Designing the problem by inspiring a real-life problem and testing it with real-life data including the priority specifications are the main contributions of this study. In conclusion, we believe that using optimization and simulation mutually is a convenient approach for decision making under uncertainty.

Chapter 3

PROBLEM DEFINITION AND SOLUTION METHODOLOGY

In this chapter, we first give a formal definition of the problem studied in this thesis. We present our assumption on the warehouse type, order-picking operations, storage area, and product types in Section 3.1. Formal definitions and details of simulation and optimization models are detailed in Section 3.2.

3.1 Problem Definition

In this study, we consider a distribution warehouse where products from different manufacturers are stored and then distributed to dealers. We are inspired from the final product warehouse of a major automotive manufacturer in Turkey, and tested our proposed methodology as a case study using their data. Despite the fact that we specifically consider the finished goods warehouse of an automotive manufacturer, our proposed solution can be extended to any warehouse that operates under a unit-load, picker-to-parts, and single-command scheme. Therefore we provide a general definition for our problem. We suppose that there are various products stored with different characteristics. The products show differences in terms of physical size, and therefore storage space requirement. According to product features, some products are considered to be luxurious. Therefore, another classification measure is whether the product is luxurious or not. The third classification is based on the product's origin: imported or domestic.

We assume that the layout of the finished goods warehouse is given and the locations of storage spaces, are known. There is a predefined direction of flow between the aisles. There are multiple ports, some of them are the input (entrance) ports and the other ones are the output (exit) ports. The warehouse is composed of different regions, each of which can be utilized for certain product groups for security concerns. The manufacturer prefers to store luxurious products in certain regions of the warehouse due to security considerations. Therefore, priority rules can be defined for different warehouse regions and product groups.

The products at the input ports are placed to an available storage space by the employees. Then, the employee returns to port to repeat another put-away operation. The retrieval process has a similar procedure. Upon receiving an order, the corresponding products are picked up by an employee to the dispatching area and the employee then returns back to the storage area. Then, the products are loaded to trucks where loading is a task handled by a third party logistics (3PL) company. Due to product characteristics, only one product can be put-away or retrieved in an order-picking tour and order-batching is therefore not possible.

Monthly forecasts for production and sales are known for a planning period. Under these conditions, our objective is to propose a class-based storage policy such that the expected total travel distance is minimized. Minimizing the total travel distance is equivalent to minimizing the additional handling operations in the warehouse which may lead to a decrease in the labor requirement. We evaluate the new class-based policy under different scenarios and leave the final decision to decision maker (DM), letting him/her to choose a policy considering the conditions at the decision period. The scenarios include a combination of relaxations for the storage region restrictions. In an attempt to account for the seasonality, the time horizon for the study is taken as one year, however it can be conducted for shorter periods considering industry characteristics that the warehouse belongs. Given the warehouse restrictions, layout, product and forecast information, the output provides a storage space assignment for each product. The scenario analysis provided enables the decision maker to evaluate a number of alternatives developed under different configurations.

3.2 Solution Methodology

Our solution approach is composed of two stages: Simulation and optimization. The optimization model is the main tool for obtaining the best product class-to-storage location assignment. The simulation model is used for estimating the required parameters for the optimization model. When the approach is tested with real data, we use simulation again to validate that the output of the optimization yields a better solution to the system.

The two models are used consecutively for parameter estimation and performance evaluation. Certain output measures of the simulation model are used as an input to the optimization model. The resulting assignment policy from the optimization model is simulated again to assess the output of the optimization model under uncertainty and measure the improvement (see Figure 3.1). The two models are explained in detail in Sections 3.2.1 and 3.2.2.

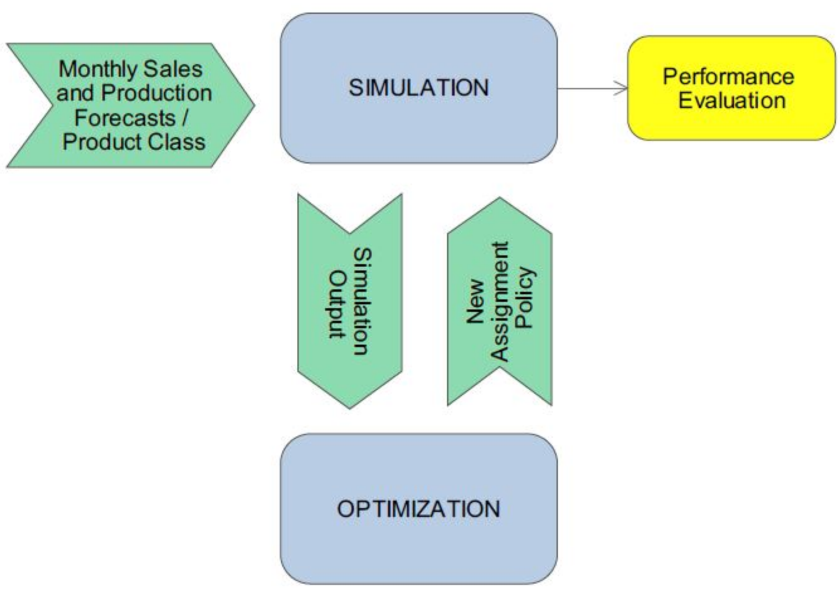

Figure 3.1: Summary of Our Methodology

3.2.1 Optimization Model

We develop an optimization model for allocating storage locations to each product class so as to minimize the expected total travel distance. The policy utilized is the class-based policy where product classes are formed with respect to various product characteristics. Products can be grouped together with respect to various features like physical constraints, market positioning, or price range. After the product classes are defined, each class needs to be assigned to certain storage locations. Our objective is to minimize the expected total travel distance. Different objectives such as minimizing maximum required storage space or increasing utilization levels of storage spaces can be studied. Our primary aim does not include those, however the impact of the new policy on these measures is also examined.

Our optimization model borrows from the model presented by Ghiani et al. [17]. They modeled the problem as a structured transportation problem. The main idea is to assign faster moving product classes closer to I/O ports. According to class-based policy, a specific set of storage spaces should be dedicated to a product class, therefore our aim is to assign more frequently moving product classes to zones that are closer to ports. To account for the movement frequency and distance at the same time, we adopted the cost function defined by Ghiani et al.[17]. In their model, they define an assignment cost for each storage space and each product class. The assignment cost depends on the movement frequency of product class per location multiplied by the distance of the location to the I/O ports. It is defined explicitly under parameter definitions.

We start presenting our model by defining the sets, parameters and decision variables. There are n product classes, s storage zones and t ports. In an attempt to reduce the problem size, we assume that storage locations are grouped in zones having different capacities. At the same time, due to product size differences, available capacity of each zone for different product classes can be different. Therefore, the cost function given in [17] is modified to account for the zone capacity for each product class.

Indices

i: product class i=1, ..., n

k: storage zone k=1, ..., s

r: I/O port r=1, ..., t

Sets

I: set of product classes I={1, ..., n}

K: set of storage zones K={1, ..., s}

R: set of I/O ports R={1, ..., t}

Parameters

p_{ir} : average number of handling operations on a product group i through port r $i \in I, r \in R$

d_{rk} : distance from port r to storage zone k $r \in R, k \in K$

l_i : maximum number of storage zones required for product group i $i \in I$

q_{ik} : available capacity of storage zone k for product class i $i \in I, k \in K$

c_{ik} : cost of assigning storage zone k to product class i $i \in I, k \in K$

$$c_{ik} = \frac{\sum\limits_{r \in R} p_{ir} d_{rk} q_{ik}}{l_i} \qquad \forall i \in I, \forall k \in K$$

Decision Variables

$$x_{ik} = \begin{cases} 1 & \text{if product class } i \text{ is assigned to storage zone } k, \qquad \forall i \in I,\ \forall k \in K \\ 0 & \text{otherwise.} \end{cases}$$

Next, we give the optimization model:

$$\min \qquad \sum_{i \in I} \sum_{k \in K} c_{ik} x_{ik} \tag{3.1}$$

s.t.

$$\sum_{i \in I} x_{ik} \leq 1, \qquad \forall k \in K \tag{3.2}$$

$$\sum_{k \in K} q_{ik} x_{ik} \geq l_i, \qquad \forall i \in I \tag{3.3}$$

$$x_{ik} \in \{0,1\}, \quad \forall i \in I, \ \forall k \in K \tag{3.4}$$

In this problem, the objective function (3.1) minimizes the total cost of assigning product classes to storage zones. The cost parameter c_{ik} denotes the assignment cost of a product class i to a storage zone k. The cost parameter accounts for the movement frequency of the product class i and the distance of zone k at the same time, since the objective is to assign frequently moving products closer to I/O ports. In the calculation of c_{ik}, the average number of handling operations per each storage zone dedicated to product i, through each port r to storage zone k, given by $\frac{p_{ir}}{l_i}$, is used. In other words, the assignment cost incorporates the average movement frequency per storage location in the assigned zone. l_i denotes the required number of storage spaces to be reserved for product class i. The requirements for each class are equivalent to the maximum of the number of products observed in the warehouse at any time. The total movements of a product class are amortized over all of the storage spaces reserved for the class to calculate the movement frequency. Then, it is multiplied by d_{rk}, the distance of zone k to each port r. This accounts for the cost of assigning an individual storage space in zone k to product class i. However, the zones are assumed to be dedicated to a class and have different capacities, therefore, the unit cost is multiplied by the capacity of zone k available for product class i given by q_{ik}. This yields the assignment cost of zone k to product class i. Note that, the cost function assumes that all of the storage spaces are uniformly utilized. The constraint set (3.2) ensures that a storage zone is dedicated to at most one product class. The constraint set (3.3) imposes that the total capacity of the zones assigned to product class i, should be at least as large as the minimum required capacity for class i. The minimum required capacity l_i, represents the expected maximum number of items from product class i, present in the warehouse in the given time horizon. The ranges of the decision variables are specified by the constraint set (3.4).

As stated in the problem definition, the warehouse is assumed to be composed of multiple regions where each can be reserved for certain product classes for security concerns. Alternatively, some of the regions and external storage spaces leased can have priority over the others, while assigning the product classes. A product class should first be assigned to the prioritized region before being assigned to other regions. For instance if region 1 has priority over region 2 for class 1, then a product from class 1 cannot be placed to region 2, if all zones of region 1 is not assigned to some class. To address this situation, we added a group of constraints and variables, referred to as Priority Constraints.

Priority Constraints

Subsets

I': set of specific product classes , $I' \subset I$

K': set of specific storage zones belonging to a particular warehouse region , $K' \subset K$

Additional Decision Variable

$$y = \begin{cases} 1 & \text{if all storage zones in the prioritized warehouse region is assigned to} \\ & \text{some product class} \\ 0 & \text{otherwise.} \end{cases}$$

Additional Constraints

$$x_{ik} \leq y, \quad \forall k \in K \setminus K', \forall i \in I' \tag{3.5}$$

$$y \leq \sum_{i \in I} x_{ik}, \qquad \forall k \in K' \tag{3.6}$$

$$\sum_{k \in K'} \sum_{i \in I} x_{ik} \leq |K'| - 1 + y \tag{3.7}$$

Constraint set (3.5) ensures the priority by implying that if the particular product class is assigned to any zone in $K \setminus K'$, then the specified warehouse region with priority should be full. Constraint set (3.6) implies that if $y = 1$, i.e. the specific warehouse region is full, then each storage zone in K' should be allocated to a product class. Similarly, constraint set (3.7) implies that if $y = 0$, then there is at least one empty storage zone in K'. All in all, the Priority Constraints enforce the assignment of a specific product class to a particular warehouse region unless all of the zones in that region are assigned to a product class. If there are still unassigned zones in the prioritized region and there are products to be assigned, then the constraint set forces assigning these products to the prioritized region first. If there is still a need for capacity, then assignments to the remaining regions are made. Priority for multiple regions and product classes can be defined by introducing new variables and adding the corresponding set for each region.

We now discuss the parameters of our optimization model. We assume that the product classes are determined based on product characteristics. The number of handling operations on product class i through each port r, denoted by p_{ir}, can be estimated from the production and sales forecasts. Production forecasts during the time horizon will determine the handling operations through input ports, while sales forecasts would translate into handling activities through output ports. The distance d_{rk} from the ports to storage zones can be calculated from the given layout. The available capacity of each storage zone for each product class can be inferred from the product sizes and storage zone dimensions. The maximum number of storage locations required for each product class cannot be estimated with a direct approach unless it is recorded in the database. Moreover, for the future implementations of this methodology, the expected maximum number of products from a class could not be known at the beginning of the planning horizon. Its unavailability also obstructs the calculation of the cost parameter. Therefore, we estimate the parameter l_i by developing a simulation model. In the next section, we describe how the simulation model is designed.

3.2.2 Simulation Model

For deriving insights and performance indicators for the systems where the available data is limited, simulation is the most effective tool. Therefore, we attempted to handle the uncertainty in the warehouse operations by developing a discrete-event simulation model in MATLAB. The simulation model is written from scratch and consists approximately 600 lines of code. The main deliverable of the simulation model is an estimation for the l_i parameter. Besides the l_i parameter, we aim to estimate system performance measures like zone and overall warehouse utilization rates and the maximum number of storage spaces utilized in a given time horizon. Moreover, uncertainty in production and demand amounts can be reflected in the model using fitted distributions for arrival and departure patterns. If data for arrival and departure times for each product class is available, the validation of the simulation model can be done. Also, simulation enables us to evaluate the performance of the newly suggested storage policy and make a comparison in terms of the average performance measures calculated. Running the simulation model with exact arrival-departure times and fitted arrival-departure distributions requires modifications for arrival and departure processes; therefore we developed two separate models. We will refer to the simulation model with exact event times as *Exact Model* and the one with fitted distributions as *Approximate Model*.

The required input parameters for simulation are:

- Arrival and departure times / distributions
- Distances of each storage zone to each port
- Capacities of each storage for each product class
- The storage assignment policy:
  - For class based storage: product class - storage zone assignments
  - Rule for placing and picking the products from the assigned zones
- The initial inventory amounts at the beginning of the time period

The simulation model replicates the warehouse behavior for a given time period. Based on the class-based storage policy, the assigned zones for each product class are given as input to the system. If required, the zones are prioritized according to a parameter (distance, cost, or preferred order). As a result, a zone sequence for entrance and exit is assumed for each class. The available capacity of each zone for each product group, and the distance of each zone to each I/O port are given as other input parameters. Note that, for distance calculation we use rectilinear distances measured from the centroid of the storage zone to the centroid of the dispatching area.

First of all, the initial inventory is placed to the available zones according to the sequence defined for each product class. The products are placed starting from the first available storage zone. For the exact and approximate model the generation of the arrival and departure processes differs, therefore we present them separately.

Approximate Model

- Given the arrival and departure distributions, the first interarrival and interdeparture times are generated for each product class.

- The minimum interarrival and interdeparture is selected among them for both departure and arrival. Note that, in an attempt to capture seasonality, there may be multiple distributions for shorter time periods during the horizon. For instance we used monthly distributions for each product class. In that case, current simulation time should also be taken into account while generating a new inter-event time.

- To find the arrival and departure times, the selected inter-event time is added to the current simulation time.

- Then, the arrival and departure times are compared, and the time of next event to occur is set.

- The chosen inter-event time is decremented from interarrival and interdeparture times, i.e., the time is advanced by the magnitude of elapsed time. The interarrival and interdepartures represent the remaining time until their occurrence.

- If an arrival event occurs, the zone for placing the product needs to be determined. From the available zone sequences, the first zone with available capacity is found to store the product.
- Then, the statistics of utilization (of chosen zone and overall warehouse), distance traversed and maximum number of products (per product type and class) in the warehouse is updated.
- The current time is advanced to the arrival time.
- A new interarrival time is generated for the entered product class.
- The procedure is similar for an departure event. The departing product is again selected from the exit sequence assigned to the product, it is picked from the first available zone the product is present.
- Again the statistics are updated.
- After an event is completed, the algorithm turns back to the stage where the minimum interarrival and interdeparture time is selected. This loop continues until the time horizon ends.

Exact Model

The procedure for the Exact Model is similar to the Approximate model except for the arrival and departure time generation. In Exact Model, we use the exact arrival and departure times that are provided in the data set, in other words we conduct a trace-driven simulation. Therefore, the only modification to the previous model is as follows:

- Given the arrival and departure times and respective product classes, the selection of event times and types are made based on the procedure defined in approximate model. The difference is that after an event is occurred, the used event time is deleted from the events list. The process continues until the list of arrivals and departures is emptied.

For the approximate model, the process is repeated for desired number of replications, in our case 10, to find the long-run averages of the performance measures. In each replication, a seed is determined for random number generation. Seed numbers are set to the value of the replication number during a simulation run. This ensures the usage of the same seeds in each replication of different experiments that will be conducted for the scenario analysis. This implies using the same setting for each scenario and making an unbiased comparison between them. The scenarios include using different number of product classes and relaxing storage region priorities for certain product classes. Further details on scenarios are provided in Chapter 4. The flow chart representation of the simulation model is given in Figure 3.2.

In this chapter, we introduced our optimization and simulation models. In the next chapter, we present and discuss our computational results using the data obtained from a major automotive manufacturer. Our experiments using past data reveal that the total travel distance can be reduced between 4% and 12% depending on the scenario when the proposed simulation-optimization approach is used.

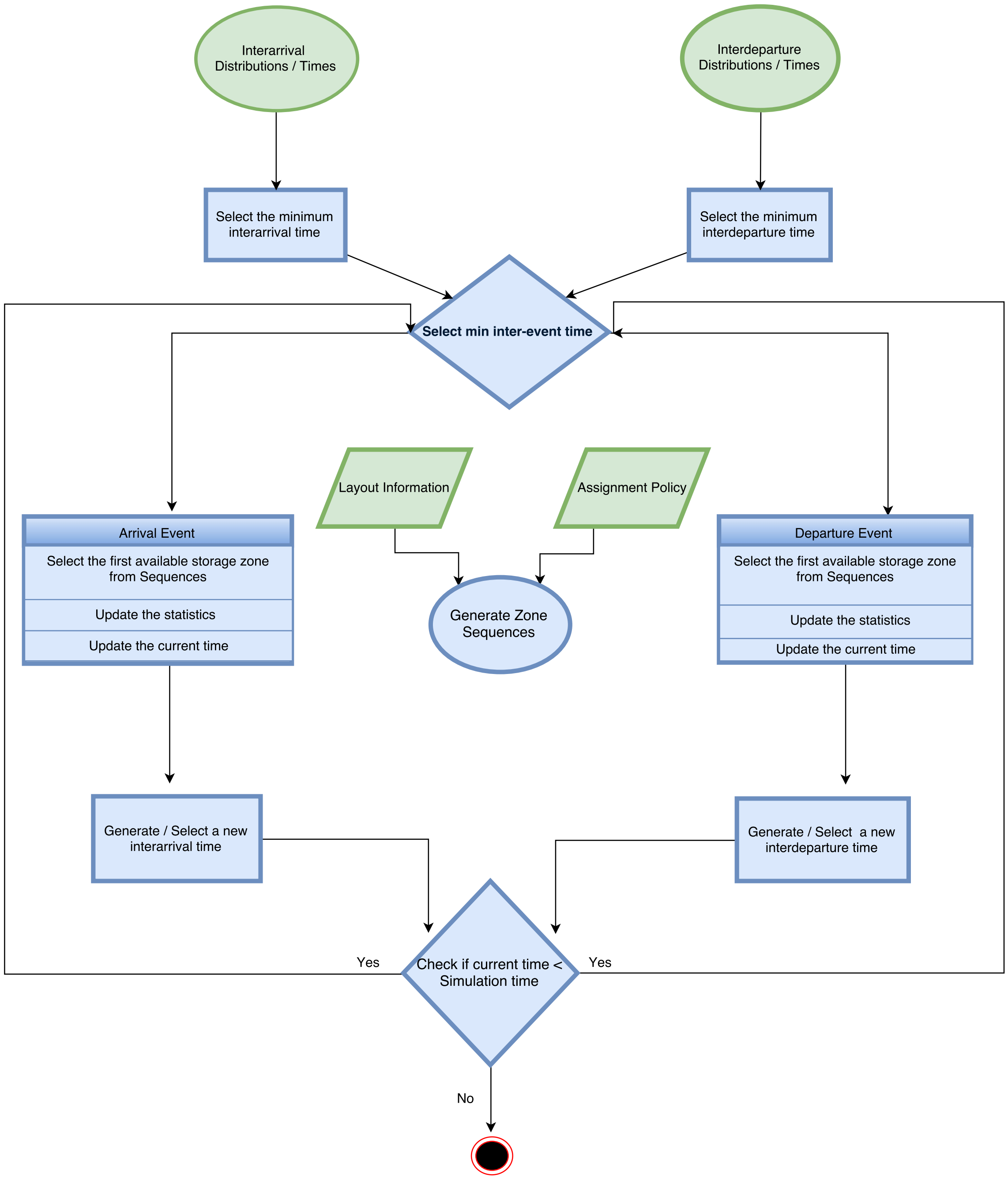

Figure 3.2: Flow Chart of a Simulation Replication

Chapter 4

EXPERIMENTAL RESULTS

In this chapter, we present and discuss our computational results using real data obtained from a major automotive manufacturer. In Section 4.1, the warehouse and product characteristics, and operations are introduced. Our computational results are presented in Section 4.2.

4.1 A Case Study of a Distribution Warehouse in Automotive Manufacturing

For the computational experiments, we examined the distribution warehouse of one of the leading automotive manufacturers in Turkey. The warehouse under investigation is a parking space located within the company's manufacturing facility, where finished vehicles are stored to be distributed to domestic and international markets. The warehouse has two input and one output port. The vehicles produced in the factory and the ones imported from the international manufacturers are two product groups that flow through the input ports. One input port is dedicated to the domestic group (produced in the facility), and the other one to the imported group. The vehicles are distributed to domestic and international markets, however the international distribution is out of our scope. Export to overseas is done via ships from a nearby harbor, and they are dispatched immediately after production. Therefore they do not occupy any storage space. Consequently, our analysis will include the vehicles distributed to the domestic market. There is only one output port for distribution.

The vehicles can be classified according to different features. One of them is their origin of production: domestic and imported. The second aspect is the physical size of the product. The physical size of the products determines the space they occupy in the parking area. There are three different product groups in terms of size. The first group includes the standard personal cars (PC) which have parking space requirement of size 2.5×5 meters per car. The second group is composed of the medium commercial vehicles (MCV) and each vehicle requires a parking space of size 2.8×6.6 meters. The third group includes SUV's, each requiring a parking space with dimensions 2.5×5.5 meters. The third classification is based on product features; some vehicles are categorized as luxurious and the remaining as standard. Luxurious vehicles require higher levels of protection and are given priority for specific regions during the put-away.

There is an option for leasing external storage spaces when faced with insufficient capacity. The leased places are variable, they can be leased for different time periods depending on the production and demand rates. If a product needs to be stored in external spaces, the transfer is done by the manufacturer. However, the handling operations at the external spaces and distribution from there are under responsibility of the 3PL company. We are given the information of the used places within the time horizon of the data. The parking area has a capacity of 9195 vehicles measured in terms of a PC and there are six parking spaces leased (external parks) with a total available capacity of 4350 vehicles measured in terms of a PC.

The warehouse is composed of five different regions and the warehouse management utilizes each region according to product classifications. The luxurious products require higher protection, therefore they are given priority for being located to one of the warehouse regions. Regarding the priority, all small (PC) and medium (MCV) sized vehicles can be placed in this region. The second region is dedicated to commercial vehicles since they require the largest space per vehicle. Yet another region is dedicated to the SUV group which is both luxurious and has a different physical size. The fourth region is used for the vehicles having the smallest size (PC). The fifth region is used when the park is fully utilized. All product groups can be placed there. The external parks are mainly preferred for the imported group, however it can be used for all product groups. However, parking the luxurious vehicles in external spaces is not preferred unless the (internal) parking space is completely full.

The warehouse operates under a unit load, single-command and picker-to-part policy adopting the closest-open-location to exit rule. Order batching and multiple picks per order are not possible due to the product characteristics. During the location selection, the defined priorities for the product classes are considered. The vehicles received at the input ports are driven by employees to the available location closest to the output port. The rule can be specified as a preferred order rule. If the first preferred region is not available for a product class then it is placed in the next best region. Then the employee is picked by a service bus and he returns to back the input port. Similarly, when an order is received, the employee goes to the ordered vehicle's location and drives it to the dispatching area where it will be loaded to trucks. After the order-picking, the employee repeats the same operation. If a domestic vehicle is parked in one of the external parks, it is sent there by the manufacturer. An imported vehicle is firstly shipped to the factory from the harbor via trucks of a 3PL company. If it is decided to be parked in one of the external parks, it is transferred there by the manufacturer. The vehicles parked to the external parks are distributed from there without being transferred back to the main facility. The distribution from the external parks and the warehousing operations there are handled by a 3PL company.

The layout of the warehouse is given with predefined parking lots. There is a fixed direction of flow between the aisles. The distances between the I/O ports and storage locations are calculated accordingly.

Our aim is to propose a class-based storage policy that will minimize the expected travel distance during the put-away and order-picking. To measure the improvement, we simulated an approximation of the existing system and calculated the distance traversed based on the available data set. For the simulation of the existing system, an approximation is used due to lack of available data. The details are provided in Section 4.2. Then, optimal product class and storage location assignments are found using the optimization model, under different scenarios. The resulting policies are simulated to evaluate the reduction in the travel distance.

The company provided the recent three years' data for our analysis. The data includes list of arrivals and list of departures for each product type. However, the waiting time information for each vehicle and their storage locations are not available, which caused us to simulate an approximation of the existing system. The experiments are conducted for all three years, which reinforces the accuracy of the results. In the next section, we present the approach for product class formation.

4.1.1 Product Class Formation

There are 36 different products, i.e. vehicle models, stored in the warehouse. As discussed in the literature, product classes are formed when complete information on arrival and departure times is not available. It is more likely to mitigate the forecast errors by aggregation. Moreover, forming a different class for each product type, requires dedicating distinct storage spaces according to class based storage policy, therefore for 36 classes the parking space requirement will be very high. Also, with 36 products the problem size gets considerably large, therefore product classes are formed by aggregating similar vehicle models.

For class-based storage policy, we considered two different classification options. In the first one, the products are classified regarding the defined product categories in Section 4.1 (size, origin of production and luxuriousness) and the segmentation applied in the automotive industry. Since we aim to propose a classification that will be valid in the long run by reflecting the seasonality in supply and demand rates, this hybrid classification is adopted. The traditional segmentation done in the automotive industry classifies products according to criteria such as product features, product size, weight, volume and technical specifications. The segments are composed of a group of vehicle models that show similarity in terms of the specifications mentioned. To distinguish the origin of production we added a further division. If products from domestic and imported group are categorized under the same segment, the class is divided into two forming two new product classes. The division is due to the waiting time pattern differences between the two groups, which is reported to us by warehouse management and also observed from the data set. As a result, we obtained 11 different product classes. Arrival and departure patterns are generated based on these classes in all random simulation models.

The other classification option aggregates products into 4 classes. In this aggregation, the products are aggregated considering the origin and physical size. All of the medium sized vehicles (SUV) are imported and all of the large sized vehicles (MCV) are domestic, therefore they are grouped according to their sizes. Small sized vehicles are further divided to distinguish the origin of production. The resulting classes consist of imported PC's, domestic PC's, SUV's and MCV's respectively. The ABC analysis based on the number of handling operations also supports grouping products into 4 classes. We analyzed the ratio of number of handling operations for each segment, through the annual number of production and sales amounts. Tables 4.1, 4.2 and 4.3 show the analysis for Year 1, 2 and 3 respectively. The first columns of all tables report the corresponding ratio of number of entrances per segment to the total number of entrances. Similarly, the second columns report the ratio of movements during exit. The third columns report the ratio of movements during both entrance and exit to the total number of all movements. The numbers displayed in all tables are converted to percentages and color scaled using Excel to indicate similarities. Excel color scale assigns the colors according to values; the minimum value is colored in red, the maximum value is colored in green and the median is colored in yellow. The remaining values are colored proportional to their values in this color scale. Similarly in our analysis, green scale shows the high, and yellow scale shows the moderate percentages while red scale shows lower percentages.

In Table 4.1, there is a similar pattern for all three columns which means entrance, exit, and the total movement frequencies are similar for all classes. It is observed that the segments can be grouped into three with respect to the movement percentages. Segment 1 and 5, shown with green, account for more than 80 % of the movement, and can be grouped under the same class. In our classification, the two form the second class. According to Table 4.1, the next ones with similar percentages are

Table 4.1: Percentage of handling operations per segment for Year 1

segment	% entrance	% exit	% overall
1	58.42	56.85	57.63
2	0.00	0.01	0.01
3	4.19	3.94	4.07
4	0.35	0.36	0.35
5	28.57	30.60	29.59
6	5.89	5.76	5.83
7	1.43	1.51	1.47
8	0.00	0.00	0.00
9	0.02	0.02	0.02
10	1.07	0.91	0.99
11	0.04	0.03	0.03

segments 3, 6 and 10, colored in yellow range. The remaining segments account for a small percentage of the total movement and are shown in tones of red. We assigned segment 3 to class 4, and segment 10 to class 3 considering their different physical requirements. The remaining is classified under class 2. Therefore, the analysis shows that our classification method for Year 1 is consistent with ABC analysis.

Table 4.2: Percentage of handling operations per segment for Year 2

segment	% entrance	% exit	% overall
1	51.96	53.29	52.62
2	0.00	0.00	0.00
3	4.62	4.73	4.68
4	0.27	0.35	0.31
5	32.08	31.40	31.74
6	5.43	5.25	5.34
7	1.23	1.17	1.20
8	0.00	0.00	0.00
9	0.00	0.02	0.01
10	1.62	1.32	1.47
11	2.80	2.46	2.63

From Table 4.2, it is verified that segments 1 and 5 are responsible for most of the movement. The remaining segments account for less than 20% of the movement, and can be classified under the same group. When the physical restrictions are added, Year 2 also supports our classification method.

Table 4.3: Percentage of handling operations per segment for Year 3

segment	% entrance	% exit	% overall
1	52.05	50.37	51.17
2	0.00	0.00	0.00
3	7.76	7.72	7.74
4	0.37	0.38	0.37
5	32.23	32.68	32.47
6	2.37	2.90	2.65
7	0.90	1.11	1.01
8	0.00	0.00	0.00
9	0.00	0.00	0.00
10	2.10	2.39	2.25
11	2.22	2.45	2.34

In Table 4.3, a similar trend is also observed for Year 3. Segments 1 and 5 account for 85% of the movement. The next one with the highest percentage is segment 3 and the remaining segments together add up to 10% of the movement. If segment 10 is separated considering the physical requirement, again we end up with our classification method.

Throughout the experiments, both of the 4-class and 11-class alternatives are studied. While generating arrival and departures in the random simulation model, distributions used are based on 11-class aggregation for both classification alternatives to reflect the seasonality better. It also helps to distinguish between the product types. In the next section, we present the modeling assumptions for approximating the existing system.

4.2 Modeling Assumptions

We first simulated the system with the existing closest-open-location policy using the exact data. Next, we simulated the system with the new policy alternatives using the exact data and showed the possible improvements that could have been made by applying the suggested class-based policy. Then, for future applications we modified the model to utilize forecasts and account for uncertainty. The models with exact and random data set are referred to as Exact Model and Approximate Model. Both models are designed as an approximation of the existing system due to lack of information/data, therefore several assumptions are made. In the Section 4.2.1, the assumptions valid for both models are listed.

4.2.1 Assumptions for Exact Model

The Exact Model is used to simulate the existing case and the newly suggested policies. In the data set that we are provided, we have arrival and departure dates, times, and vehicle models. However, the location information is not recorded, therefore we do not know which location each vehicle is placed. We only know the storage policy implemented by the warehouse management. There are different warehouse regions and there are predefined priorities for placing each vehicle type to these regions. Regarding these priorities, an incoming vehicle is placed to the best open parking lot, closest to the exit port. When planning for the future, only production and sales forecasts will be known at the beginning of the horizon. Considering this fact, we approximated the system under several assumptions. All of the assumptions on 'Exact Model' are listed below.

A1. Vehicles are aggregated into 11 classes, referred to as segments, and within a segment all vehicles are considered to be identical.

A2. There is a priority sequence for warehouse regions, as applied by the company. When an arrival occurs, the vehicle is placed to the best open parking lot closest to the exit port. During the departure, the departing vehicle is selected according to this sequence to empty the most favorable zones first.

A3. The location addresses of initial inventory are not available. Therefore, during the initialization, they are placed according to the existing policy to the empty warehouse. However, the distance traveled to place the initial inventory is not added to the traversed distance calculation.

A4. In total, there are 13545 parking spaces. When the optimization model is considered, the problem size gets bigger inevitably, and interpreting the solution set becomes a major task. To deal with this, the parking lots are also aggregated into zones. During the aggregation, the existing layout and physical requirements of the vehicles are considered and for a zone, the best possible unit compatible with these constraints is selected. Each zone has a capacity of 36 PC's, which is equivalent to 27 SUV's or 24 MCV's. Due to the layout, some irregular zones are needed to be formed. If possible, the corresponding capacities for the other types are calculated. Otherwise, the usage of the irregular zones for other types is prohibited. A total of 416 zones are formed.

A5. The distance from each port to each zone is calculated according to the existing traffic rules. The distances are taken to the geometric center of the zones.

A6. The external parks are also divided into zones in the same manner. However the distance to all zones within an external park is taken as the same with the distance of the external park to the main facility. Dispatch from external parks and internal operations of the external parks are done by the 3PL company, so the distance traversed within the external park is out of our objective, therefore not calculated. Since the distance traversed during exit is also not handled by the company, the distance of external zones to exit port is taken as 0.

4.2.2 Assumptions for Approximate Model

For deciding the optimal storage assignment policy for future, the only information available at the beginning of the planning horizon, in our case a year, is the forecast data. Our aim is to develop an assignment policy using annual production and sales forecasts. While doing so, uncertainty should also be added to the system to reflect the uncertainty of forecasts. Therefore, for arrival and departure processes, probability distributions are used. Initially, tried to find a fit for the distributions, however a good fit could not be found. All of the distributions tried gave very small p-values for the fit which implies that we should not accept the specified distribution. Therefore, the monthly arrival and departure distributions are assumed to follow a Poisson process. The main reason to use Poisson is the ease of implementation with the available information. The monthly forecast values can be used to obtain the rates of exponential distributions of interarrivals and interdepartures. Also, Poisson is a commonly used distribution in the literature of simulation. For the approximate model, the only different assumption from exact model is the Poisson assumption, assumptions A2-A6 also hold for this. Therefore, the last assumption is listed as A7.

A7. The arrival and departure process for the approximate model is assumed to follow a Poisson process, i.e the interarrival and interdeparture distributions are assumed to be exponential.

In an attempt to show the Poisson assumption provides a good estimation, the simulation model is validated through the comparison of Exact and Approximate model results. The validation results are presented in Section 4.4. In the next section we present additional notes and the results of the existing system.

4.3 Simulation Results of the Existing System

Since the used storage locations and the actual distance traveled are not recorded, we need to estimate the average total distance traveled by a simulation. For the simulation of the existing system, we used the Exact model with the exact data. We adopted the given arrival and departure dates and times, by converting the events times to days elapsed from the beginning of the year. We tried to simulate the real system by the assumptions described in Section 4.2.1. For the departure, we only have the list of departure times for each vehicle type without the actual location information. However, at the beginning of the planning horizon this information will not be available, therefore for the simulation we needed to make an assumption for selecting the departing vehicle as stated in A8. The warehouse parts are prioritized or limited for the usage of certain product classes by the warehouse management. Other than that, the vehicles can use the storage locations independent of type. This is also valid in our simulated system, we allow the product classes to use the storage zones simultaneously without violating the predefined restrictions. This last rule is stated as A9.

A8. For the existing system, we assumed that the vehicle from the demanded segment which is located closest to the exit port is selected for departure.

A9. While simulating the existing policy, the vehicles with different physical restrictions (belonging to different product classes) can use the same zone simultaneously unless it is restricted by the warehouse management. The capacity update is done by making a conversion for the required space for each vehicle.

Assumptions A2-A6 are also valid for the existing system. Under these assumptions, the system is simulated for Year 1, 2 and 3. The results for the simulation are reported in terms of total distance traveled, number of storage zones used out of 416 zones, number of external zones used, and the average utilization of all available storage zones during the year.

The utilization is calculated as the time average of the total park utilization: After each event, the total number of vehicles in the park is calculated in terms of a PC, and divided by the total available capacity in terms of a PC to calculate utilization between two events (the conversion factors used : 1 MCV=1.5 PC, 1 SUV=1.33 PC). The inter-event time, i.e the time elapsed between the last event, is multiplied by the calculated utilization within this time window. This cumulative summation is done until the end of the time horizon, and finally divided by the total time elapsed. Let t_i be the time of i^{th} event. N_{t_i} denotes the number of vehicles until time t_i, in terms of a PC. K is the total park capacity in terms of a PC, and T denotes the time horizon. Following these notations the utilization calculation can be expressed as:

$$Utilization = 100 \times \frac{\frac{\sum_{i=1}^{lastevent} N_{t_i} \times (t_i - t_{i-1})}{K} + (T - t_{lastevent}) \times N_{t_{lastevent}}}{T}$$

It is important to note that, in all simulation models we assume that all of the 6 external parks are available at the beginning of the year, and the utilization calculation is made using all available zones. In some years all of the external parks are not used and therefore the utilization values appeared to be lower. Therefore, the number of external parks used is also reported. Results for years 1, 2 and 3 are reported in Table 4.4. The results in Table 4.4 are used to evaluate the newly suggested policies. In

Table 4.4: Results of the Simulation of the Existing System for Years 1, 2, and 3

	Year 1	Year 2	Year 3
Total Distance Traveled (meters)	176951767.48	188405643.34	131147182.58
# of Storage Zones Used	386	408	342
Average Utilization	0.60	0.66	0.53
# of External Parks Used	5	6	3

the next section, we provide a validation for the model that is developed for future implementation. The detailed results of the existing system is compared with the Poisson approximation of the system, i.e., with Approximate Model.

4.4 Validation of the Simulation Model

To validate the simulation model, the results of models with exact data (exact model) and Poisson approximation (approximate model) are compared. The approximate model results are obtained as average of 10 replications. Total numbers of vehicles entering and exiting the system are the basic indicators to justify the system. The results for each segment and the percentage differences are presented in Tables 4.5, 4.6, and 4.7. The percentage differences are calculated as the ratio of change from the exact model to the value of the exact model.

Table 4.5: Validation for Year 1

Segment	Number-in			Number-out		
	Poisson estimate	Exact data	% Difference	Poisson estimate	Exact data	% Difference
1	68180.9	68311	-0.19	67345.6	67227	0.18
2	0	0	0.00	12.1	13	-7.44
3	4939.7	4904	0.72	4688.7	4659	0.63
4	405.8	407	-0.30	424.8	423	0.42
5	33411	33404	0.02	36162.9	36189	-0.07
6	6882.1	6890	-0.11	6881.6	6815	0.97
7	1666.8	1675	-0.49	1804.5	1790	0.80
8	0	0	0.00	1.8	2	-11.11
9	52.6	29	44.87	22.2	23	-3.60
10	1259.1	1256	0.25	1078.2	1071	0.67
11	53.2	45	15.41	35.9	36	-0.28

In Table 4.5, the results for Year 1 are displayed. Almost all of the differences are less than 1%. The ones with the higher percentages are very small compared to others, and error appears due to scale. For year 1, this table validates that Poisson is a reasonable assumption.

Table 4.6: Validation for Year 2

Segment	Number-in			Number-out		
	Poisson estimate	Exact data	% Difference	Poisson estimate	Exact data	% Difference
1	62569.3	62610	-0.07	64270.7	64382	-0.17
2	0	0	0.00	4.1	5	-21.95
3	5598.6	5571	0.49	5704.6	5718	-0.23
4	323.8	329	-1.61	418.8	426	-1.72
5	38704.9	38653	0.13	37834.9	37939	-0.28
6	6513.5	6541	-0.42	6364.1	6338	0.41
7	1464.4	1480	-1.07	1419.4	1410	0.66
8	0	0	0.00	0	0	0.00
9	1.8	2	-11.11	28.2	30	-6.38
10	1914.3	1947	-1.71	1594.1	1595	-0.06
11	3366.8	3370	-0.10	2966.9	2975	-0.27

In Table 4.6, the same results for Year 2 are presented. Except for segment 2 and 9 all differences are less than 1%. For segments 2 and 9, error occurs due to scale and can be ignored. This table validates the Poisson assumption for the given system.

Table 4.7: Validation for Year 3

Segment	Number-in			Number-out		
	Poisson estimate	Exact data	% Difference	Poisson estimate	Exact data	% Difference
1	45053	45030	0.05	47844.5	47887	-0.09
2	0	0	0.00	0	0	0.00
3	6760.3	6714	0.69	7348	7335	0.18
4	321.6	316	1.77	346	360	-4.05
5	27884.3	27882	0.01	31009.3	31070	-0.20
6	2066	2053	0.63	2741.5	2758	-0.60
7	769.3	777	-0.99	1038.5	1057	-1.78
8	0	0	0.00	0	0	0.00
9	0.7	1	-30.00	0	1	0.00
10	1759.1	1820	-3.35	2206.8	2271	-2.91
11	1955.8	1924	1.65	2313.7	2329	-0.66

Table 4.7 shows that the differences are also less than 1% for all segments except

for segment 4 and 9. Difference in segment 9 is again due to scale, and the difference in segment 4 is tolerable. Therefore, the Poisson assumption is also reasonable for Year 3.

Another measure for validation is the maximum number of vehicles observed during the time horizon. We do not expect the peak points of the exact data and Poisson distribution to match, however to be a valid approximation the difference should be under some level. For both 4 and 11 class options, we recorded the peak numbers per product class, for random and exact model.

Table 4.8: Maximum number of vehicles observed per class during Year 1

11- class	Poisson approximation	Exact	% difference
1	5264.9	6437	18.21
2	18	18	0.00
3	906.1	955	5.12
4	185.8	201	7.56
5	5316.3	5316	-0.01
6	798.1	886	9.92
7	400.9	399	-0.48
8	2	2	0.00
9	30.5	24	-27.08
10	283.6	415	31.66
11	17.9	13	-37.69
4-class	**Poisson approximation**	**Exact**	**% difference**
1	1359.8	1425	4.58
2	9127.6	9658	5.49
3	283.6	415	31.66
4	906.1	955	5.12

Table 4.9: Maximum number of vehicles observed per class during Year 2

11- class	Poisson approximation	Exact	% difference
1	6095.1	6167	1.17
2	5	5	0.00
3	1014.5	1185	14.39
4	150.2	150	-0.13
5	3958.2	4146	4.53
6	1121.5	1383	18.91
7	421.2	461	8.63
8	0	0	0.00
9	28.2	29	2.76
10	713.4	752	5.13
11	415	473	12.26
4-class	Poisson approximation	Exact	% difference
1	1790.9	2192	18.30
2	8436.1	9055	6.83
3	713.4	752	5.13
4	1014.5	1185	14.39

Table 4.10: Maximum number of vehicles observed per class during Year 3

11- class	Poisson approximation	Exact	% difference
1	4935.6	5377	8.21
2	0	0	0.00
3	1024.7	1190	13.89
4	81.6	74	-10.27
5	3423.4	3630	5.69
6	705.1	705	-0.01
7	284.5	280	-1.61
8	0	0	0.00
9	0.7	1	30.00
10	451	451	0.00
11	564.6	643	12.19
4-class	Poisson approximation	Exact	% difference
1	1434.1	1434	-0.01
2	7945.6	8270	3.92
3	451	451	0.00
4	1024.7	1190	13.89

The common observation derived from Tables 4.8, 4.9 and 4.10 is that the peak values obtained by the Poisson distribution is generally lower than the exact maximum values. A further observation justifies the effect of aggregation; when the results of 4-class aggregation option are analyzed, it is seen that the difference percentages are smaller. In year 1, class 3 has a difference value of 30% unlike Year 2 and 3. The reason of this greater difference is that the vehicles in class 3 are introduced to the market in Year 1. Thus, the production and demand structure is not stabilized yet. For this reason, this difference can be ignored. In the 4 class option segments 2, 4, 6, 7, 8, 9, 11 are aggregated under class 1 and segments 1 and 5 are aggregated under class 2. The remaining two segments are classified individually. From all three tables, it is inspected that the individual differences are higher compared to aggregated classification. Existence of differences in both classification options is an indicator for the possible overflows when the class based strategy is applied to the exact data. Since the exact maximum values observed for each class are generally higher than the Poisson approximation, the dedicated parking spaces will not be enough, and some overflow will occur. The overflow possibility is handled and tracked in the simulation of alternative scenarios. Moreover, the possible effects of the overflow in future implementations are also analyzed. In the next chapter, we define the scenarios and then discuss the results.

4.5 Scenario Analysis

To identify an improved policy in terms of total distance traveled, we experimented with several scenarios using the proposed approach. We first evaluate the two product class formation options: 4-class and 11-class. Next, we consider different resource availability constraints for both classification options. We study two cases for storage zone availability constraints. In the first case, the storage zones are assumed to be used with respect to the limitations defined by the company, i.e. some of the zones can only be used by certain product classes. In the second case, we relax these restrictions and assume that every product class can use every storage zone subject to capacity restrictions. Configurations for each scenario are summarized in Table 4.11.

Table 4.11: Configuration for each scenario

Name	**Explanation**
Scenario 1:	4-class - Restricted Zone Usage
Scenario 2:	4-class - Unrestricted Zone Usage
Scenario 3:	11-class - Restricted Zone Usage
Scenario 4:	11-class - Unrestricted Zone Usage

For proposed class based policies, the maximum required capacity for each class is obtained via the initial simulation models. To decide which storage zone to assign for each product class, the optimization model is used. Assigning a product class to a storage zone means dedicating this specific zone to this specific class. This is different from the existing system, therefore it requires to make a modification to the simulation model that will be used to assess the performance of the new class-based policies. Following this, we present the next assumption:

A10. While simulating the new class-based policies, the zones assigned by the optimization model can only be used by the assigned product class. In other words, the storage zone is dedicated to the assigned product class. This rule will be referred to as zone dedication.

The optimal assignments given by the model are returned as a set of zones, however, the optimization model does not provide any information about how to place the incoming vehicles to the specified zones. In the literature, within the class-based storage the products are stored randomly. However, in such a large-scale instance, defining a set of storage spaces and applying a random storage will be impractical, since there does not exist a system for tracking locations. Therefore, we evaluated two alternatives for the storage of the incoming vehicles. The first alternative is to store the vehicles based on the distances of zones to the exit port, similar to the existing case. This alternative will be referred to as the *distance-based* scenario. The second alternative is based on using the optimization model's cost parameter to decide.

However, the capacity of the storage zone is excluded from the cost parameter since the zones are already dedicated to that product class and the decision is about placing an individual vehicle. Therefore, we use the cost parameter as $\frac{\sum_{r \in R} p_{ir} d_{rk}}{l_i}$ for each storage zone k and each product class i. This alternative will be referred to as the *cost-based* scenario. While simulating the system with the optimal assignment policies, the returned zones for each product class are sorted according to the examined scenario. If the scenario with the restricted zone usage is adopted, then the zones are first prioritized according to the warehouse region they belong. Then, the zones are sorted within each region based on cost or distance values. If the scenario with unrestricted zones is adopted, the priorities are defined over internal and external zones, and then the zones are sorted similarly.

Another modification requirement occurs due to the zone dedication policy introduced by class based storage. The maximum number of vehicles observed together in the warehouse for each segment is found via simulation. Then, these values are translated into capacity requirements and the zones are assigned to each product class so as to satisfy these requirements. The modification arises due to the change of policy: In the existing case, the zones can be used by multiple product classes, however, in class-based policy, zones are dedicated to specific product classes which may lead to insufficient capacity. In such a case, the optimization model becomes infeasible failing to satisfy the capacity constraint. To resolve this, we calculated the number of zones that are available to all product classes, for both restricted and unrestricted scenarios. The zones included in the calculation are the zones with capacity 36, 36, 27, and 24 respectively for each class. If the zone requirement of the data set is greater than this number, 'artificial zones' are added to meet the requirement. An additional constraint set, defined as 'Priority Constraints' in Section 3.2.1, is used to prevent the assignment to the artificial zones, if all of the existing zones are not assigned to some product class. To represent the artificial zones in the simulation model, a single zone with an infinite capacity is added, and all of the product classes are allowed to use this zone. This zone is given the lowest priority, hence it is only used when all existing zones are completely used up. The usage of artificial is tracked. This last assumption on the model is stated as A11.

A11. To deal with the possibility of insufficient capacity due to zone dedication, artificial zones are created in optimization and simulation models. For the optimization model, an upper bound on the number of artificial zones are calculated based on the total required number of zones and added to the model to prevent infeasibility. Moreover, 'Priority Constraints' are added to prevent the assignment to the artificial zones unless all of the existing zones are assigned to some product class. For the simulation model, an artificial zone with an infinite capacity is added, and each product class is allowed to use this artificial zone. This zone is given the lowest priority to allow its use only when required. The distance of artificial zones to each port is assigned as the maximum distance among all zones.

Finally, we investigate the effect of using l_i values obtained using the Poisson approximation. The purpose of this analysis is to see if the differences between the exact values of maximum (peak) number of vehicles and the estimates arising from a Poisson approximation create a significant difference in terms of the total distance traveled. Understanding this difference will give us insight for applying our methodology in the future as the exact values will no longer be available. In the next section, we summarize and discuss the results of each scenario.

4.6 Computational Results

All of the computations are performed on a computer with 8 GB RAM, Intel Core i5-3340M 2.70 GHz processor, and 64-bit Windows 7 Professional operating system. The optimization model is coded in GAMS 23.7 and all the MIP problems are solved via Gurobi version 4.5.1. The simulation model is coded in MATLAB R2014b.

4.6.1 Results of Experiments with Perfect Information

In this section, we used the given past exact data sets for the experiments, i.e. perfect information on arrival and departure times was available and a performance evaluation is made through this exact data. For the data set of each year, four scenarios are analyzed. Several statistics of the optimization problems and the details of optimal assignments for each product class are presented in Tables 4.12 to 4.35. For the assignments, the percentage of the number of vehicles assigned to internal parking zones and external parking zones are examined. The internal zones are located within the facility and therefore closer to I/O ports. The external zones are outside of the facility and leased. Thus, utilizing internal zones is more important, and it is better to assign vehicles moving more frequently to these zones. We reported the percentage of assignments for each class to display the product classes that are moving more frequently. The solver time limit for all of the optimization models is set to 7200 seconds. Most of the models are solved to optimality under this time limit, a small number of models are terminated due to the time limit with an optimality gap of around 0.05%. The optimality gap is defined as the difference between the solution and the best bound divided by the best bound. The objective function of the optimization model signifies the total assignment cost. Since we define the improvement in terms of the travel distance, the objective values are not reported.

From simulation results, we present the total distance traveled, total number of zones and external parks used and the overall park utilization. We provided the number of external parks used through the simulation to reflect the need extra space. Due to zone dedication, we know that class-based storage requires more storage spaces compared to existing policy. Therefore it is used to analyze if there is a significant increase in the number of external parks leased. We measure the improvements in travel distance between each scenario and the existing case, by comparing the distances given by simulation results. The improvement values are reported as %Improvement in the tables. The results are presented for years 1, 2 and 3 consequently.

4.6.2 Results of Year 1

Table 4.12: Optimization Results of Year 1 - Scenario 1

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	0.63	99.37
CPU time (sec)	0.248	2	83.62	16.38
# of constraints	420	3	48.08	51.92
# of binary variables	1664	4	74.87	25.13

Table 4.13: Simulation Results of Year 1 - Scenario 1

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	184919354.14	165639686.42
% Improvement	-4.50%	6.39%
# of External Parks Used	6	6
# of Zones Used	392	392
Utilization	61.53%	61.45%

Results of Scenario 1 reveal that most of the vehicles from product class 2 and 4 are assigned to internal zones. About half of the vehicles from class 3 are also assigned to internal zones, while almost all of the vehicles from class 1 are assigned to external zones. This shows that class 1 move less frequently than the other classes and reserving the internal zones for other classes will be better in terms of the total traveled distance. When this assignment is simulated using the data of year 1, we obtained two different results for cost-based and distance-based policies. As discussed, the storage of the vehicles within the assigned zones also effects the performance of the policy. When the placement is done according to distance, it turns out that the system performed 4.50% worse than the existing policy. On the other hand, the cost-based system yielded 6.39% improvement in the overall distance traveled. Therefore, in this scenario, we observe that product classes 2 and 4 are the most frequently moving group, while product class 1 is the slowest. So, classes 2 and 4 are assigned mostly to internal zones and class 1 to external zones. When the vehicles are stored with this assignment policy and cost-based scenario, an improved result in terms of total traveled distance is obtained.

Table 4.14: Optimization Results of Year 1 - Scenario 2

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	1.75	98.25
CPU time (sec)	0.6	2	90.04	9.96
# of constraints	420	3	2.83	97.17
# of binary variables	1664	4	47.28	52.72

Table 4.15: Simulation Results of Year 1 - Scenario 2

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	174152446.48	154563975.04
% Improvement	1.58%	12.65%
# of External Parks Used	6	6
# of Zones Used	393	393
Utilization	61.21%	61.15%

Switching to Scenario 2 requires removing the zone restrictions currently applied by the warehouse management. Relaxing this restriction enlarges the feasible region and enables a set of assignments that were not previously possible. From Table 4.14, it is observed that most of the vehicles assigned to external zones from product classes 3 and 4 are reassigned to external zones compared to Scenario 1. This shows that the warehouse region reserved for product classes 3 and 4 in the existing case, can be utilized more efficiently by assigning them to classes 1 and 2. This gives rise to the insight that if the security concerns could be handled for the external parks, this scenario is likely to be more beneficial. Both cost-based and distance-based options provided an improvement, while the cost-based option led an improvement up to 12%.

For both Scenarios 1 and 2, a disadvantage could be the number of external parks required for the new policy. Since the class based policy requires dedicating a zone to the assigned class contrary to existing policy, this creates a slight increase in the required number of zones. This might cause leasing one more external park as in Scenario 1 and 2. In the existing case, five external parks were sufficient, however the new policy requires six external parks. On the other hand, the capacity of the leased parks can be determined by analyzing the results at the beginning of the time horizon. As we do not have the information of the leasing costs, the assignments are made solely based on the travel distance. It is possible and sometimes the case that there are several zones with low capacities left unassigned due to the cost function. At the decision point, the management can consider utilizing these zones, if the requirement is low and the leasing cost is high. A simulation study, in which the utilization of the unused zones is considered, is presented in Section 4.6.5. This study is conducted for the case where estimate values arising from a Poisson approximation are used.

Table 4.16: Optimization Results of Year 1 - Scenario 3

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	95.68	4.32
		2	0.00	100.00
		3	74.87	25.13
CPU time (sec)	3.819	4	0.00	100.00
		5	35.89	64.11
		6	1.58	98.42
# of constraints	2320	7	0.75	99.25
		8	100.00	0.00
		9	0.00	100.00
# of binary variables	5930	10	48.08	51.92
		11	38.46	61.54

Table 4.17: Simulation Results of Year 1 - Scenario 3

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	231192275.11	214601170.70
% Improvement	-30.65%	-21.27%
# of External Parks Used	6	6
# of Zones Used	415	415
Utilization	55.28%	55.20%

Scenario 3, we consider 11 product classes. In Scenarios 1 and 2, these 11 classes (segments) are aggregated under 4 product classes. When the assignments of each segment is compared with the assignments of the classes that they belong to in Scenario 1 and 2, the assignments are similar. Most of the domestically produced PC's are assigned to internal zones and imported PC's are assigned to external zones. The assignment breakdown for SUV and MCV remained the same. However, when simulation results with the exact data are analyzed, we observe that there is a deterioration for both cost and distance based method. Also, the number of zones and external parks used is increase due to the increase in number of classes which is expected. This shows that Scenario 3 is not preferable for Year 1.

Table 4.18: Optimization Results of Year 1 - Scenario 4

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0.05%	1	95.68	4.32
		2	0.00	100.00
		3	19.67	80.33
CPU time (sec)	7202.98	4	0.00	100.00
		5	55.08	44.92
		6	1.58	98.42
# of constraints	2176	7	0.75	99.25
		8	0.00	100.00
		9	0.00	100.00
# of binary variables	5798	10	2.64	97.36
		11	14.29	85.71

Table 4.19: Simulation Results of Year 1 - Scenario 4

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	221163243.54	204252176.00
% Improvement	-24.98%	-15.42%
# of External Parks Used	6	6
# of Zones Used	415	415
Utilization	56.52%	56.52%

Scenario 4 is the relaxed version of Scenario 3 in terms of zone usage. Therefore, the simulation results improve compared to Scenario 3. However, still no improvement is observed compared to the existing case, therefore this scenario is again not preferable for Year 1.

We continue with the discussion of results for Year 2.

4.6.3 Results of Year 2

Table 4.20: Optimization Results of Year 2 - Scenario 1

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	4.93	95.07
CPU time (sec)	0.345	2	88.18	11.82
# of constraints	1172	3	25.00	75.00
# of binary variables	1933	4	59.83	40.17

Table 4.21: Simulation Results of Year 2 - Scenario 1

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	201000180.95	180071062.39
% Improvement	-6.68%	4.42%
# of External Parks Used	6 + artificial zone	6 + artificial zone
# of Zones Used	413	413
Utilization	68.17%	67.92%

In Scenario 1, a similar pattern is observed with Year 1. Most of the vehicles from class 2 and 4 are assigned to internal zones, while the reverse is true for classes 1 and 3. Due to differences of production and sales amounts with Year 1, in Year 2 more zones and therefore more external parks are used. In the existing case, 6 of the external parks are already used, so artificial zones are utilized. we observed a 4.42% improvement in the cost-based simulation model despite the usage of artificial zones.

Table 4.22: Optimization Results of Year 2 - Scenario 2

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	4.93	95.07
CPU time (sec)	18.025	2	88.58	11.42
# of constraints	1067	3	0.00	100.00
# of binary variables	1848	4	77.72	22.28

Table 4.23: Simulation Results of Year 2 - Scenario 2

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	201134614.43	180090959.00
% Improvement	-6.75%	4.41%
# of External Parks Used	6 + artificial	6 + artificial
# of Zones Used	412	412
Utilization	68.04%	68.00%

In Scenario 2, it is observed that when zone restriction is removed, all of the vehicles in class 3 are assigned to external zones and vehicles from class 4 replaced them. This shows the zones reserved for SUV vehicles can be better utilized by assigning them to MCV vehicles. Again, the security concerns should be evaluated by the warehouse management. When simulation results in Table 4.23 are analyzed, we observe that cost-based storage yields 4.41% improvement.

Table 4.24: Optimization Results of Year 2 - Scenario 3

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0.05%	1	81.35	18.65
		2	0.00	100.00
		3	59.83	40.17
CPU time (sec)	7202.37	4	0.00	100.00
		5	73.95	26.05
		6	0.29	99.71
# of constraints	2977	7	0.00	100.00
		8	0.00	0.00
		9	0.00	100.00
# of binary variables	6028	10	25.00	75.00
		11	1.27	98.73

Table 4.25: Simulation Results of Year 2 - Scenario 3

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	277879632.71	257043444.93
% Improvement	-47.49%	-36.43%
# of External Parks Used	6	6
# of Zones Used	414	414
Utilization	61.93%	61.68%

Similar to Year 1, Scenario 3 does not yield any improvement. We observe a worse result in terms of travel distance in both cost-based and distance-based scenarios. However, when the assignment breakdown in Table 4.24 is analyzed, we observe that the pattern is similar to those of Scenarios 1 and 2. Furthermore, by looking at the segment-wise analysis the segments from each class to locate internally can be determined. For instance, segments 2, 4, 6, 7, 8, 9, 11 form product class 1. From the results of this scenario, we observe that some portions of the segment 11 and 6 are assigned to internal zones. Therefore during the assignment of product class 1 in Scenario 1, the vehicles from segment 11 and 6 can be preferably located to the assigned internal zones. Apart from this observation, this scenario again validates the inferiority of 11-class formation.

Table 4.26: Optimization Results of Year 2 - Scenario 4

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0.07%	1	81.48	18.52
		2	0.00	100.00
CPU time (sec)	7201.84	3	24.08	75.92
		4	0.00	100.00
		5	96.14	3.86
		6	0.51	99.49
# of constraints	2820	7	0.00	100.00
		8	0.00	0.00
# of binary variables	5897	9	0.00	100.00
		10	0.00	100.00
		11	1.06	98.94

Table 4.27: Simulation Results of Year 2 - Scenario 4

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	266373857.71	247259406.79
% Improvement	-41.38%	-31.23%
# of External Parks Used	6	6
# of Zones Used	415	415
Utilization	62.44%	62.45%

Scenario 4 also does not lead to an improvement over the existing system and gives rise to similar insights with Scenario 3.

We continue with results of Year 3.

4.6.4 Results of Year 3

Table 4.28: Optimization Results of Year 3 - Scenario 1

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	11.58	88.42
CPU time (sec)	0.213	2	95.77	4.23
# of constraints	420	3	35.29	64.71
# of binary variables	1664	4	59.83	40.17

Table 4.29: Simulation Results of Year 3 - Scenario 1

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	135288811.75	120614670.52
% Improvement	-3.15%	8.03%
# of External Parks Used	3	3
# of Zones Used	364	364
Utilization	55.93%	55.91%

Scenario 1 for Year 3 leads to similar results with Year 1 and 2. Most of the vehicles from classes 2 and 4 are assigned to internal zones, and class 1 is assigned to external zones. Compared to Year 1 and 2, the percentages assigned to internal zones for class 1 and 2 increased, while the same decreased for class 4. This indicates the increase in the movement frequency of the vehicles in classes 1 and 2.

Table 4.30: Optimization Results of Year 3 - Scenario 2

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	6.56	93.44
CPU time (sec)	9.995	2	91.41	8.59
# of constraints	420	3	0.00	100.00
# of binary variables	1664	4	100.00	0.00

Table 4.31: Simulation Results of Year 3 - Scenario 2

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	129590049.62	115044713.24
% Improvement	1.18%	12.27%
# of External Parks Used	3	3
# of Zones Used	365	365
Utilization	55.78%	55.72%

Scenario 2 results show that, the percentages assigned to internal zones from classes 1 and 2 increased, and from class 4 decreased compared to Year 1 and 2. At the same time, we observe that when the zone limitation is removed, all of the vehicles in class 3 are assigned to external zones and all of the vehicles from class 4 are instead assigned to these internal zones. Simulation results show that the cost-based assignment provides 8% improvement in the distance traveled. Besides, 3 external parks are used as in terms of the existing case.

Table 4.32: Optimization Results of Year 3 - Scenario 3

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	93.49	6.51
		2	0.00	0.00
		3	59.83	40.17
CPU time (sec)	98.099	4	2.70	97.30
		5	77.96	22.04
		6	2.98	97.02
# of constraints	1259	7	4.63	95.37
		8	0.00	0.00
		9	0.00	100.00
# of binary variables	4576	10	88.11	11.89
		11	0.00	100.00

Table 4.33: Simulation Results of Year 3 - Scenario 3

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	155744979.60	144487466.58
% Improvement	-18.75%	-10.17%
# of External Parks Used	6	6
# of Zones Used	394	394
Utilization	55.61%	55.58%

Table 4.34: Optimization Results of Year 3 - Scenario 4

Solution Report		Assignment Results		
		Product class	% Internal	% External
Gap	0%	1	93.49	6.51
		2	0.00	0.00
		3	87.90	12.10
CPU time (sec)	33.85	4	40.54	59.46
		5	78.18	21.82
		6	3.55	96.45
# of constraints	1259	7	0.00	100.00
		8	0.00	0.00
# of binary variables	4576	9	100.00	0.00
		10	0.00	100.00
		11	4.82	95.18

Table 4.35: Simulation Results of Year 3 - Scenario 4

Simulation Results with Optimal Assignment		
	Distance-Based	Cost-Based
Total Distance (meters)	151214903.36	139524960.16
% Improvement	-15.30%	-6.38%
# of External Parks Used	6	6
# of Zones Used	393	393
Utilization	55.50%	55.56%

Scenarios 3 and 4 lead to similar results with those from Years 1 and 2. Both scenarios imply that any improvement in the travel distance cannot be obtained.

Overall, all of the scenarios yield similar results for three years. Scenario 3 and 4 do not lead to an improving result for any of the years, therefore we conclude that 11 product class option should not be implemented. The more the number of classes increases, more storage spaces are required due to class-based policy. By definition, in this policy, different set of zones are reserved for each class, and they cannot be used for other classes although they are empty. As the number of classes increases, the number of storage locations staying empty increase. As a result, it is highly possible that more locations closer to I/O ports stay empty for a time period. Therefore the solutions tend to get worse, when the number of classes increases. Our experimental results with 11-class is also an evidence for this inference.

Improvement in travel distance is obtained both in Scenario 1 and 2. The simulation results show that classifying products into 4 classes can yield a better system performance in terms of traveled distance. Also, it is observed that overall utilization increases. The only disadvantage can be the requirement of more space due to zone dedication, however this requirement can be reduced by using some of the unassigned zones. To take it a step further, simulation results showed the importance of the placement of the vehicles within the assigned zones. Instead of starting from the closest zone to the exit port, we utilized the information on the cost function again. We use the distance to both input and output ports weighted by the magnitude of the movement frequency, and store the incoming vehicles to the zones in the order of their assignment costs. Differentiating between Scenario 1 and 2 is a decision to be made by the warehouse management considering the zone restrictions. Switching from scenario 1 to 2, in other words removing the zone restrictions, showed that having a special warehouse region for class 3 is not preferable for the given production and demand data. When the restrictions are removed internal zones assigned to class 3 are assigned to other classes, generally to class 4. This is an indication for the management that if the security concerns for class 3 could be handled at the external parks, locating them to external parks will lead to bigger savings in terms of the traveled distance. Moreover, due to cost structure of the optimization model, the solution is dependent on the production and demand rates and it is observable from the results when the assignment percentages of different years are compared. To suggest the future implementation of 4-class scenario, we need to show that using the Poisson estimation gives a similar result with the experiments done with the exact data. In the next section, we present the results of the experiments carried out using Poisson estimation of the existing system.

4.6.5 Results of Experiments with Imperfect Information

In the previous section we reported the results of the experiments when exact data is used, i.e. when perfect information is available. However, for future implementations, the only available information would be production and sales forecasts at the beginning of the planning horizon. The simulation model with the forecasts will use a Poisson approximation of the system according to our methodology. Thus, we also need to show that the assignment policy obtained via the simulation of the Poisson approximation of Year 1, 2 and 3 gives a similar outcome when simulated with the exact data.

Suppose that the production and sales forecasts for three years were really accurate and the warehouse management used our methodology to obtain an assignment policy. We used the l_i values obtained with the simulation of the Poisson approximation of the model (Approximate model). The values are presented in Tables 4.8, 4.9 and 4.10. The optimization model is solved for each year with these l_i values and the resulting assignment policy is simulated again using the exact data. We add a minor modification to the simulation model. As stated before, due to capacity differences, there might be some unassigned zones in the internal zones or in the used external parks. To improve the policy, we allowed the simulation model to use these zones before using an artificial zone. However, these unused zones are not dedicated to a product class and are allowed to be used by different product classes. Optimal assignment percentages and simulation results for Scenario 1 and 2 with Poisson approximation are presented in Tables 4.36 to 4.41. The difference in total distance traveled between simulation with exact l_i values and simulation with using estimations of l_i values by a Poisson approximation are reported as % Difference. It is calculated by dividing the amount of change from the exact distance value to the exact distance value itself. A positive percentage indicates a decrease in the total distance traveled, while a negative percentage indicates an increase.

Table 4.36: Results of Year 1 with Imperfect Information - Scenario 1

Assignment Results			Simulation Results with Optimal Assignment		
Class	% Internal	% External		Distance-Based	Cost-Based
1	0.00	100.00	Total Distance (meters)	180618083.20	160881731.19
2	88.58	11.42	% Difference	2.32%	2.87%
3	63.64	36.36	# of External Parks Used	6	6
4	78.83	21.17	# of Zones Used	396	396
			Utilization	61.52%	61.44%

Table 4.37: Results of Year 2 with Imperfect Information - Scenario 1

Assignment Results			Simulation Results with Optimal Assignment		
Class	% Internal	% External		Distance-Based	Cost-Based
1	2.18	97.82	Total Distance (meters)	194776251.50	173901484.05
2	95.42	4.58	% Difference	3.09%	3.42%
3	25.93	74.07	# of External Parks Used	6 + artificial zones	6 + artificial zones
4	69.62	30.38	# of Zones Used	416	416
			Utilization	68.24%	67.99%

Table 4.38: Results of Year 3 with Imperfect Information - Scenario 1

Assignment Results			Simulation Results with Optimal Assignment		
Class	% Internal	% External		Distance-Based	Cost-Based
1	34.31	65.69	Total Distance (meters)	134090573.06	119105937.53
2	95.60	4.40	% Difference	0.88%	1.25%
3	0.00	100.00	# of External Parks Used	5	4
4	69.62	30.38	# of Zones Used	368	368
			Utilization	55.88%	55.85%

Scenario 1 results show that the difference between the simulation models with perfect information and imperfect information deviates between 1 to 3%, and utilizing the unused zones improves the policy further. The number of external parks needed remained the same as the experiments with perfect information. When the details of the assignments are analyzed, a difference is observed in class 3 in Year 3. However, when the simulation results are considered we still have an improving policy, therefore using Poisson application under imperfect information is acceptable for Scenario 1.

Table 4.39: Results of Year 1 with Imperfect Information - Scenario 2

Assignment Results			Simulation Results with Optimal Assignment		
Class	% Internal	% External		Distance-Based	Cost-Based
1	27.35	72.65	Total Distance (meters)	176826978.44	157134404.68
2	96.08	3.92	% Difference	-1.53%	-1.66%
3	0.00	100.00	# of External Parks Used	6	6
4	15.33	84.67	# of Zones Used	397	397
			Utilization	61.91%	61.92%

Table 4.40: Results of Year 2 with Imperfect Information - Scenario 2

Assignment Results			Simulation Results with Optimal Assignment		
Class	% Internal	% External		Distance-Based	Cost-Based
1	53.32	46.68	Total Distance (meters)	194058130.50	173071529.81
2	95.85	4.15	% Difference	3.51%	3.89%
3	5.59	94.41	# of External Parks Used	6 + artificial zones	6 + artificial zones
4	17.24	82.76	# of Zones Used	416	416
			Utilization	68.38%	68.39%

Table 4.41: Results of Year 3 with Imperfect Information - Scenario 2

Assignment Results			Simulation Results with Optimal Assignment		
Class	% Internal	% External		Distance-Based	Cost-Based
1	15.54	84.46	Total Distance (meters)	131987481.51	117097059.76
2	95.60	4.40	% Difference	-1.85%	-1.78%
3	11.18	88.82	# of External Parks Used	5	3
4	100.00	0.00	# of Zones Used	369	368
			Utilization	55.85%	55.83%

Similarly for Scenario 2, the deviations from the simulation model with perfect information change from -1.8% to 3 %. For Year 2, we obtained a further improvement, while Year 1 and 2 results worsened by about 2%. For the assignment breakdown, a difference is observed for classes 1 and 4 in Years 1 and 2, however, this policy still improves the existing system, and therefore it is acceptable.

From this analysis, we conclude that Poisson assumption also gives similar improvement results to experiments with perfect information, thus we conclude that our suggested methodology can be used for future implementation. In the next section, we briefly summarize the proposed methodology for future implementation as a DSS.

4.7 Proposed Implementation

Our aim is to propose a policy that can be utilized as a DSS for the warehouse management on the decision of storage location assignments for the upcoming planning period. We showed that our proposed policy gives an improved result compared to the existing policy when experimented with the real data and therefore it can be implemented for the planning in the future. The future assignment plan only requires the monthly production and sales forecasts for each segment and the layout information. The management should first run the Random simulation model just by updating the input distribution files with the monthly forecast values. As an output, the expected maximum number of vehicles will be obtained. These numbers yield the maximum required space for each product class and corresponds to l_i parameter in the optimization model. A formula for calculating an upper bound for the number of available zones is provided, which will prevent infeasibility of the model. The number obtained from the formula should be replaced by the number of available zones in the optimization model. Then, the input parameters l_i and p_{ir} values which are equivalent to the forecast values, should be updated among the input parameters of the optimization model. Then the model is solved via GAMS and the resulting assignment set is returned as an Excel file. The warehouse management should evaluate the results of Scenario 1 and 2 and decide on the policy for the next year. A representative figure for the decision process is provided in Figure 4.1. Note that the input files are flexible for making updates if an expansion or change in the layout occurs.

We showed that the proposed method yields improved solutions for the case study. However, the method can be used for the warehouses with a similar operating structure. For implementing the method in different warehouses, the important point is finding good fits for the arrival and departure distributions, or estimating them with an acceptable distribution as we did. Finally, it should be noted that the quality of the solution is highly dependent on the quality of forecast values.

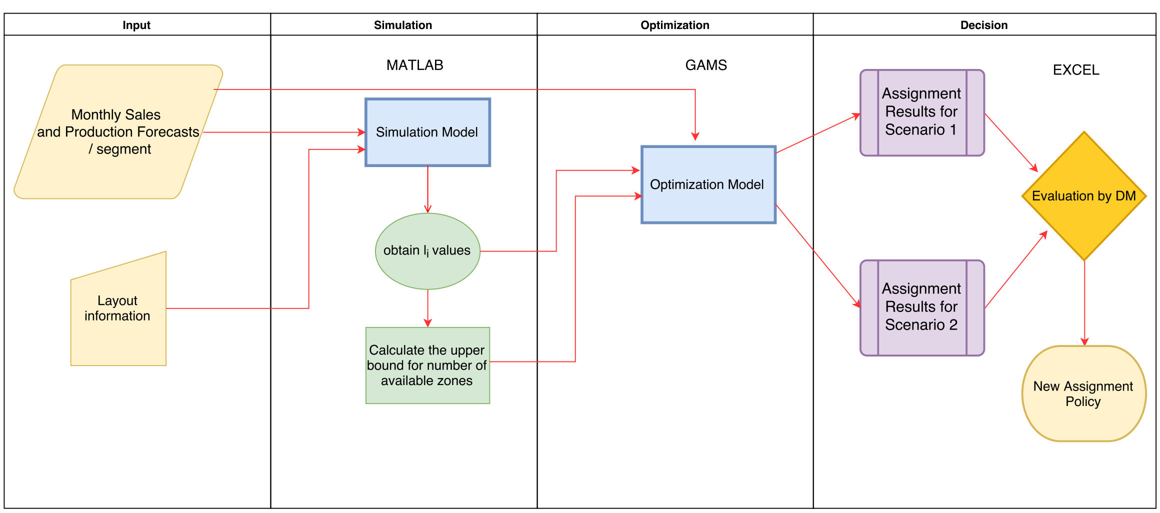

Figure 4.1: Summary of the DSS

Chapter 5

CONCLUSIONS AND FUTURE RESEARCH

Warehousing operations constitute 25% of a company's overall expenses for logistics and the cost of order-picking corresponds to 55% of the warehousing costs which cannot be ignored. Traveling is the most dominant activity during put-away and order-picking and it does not add any value but costs labor hours to the company. This indicates the high potential for improvement in warehousing costs by reducing the travel. The frequently observed structure in most warehouses is the inefficient assignment of storage spaces due to unsuitable storage policies. Generally, closest-open-location, closest-distance or random storage policies are used, which causes slow moving products to occupy the storage zones closer to the I/O ports and frequently moving products to be assigned to remote locations. This can be changed by introducing a suitable storage policy considering the warehouse structure, which is our motivation in this thesis.

We study the SLAP in unit-load, single-command, picker-to-part warehouses with multiple I/O ports operating under closest-open-location policy. The warehouse is assumed to be consisted of different regions with different capacities. Besides, the products are variable in size and some of them require higher protection during the storage. Therefore, there is a preferred order for the storage location selection; i.e, different warehouse regions have different priorities for assignment to different product groups. Under this configuration, our aim is to propose a DSS which aids the DM while planning the assignment of storage locations for each product. For the upcoming planning period, the only available information will be the forecasts for production and demand values, in other words the decision will be made under imperfect information. For solving the problem, we introduce a simulation-optimization based approach.

Within the proposed assignment model, we design a class-based storage policy where the product classes are formed according to certain product characteristics. The simulation is used as an input generation for the optimization model due to existence of uncertainty. Moreover, we use simulation also as an assessment tool during the study. We developed a simulation model which uses the forecast values and returns the maximum expected storage space requirement for each class. These requirements are used as parameters for the optimization model which aims to assign product classes to storage locations such that the expected travel distance is minimized. Optimization model aims to assign frequently moving products to closer locations while satisfying capacity limitations and storage space requirements for each product class. The output of the optimization model is the set of optimal locations for each product class. Then, we formed two scenarios with different zone restrictions which will be provided to the DM for evaluation. To show that these optimal assignments give rise to an improved result in terms of travel distance we tested our approach with a real data set. For the analyzed data set, the simulation model performs the arrival and departures as a Poisson process and its validity is also verified by comparing the simulation results conducted with the exact data.

We obtained the data from one of the largest automotive manufacturers of Turkey, from which our thesis problem is inspired. We obtained the recent 3 years' data of the finished goods warehouse of the company. The warehouse operates as a distribution warehouse and all of the specifications fit to our problem configuration. We performed the evaluation for each year separately. To assess the performance of our approach, we first simulated an approximation of the existing system. As stated before, we also used this data for simulation under the Poisson assumption and compared the results of both models. According to results of all years, we concluded that Poisson process is an acceptable assumption for arrival and departure processes.

Next, we designed four scenarios. The scenarios include two different class formations and two different capacity restrictions. We used the expected number of vehicles obtained from the simulation of the existing system, and used it as a parameter for the optimization model. We solved the models for each scenario and obtained the best possible assignments for each class. Then, to see if these scenarios provide a better solution than the existing system, the system is simulated again with the optimal assignments using the exact data for arrival and departures. The total traveled distances are compared to identify the improving scenarios. Also, overall utilization, number of storage zones and external parks utilized are used for performance evaluation. Our computational results revealed that two of the scenarios yield improved results for all years, while the remaining two scenarios with the other classification option were consistently inferior to the existing case. This implies that for this specific warehouse, the first classification should be used while applying a class based policy. All in all, we conclude that our method can provide solutions with reduced travel distances.

As a last step, we showed that Poisson assumption for arrival and departure processes also gives similar results with the exact data, and can be used for future implementations. We used the exact number of arrival and departures as forecast values and simulated the system using the Poisson assumption. Following this, the optimization model is solved with the obtained parameters from the simulation model. Then, system is simulated again using the resulting assignments and with exact data. It is seen that the results are similar, thus the proposed methodology is suitable for future implementation.

We concluded that our proposed simulation-optimization based approach can be modified and used for warehouses with similar specifications to determine storage location assignment for each product class. However, it should be emphasized that the solution quality is highly dependent on the forecast accuracy and fitted distributions (or assumptions) for the arrival and departure times.

This study can be extended by using different class formation methods. If there is available data, a clustering analysis can be to search for different class forming opportunities. Performance of different storage policies for this setting can also be analyzed to compare with the class-based storage. Another research direction could be investigating different cost functions for the optimization model, specifically by removing the uniformity assumption on the utilization of the storage spaces.

BIBLIOGRAPHY

[1] R. De Koster, T. Le-Duc, and K. J. Roodbergen, "Design and control of warehouse order picking: A literature review," European Journal of Operational Research **182**, 481–501 (2007).

[2] J. Gu, M. Goetschalckx, and L. F. McGinnis, "Research on warehouse operation: A comprehensive review," European Journal of Operational Research **177**, 1–21 (2007).

[3] J. J. Bartholdi III and S. T. Hackman, "Warehouse & distribution science: release 0.96," (2011).

[4] S. Sharma and B. Shah, "A proposed hybrid storage assignment framework: A case study," International Journal of Productivity and Performance Management **64**, 870–892 (2015).

[5] Y.-F. Chuang, H.-T. Lee, and Y.-C. Lai, "Item-associated cluster assignment model on storage allocation problems," Computers & Industrial Engineering **63**, 1171–1177 (2012).

[6] M. E. Fontana and C. A. V. Cavalcante, "Using the efficient frontier to obtain the best solution for the storage location assignment problem," Mathematical Problems in Engineering **2014** (2014).

[7] J. P. Van Den Berg, "A literature survey on planning and control of warehousing systems," IIE Transactions **31**, 751–762 (1999).

[8] M. Goetschalckx, *Warehousing in the Global Supply Chain Advanced Models, Tools and Applications for Storage Systems* (Springer, 2012), chap. Storage Systems and Policies, pp. 31–51.

[9] M.-C. Chen and H.-P. Wu, "An association-based clustering approach to order batching considering customer demand patterns," Omega **33**, 333–343 (2005).

[10] T. Le-Duc and R. M. B. M. de Koster, "Travel distance estimation and storage zone optimization in a 2-block class-based storage strategy warehouse," International Journal of Production Research **43**, 3561–3581 (2005).

[11] C. J. Malmborg, "Storage assignment policy tradeoffs," International Journal of Production Research **34**, 363–378 (1996).

[12] F. H. Staudt, G. Alpan, M. Di Mascolo, and C. M. T. Rodriguez, "Warehouse performance measurement: A literature review," International Journal of Production Research pp. 1–21 (2015).

[13] W. H. Hausman, L. B. Schwarz, and S. C. Graves, "Optimal storage assignment in automatic warehousing systems," Management Science **22**, 629–638 (1976).

[14] V. R. Muppani and G. K. Adil, "Efficient formation of storage classes for warehouse storage location assignment: a simulated annealing approach," Omega **36**, 609–618 (2008).

[15] P. Montulet, A. Langevin, and D. Riopel, "Minimizing the peak load: an alternate objective for dedicated storage policies," International Journal of Production Research **36**, 1369–1385 (1998).

[16] R. Accorsi, R. Manzini, and F. Maranesi, "A decision-support system for the design and management of warehousing systems," Computers in Industry **65**, 175–186 (2014).

[17] G. Ghiani, G. Laporte, and R. Musmanno, *Introduction to Logistics Systems Planning and Control* (John Wiley & Sons, 2004).