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Article

Pallet Distribution Affecting a Machine's Utilization Level and Picking Time

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Abstract: Space and labor are the two internal resources within a warehouse or cross-dock center which seek attention. Meaningful efforts in optimizing these two resources can reduce the operational cost or time of the goods delivery. The timely allocation of resources to order picking not only reduces the makespan and operational time but can also evade delay. In decentralized settings, where all the information is not properly shared between the players of the supply chain, miscommunication results in delays in product delivery. In this study, efforts were made to determine the pallet quantity of different product types in an order quantify when there is a gap in information shared and, based on that, the allocation of material handling devices or pickers was conducted. Each handling device is bounded by a workload to eliminate the option of idle resources and ensure it is utilized properly. A mixed integer linear programming model was formulated for this study and was solved using Lingo. Numerical experiments were performed under varying resource numbers and pallet quantities to investigate the circumstances where the number of pallet types and allocation of machines have the highest benefit. The results confirm that a change in the pallet quantity of the products increases the total picking time. However, an increase in the number of handling devices minimizes the level of over-utilization of a particular machine.

Keywords: resource scheduling; order picking; logistics; warehouse management; picking time

MSC: 90B05; 90B06

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1. Introduction

The efficiency of a supply chain is dependent on how well a warehouse and its operations are being managed. Cargo handling is an important parameter of warehouse management. Loading and unloading at a warehouse or logistics facility, transportation, warehousing management, sorting, assortment, and picking are the six main areas of cargo handling which are more challenging to visualize. These duties have a significant impact on logistical productivity and quality. As cargo handling is an essential component of logistics, losses incurred in this area directly raise the cost of logistics. In logistics, the received cargo is checked against the receiving cargo list where the quantity and quality of the products are properly inspected and, upon acceptance, are shifted to the warehouse. Later, the stored goods distribution processing and packaging are performed. Innovation in science and technologies has brought a makeover in material handling machinery. "Material handling" refers generally to the equipment that facilitates more effective cargo handling. It can also refer to any machine that accelerates automated handling or makes it simple to transport items around. In general, there are four categories of material handling equipment. Storage and handling equipment, bulk handling equipment, industrial trucks, and automated systems. It is the industrial trucks, comprising of hand trucks, side loaders, pallet trucks, forklifts, conveyors, and industrial robots which are maximally used in warehouses and distribution centers and help in cutting down labor costs and loading times.

Most of the research related to warehouse picking has highlighted order picking as the most expensive and labor-intensive operation for a warehouse [1] or cross-dock center. It is the process that includes picking and segregating the individual products from a fulfillment facility based on the customer's demand while verifying the item numbers and quantities listed on a picking list for shipping instructions [2]. It contributes to about 55% of the operational cost of any distribution center. Hence, while selecting a picking method, facility managers and business owners must be cautious because it can make or break the efficiency of warehouse operations. There are two picking techniques followed in order picking (shown in Figure 1). Firstly, single picking, where products are gathered one at a time for each shipping location, and secondly total picking, where products are gathered in advance and categorized by shipping location.

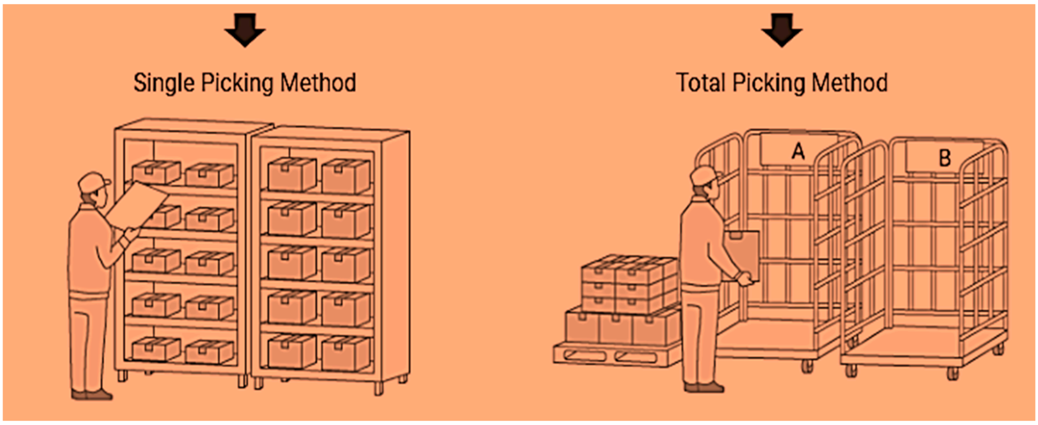

Figure 1. Order picking techniques (Order picking techniques, Kingdom of Bahrain, accessed 25 April 2023. Storage and Cargo Handling | Role of Logistics | Barcode Solutions for Logistics, KEYENCE America).

The size of the facility, the availability of funds and labor, the quantity and frequency of customer orders, and the number of SKUs in stock are just a few of the variables that might affect the picking strategy chosen by a warehouse. Furthermore, warehouse space and labor are the two internal resources that, when optimized, can increase the profitability of the business. It is also critical to decrease the number of idle resources and enhance resource utilization in order to cut the cost of labor when picking orders.

It is well understood from past research that order picking can be easy with a proper choice of material handling equipment and workload balancing of the pickers, which reduces the chances of product damage or productivity fall of a company [3]. In this direction, various order picking problems were analyzed and classified by Gils et al. [4]. The majority of the order picking tasks in a distribution center involve sorting and organizing items based on destinations and client requests. In general, the actions involve lifting, moving, picking, putting, packing, and other tasks. Picking is classified into box picking and client picking based on the product's shape, the type of process, the type of picking system, and other factors. Pre-picking and automatic picking are used in the picking process in some businesses. Pre-picking is the process of checking client orders and organizing products by box, pallet, or auto picking unit before the auto picking system classification. The method of categorizing pre-picked products based on the units of client, order, and vehicle is known as auto picking (or semi-auto picking) [5]. Jamili et al. [2], in their study, strived to divide the pickers so that the effort for the businesses is matched, particularly with complimentary demand patterns.

The optimization process in the warehouse may be broken down into two phases: first, it is important to analyze the current warehouse state, and then, it is important to provide proposals for improvement [6,7]. An extensive study of the literature has revealed that there has been a good amount of research on resource and vehicle scheduling in warehouse management and cross-dock centers focusing on minimizing the processing time [8], handling cost [9], makespan, or lead time [10] or on optimizing the internal resources like labor, space, and dock doors. Minimal research on scheduling of trucks within a cross-dock center was also modelled as a two machine flow shop scheduling problem [11]. Some of the work related to resource management evaluated the effect of collaborative resource management on the overall cost and utilization levels of internal resources. CPLEX 12.6 solver, GUROBI optimizer version 9.0, were some of the types of optimization software which were used in resource scheduling in past research, focusing on both the number of instances that can be proved optimal and the solution quality over time [12]. Researchers investigated different optimization possibilities for the warehouse system in their papers [13–17] including the use of mathematical models and genetic algorithms, lean management tools (UML, VSM, Genba Shkumi philosophy), and the Multidimensional Scaling Algorithm. In addition to the aforementioned models, the Floyd–Warshall algorithm was merged, integrated, and improved with the ant colony optimization metaheuristic by the authors [16–19] for the optimization of warehouses. Some authors also performed optimizations using the MATLAB program. Additionally, modern technologies like artificial intelligence [20], virtual reality, robotics, and augmented reality are applied to enhance warehouse operations. In order to enhance warehousing operations, warehouse automation systems are being used more frequently [21–23]. Even though a considerable amount of good research has been performed in scheduling and the assignment of resources, it is a complex subject area and the alteration of variables and parameters always offers a new scope of research.

2. Literature Review

The literature review of this article was placed in accordance with the keywords.

2.1. Resource Scheduling

It has often been encountered that the major portion of the operational cost within a cross dock is driven by two main operational decisions. Firstly, assigning vehicles to dock doors, and secondly, scheduling containers at the cross dock. The scheduling of resources inside a terminal is a challenging issue in and of itself for a given truck timetable. It needs meaningful effort in order to make appropriate use of limited resources such as labor and machines [8]. These tasks were modeled as a machine scheduling issue by Li et al. [24] and A'lvarez-Pe'rez et al. [25], who also provided various meta-heuristics for its resolution. Li et al. [24], in their model, did not consider the traveling time of the container from the inbound to the outbound area. They conceptualized the cross-docking problem as a machine scheduling problem embedded with earliness and tardiness penalties. Fonseca et al. [11], in their work, presented intriguing ways to solve the cross-docking flow shop scheduling problem. They inspected time indexed formulation and a hybrid Lagrangian metaheuristic framework for solving the scheduling problems. A'lvarez-Pe'rez et al. [25], in their study, examined a scheduling issue that enabled a warehouse to serve as a cross dock where the cargo transit storage time was kept to a minimum using just-in-time scheduling. Since precise resource scheduling determines the actual time difference between each inbound and outbound job, truck scheduling is highly correlated with this issue. Monemi and Gelareh [26] studied truck scheduling and door assignment problems considering the resource constraint. They discussed two cases in their study. In the first case, the experts were confident in the processing time estimates for each truck and only suggested a different combination of resources, whereas in the second case, a small number of resource deployment scenarios for serving trucks were suggested by the authors, each of which was paired with a different combination of resources and a different processing time.

2.2. Order Picking

Order picking is an expensive process [1] due to its dependency on pickers. The order-picking procedure is given the most attention as one of the major research areas in the storage system management segment [27]. In order to increase the effectiveness of warehouse order-picking operations, Lee et al. [28] performed research that offered a systematic and integrated technique that extends the correlated storage assignment strategy. Correlated storage assignments can significantly lower travel expenses but because of the imbalanced traffic flow, they may cause traffic congestion. In order to reduce the trip time and picking delays, the research suggested the correlated and traffic-balanced storage assignment (C and TBSA), which was modeled in two stages: clustering and assignment. To cut the cost of labor when picking orders, it is also critical to decrease the number of idle pickers and enhance picker utilization. A new line of research was conducted in this area with the goal of balancing the workload of pickers. In the context of order picking, Vanheusden et al. [29] initiated the operational workload balance challenge with their focus on equally distributing the orders throughout the day to prevent workload peaks and then hiring the necessary number of pickers to maintain a balanced schedule. They came up with the suggestion that utilizing a balanced timetable can improve order selection efficiency. Scholz et al. [30] studied the joint order batching, assignment, sequencing, and routing problem in minimizing order tardiness. How the related tours should be built and how the customer orders should be batched (grouped) were considered in the initial decision making. The pickers were then given batches and their sequences to reduce the total lateness of the orders. Gils et al. [4] also worked on the same line of research concentrating on batching, routing, and picker scheduling in order to minimize the order pick time. The authors additionally confirmed that resolving the combined issue yielded average performance gains of 16.9% for the actual spare parts warehouse used in their case study. In response to the arrival of urgent orders and disruption events, Dauod and Won [31], in their study, provided a dynamic-order picking (DOP) system where batches and picker paths are continuously updated. To enable a seamless replanning function, they took picker conflicts in constrained aisles into account in the suggested structure.

Jamili et al. [2] focused on picking orders before their due time in a collaborative warehouse where sharing of resources between multiple users was considered. They also proposed that sharing pickers had much more of an effect on the overall tardiness than sharing dock doors. It was also noted that the optimum collaboration advantage for both resources occurs at the medium level of use. They also asserted that their obtained result showed an improvement of 61% of the base case instances in a collaborative environment compared to a non-collaborative environment. Zhang et al. [32] introduced new technology in order picking, introducing autonomous picking robots that can work in a shared workspace alongside human pickers. This technology made it possible for humans and robots to work together and independently, increasing the flexibility of system design. Castier and Martínez-Toro [33] presented work that focuses on small enterprises that might not be able to afford the building of specially built storage facilities or utilize advanced picking tactics. It proposes a method to arrange the storage, picking sequences, and picking paths in warehouses. Srinivas and Yu [34] worked on a collaborative human robot order picking system, distributing (among humans and robots) the retrieval work and handling of item transportation to the depot, respectively. The numerical experiments confirmed that the suggested solution methodology performed better than other strategies. Additionally, their findings indicated that the composition of the human–robot team, AMR speed, AMR capacity, and warehouse layout all have an effect on the picking efficiency.

2.3. Logistics

Logistics act as a physical link between the various entities of a supply chain enabling the smooth flow of materials between them [35]. Some major operations such as freight transportation and warehousing are included in logistics activities. Over the years, it has refurbished its approach with the introduction of the newest strategies like cross docking, collaboration on transportation, etc. Cross docks' optimization problems in the context of physical internet or PI were introduced by Chargui et al. [36]. They talked about how this present concept of cross docking has revised the traditional cross-docking methods and changed the way cross-docking platforms were typically designed, managed, and optimized. The different cross-docking optimization problems emerging from the PI paradigm were then discussed at the strategic, tactical, and operational decision levels in order to highlight the unique characteristics that set the PI cross docks apart from the "conventional" cross-docking platforms. These practical approaches have definitely improved the operational efficiency, cost-effectiveness, and environmental concerns [37]. Collaborative urban transportation was studied deeply in recent publications with their major goal being to reduce the detrimental effects of freight transportation in urban settings, such as congestion, pollutants, and space consumption [38]. The optimization and modelling approach of logistic networks in maintaining an efficient supply chain management was studied by Mahjoub et al. [39] Apart from modeling the dynamics of vehicles and timetables at various locations of suppliers, warehouses, and consumers, they also extended the scope of their research to the loading, unloading, and delivery times of goods from suppliers to customers while accounting for their pertinent characteristics (e.g., number, nature, and destination). Reverse logistic models in supply chain management have also been the subject of research in recent years focusing on minimizing the total cost, carbon emission, waste reduction [40,41], etc.

2.4. Warehouse Management

Any company that keeps products in a warehouse recognizes that good management makes the difference between efficiently and precisely filling requests from consumers while keeping costs low against receiving complaints about erroneous or late shipments and higher operating costs. In order to guarantee customer satisfaction in terms of cost, quality, and timeliness, logistics is becoming more and more important. Rebelo et al. [42], in their article, demonstrated how warehouses may be a source of a competitive advantage and how a critical eye on the currently available space can result in capacity improvements with little up-front cost. This was performed by using a business as a model and implementing improvement suggestions. By considering a volume approach in their study, the authors showed that the warehouse space capacity can be increased by 9.77% while reducing the cost and damage to the products. Internal logistics planning and control, as well as warehouse management, are becoming more crucial. Today, a variety of techniques have been created for internal logistics planning, control, and warehouse management [20,43,44]. Internal logistics is crucial for adding value and maximizing revenues through the automation of internal logistics processes. A set travel time serves as an important gauge of logistical operations.

Burganova et al. [45], in their article, discussed ways to increase warehousing and logistics using currently accessible techniques while requiring the least amount of money and reducing the travel time. They reorganized the warehouse using lean techniques like the Kanban and Milk run and applied the presented design to the newly constructed hall. The end result is enhanced procedures and quicker material transfer times at the workplace; the finished product is delivered to the market faster and customers are satisfied. Voronova [46] studied complex warehouse logistics and the objectives of his research were developing strategies to increase the effectiveness of employing enough warehouses, streamlining the search and inventory procedures, and automating internal logistics. Based on the results of the research and the analysis of the warehouse real estate market, he concluded that improvement in the warehousing process is important and makes an impact on the maintenance cost. Collaboration on the internal resources in the warehouses is another popular initiative in warehouse management [2]. Perera et al. [47] provided a comparative examination of optimization methods for allocating warehouse space that was suggested in recent research. In their research, they proposed a linear programming model and a goal programming model to optimize warehouse space capacity by efficient palletizing. The enormous amount of information that needs to be processed, the sizeable number of potential solutions, and the degree of decision integration required in the modern warehousing context made it clear that there are currently significant challenges in applying these models.

2.5. Picking Time

One of the techniques to improve labor management is through analyzing picking time statistics and which, when utilized intelligently, can optimize the design and operation of machines. Anjom et al. [48], in their model, studied the effect of the picker speed, time of day, and picker cart used on the picking time. Hanson et al. [49], in their paper, presented a detailed analysis of how the physical workload and picking time of the orders vary depending on the size of the container, in particular large containers. They proposed that tilting the pallet to an angle of 45° toward the picker reduces the average picking time considerably. Grosse et al. [50] put out a framework for incorporating perceptual, mental, emotional, and physical components of human dynamics into order picking. They emphasize that the picking time and pickers' well-being are impacted by the placement of components in relation to height and depth. Engels et al. [51] proposed an exact equation for the LaPlace–Stieltjes transform of order picking time distribution. Loske et al. [52] discussed that it is the storage system that impacts the order-picking time. They experimented with a parametric log-logistic accelerated failure time model and established, from their result, that the order picking process becomes accelerated by 4.60% by using a high-density flow rack system, which directly reduces the order picking time. Furthermore, Poon et al. [53] proposed that zoning and class-based assignment rules, in comparison to random assignment policies, have been observed to tend to reduce trip lengths by 24% while boosting picking times by 21%. The authors adopted an automated data capturing technology—radio frequency identification and an advanced problem-solving technique—genetic algorithms, in order to manage material demand and the order management system and the results showcased that the integration of the above technologies helped enterprises to improve their operational efficiency on the production floor.

Careful study of the available literature on order picking and warehouse management reveals that this is a vast area of research and a slight improvement in warehouse space, or in any of the various parameters of warehouse management, can bring noteworthy change in the operational time or cost.

2.6. Contributions

As discussed previously, the optimization process in the warehouse not only analyzes the current warehouse state but also provide proposals for improvement [54–56]. So, this proposed model is aimed to provide the following:

- A proposal to improve the picking time of products within a cross dock by considering a decentralized set up where the full details and information about product delivery are not shared with all the players on the supply chain;
- In this study, the aim is not to optimize the internal resources within a cross dock. Rather, the study aims at finding the pallet quantity of each product type and the maximum number of pallets carried by each handling device to minimize the total picking time when there is a discrepancy in information shared;
- Instead of evenly distributing the orders in a day and then finding the number of pickers required, the focus has been laid on a particular order and distributing the workload between every picker and ensuring that none of the allocated pickers are idle;

- We further tried to obtain the optimal solution using optimization software Lingo 19.0 (LINDO SYSTEM Inc.1415 North Dayton street, Chicago, IL 60642), rather than cplex or gurobi, and also to estimate the resource utilization level in our work.

3. Mathematical Formulation

A major portion of the warehouse cost is being driven by the labor cost. Warehouse order picking, being the most expensive and labor-intensive operation for almost every warehouse, demands proper management. Manual labor is bounded by factors like absenteeism, safety, health issues, and efficiency level. Hence the deployment of machines for handling materials has become more popular. A machine has more carrying capacity compared to manual labor and can work relentlessly ignoring factors like health, safety, and absenteeism issues, so warehouses are gradually shifting to automation with the use of conveyor belts, pallet trucks, automated guided vehicles for material handling within a cross-dock or distribution center or warehouse facility. After the order-picking process, delivery of the orders is initiated by loading the shipping trucks at the dock doors. Until all of the truck's required orders have been picked, the collected orders are buffered in a short-term storage area near the dock door.

Centralized settings in product management emphasize the proper transmission of the required information through a central authority to the various players of supply chain management. However, product inaccuracy, the presence of defective items, and transparency are some of the noticeable issues which cannot be ignored and may hamper the operational management of the warehouse or supply chain [57–59]. In this study, a decentralized setting was taken into consideration where there exist gaps in the information shared. A cross-dock center handling different product types packed in different pallet types which are a part of varying order types to be dispatched for different locations (shown in Figure 2) is the area of focus. The order from a customer can be for different products which can be packed in different pallet types. Not knowing the number of pallets of each product type will enhance operational time. Thus, in this proposed model, we aimed at estimating the number of different pallet types for each product type when the order quantity of each product is known. The products in different pallet types are unloaded, transported, temporarily stored, sorted, picked for shipping, and loaded in specified outbound trucks with the help of handling resources. Knowing the number of pallet types against the product type makes the sorting and picking operations easy.

Furthermore, different pallets need different handling devices based on the product they carry and the carrying capacity of the device. Hence, in this study, apart from minimizing the total processing time of the product handling, the focus is also on assigning the handling resources needed for order picking within a cross-dock or distribution center in a particular time slot, when the pallet quantity and pallet types are known. An investigation into the level of resource utilization was also incorporated in this study.

Assumptions

1. Unloading and order picking of the pallets can be initiated only when the inbound truck is stationed at the receiving dock. Unloading and picking of the pallets must be finished within a specified due time;
2. The facility has enough handling resources and is a non-collaborative warehouse where the resources are being shared by a single operator and not rented from a third party;
3. Different pallet types of products were considered in the order [47]. One pallet is picked at a time following a single-order picking policy which avoids the mixing up of product and pallet types;
4. Different material handling devices were used in the service for order picking. The picking time of the pallets in this model is different for each pallet type and depends on the picker type (i.e., the material handling device used) as well as on each component's

height and horizontal distance from the picker [50]. All the handling devices are in service mode and are assigned for pallet picking;

5. The demand for each product in a planning horizon is known beforehand.

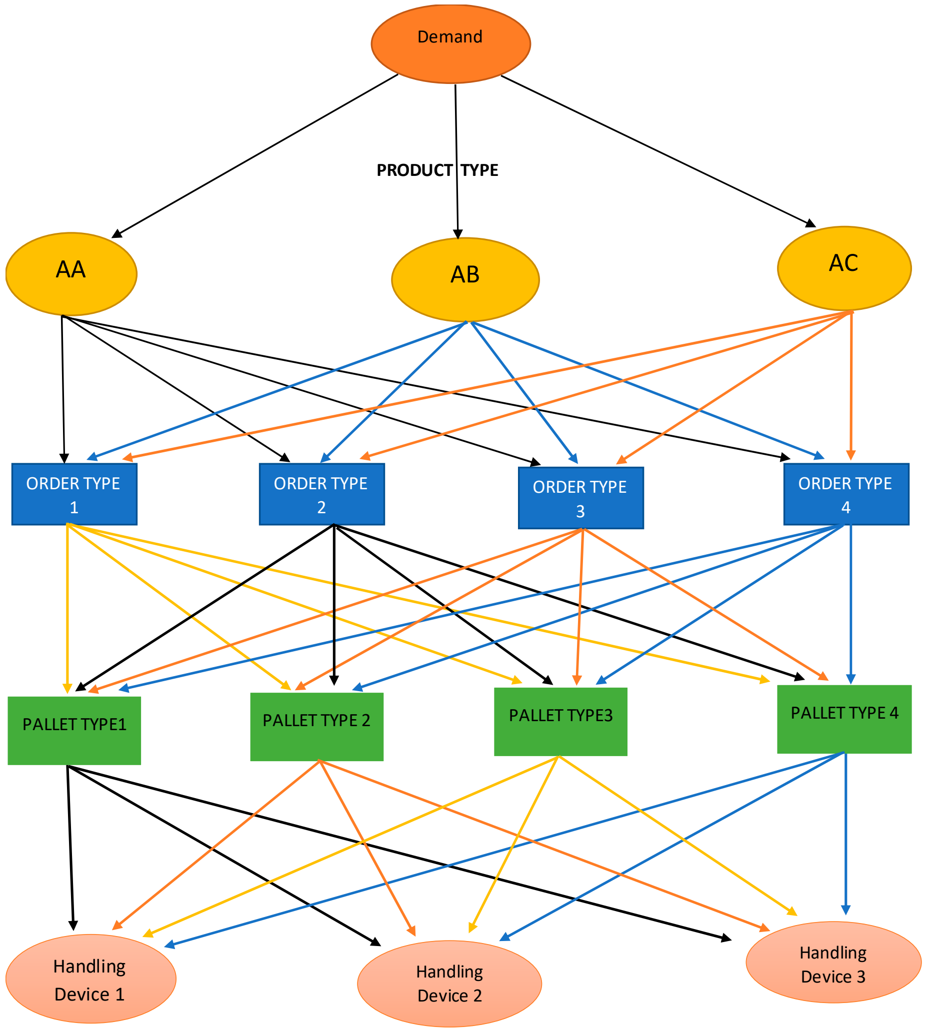

Figure 2. Schematic representation of the model.

4. Mathematical Model

The objective function of the designed mathematical model aims at minimizing the total picking time of the pallet handling by the handling devices.

$$Min\ Z = \sum_{m=1}^{M} \sum_{k=1}^{K} (Z_{km} * P_{km}) \quad (1)$$

- Product availability constraint

Equation (2) represents the available order quantity of each product type satisfying the demand requirement of products [47].

$$\sum_{j=1}^{J} (p_{ij} * Y_{ij}) \leq A \ \ \forall\, i \in I \quad (2)$$

The total number of pallets for a particular product contains different pallet types. Equation (3) represents that the number of pallets of different types for each product is equal to the daily demand requirement of pallets [47].

$$\sum_{k=1}^{K} x_{ik} = a,\ \forall\, i \in I \quad (3)$$

Equation (4) confirms that the amount of *i*th product in the *j*th order should be at least C so that a uniform distribution of product exists. The pallets are not under packed.

$$Y_{ij} \geq C \ \ \forall\, i \in I,\ \forall\, j \in J \tag{4}$$

where C is the fixed order size for a particular product.

- Machine requirement constraint

The total number of pallets of different products is addressed by the available handling devices. There is no unattended pallet; this is represented by constraint 5:

$$\sum\nolimits_{m\,=\,1}^{M} Z_{km} \ = \ \sum\nolimits_{i\,=\,1}^{I} x_{ik},\ \forall\, k \in K \tag{5}$$

Equation (6) represents the concept that all the handling devices in a planning horizon have been utilized and that there is no idle device.

$$Z_{km} \geq B,\ \forall\, k \in K,\ \forall\, m \in M \tag{6}$$

where B is the number of pallets to be carried by each machine.

- Non-negative constraint

$$x_{ik} \geq 0\ \forall\, i \in I,\ \forall\, k \in K \tag{7}$$

- Integer constraint

x_{ik} *and* Z_{km} are all integers.

$$\forall\, i \in I,\ \forall\, k \in K \tag{8}$$

5. Solution Methodology

This designed model's solution methodology necessitates a method that can handle a variety of variables. Using a traditional approach to manage a large number of variables takes time. In order to achieve the best results, a variety of strategies can be used. This study introduces the LINGO software 19.0 (LINDO SYSTEM Inc.1415 North Dayton street, Chicago, IL 60642)for solving this planning problem. It is practical, quick, and effective in resolving planning issues. LINGO has grown to be a significant instrument for solving optimization issues now because of its superior and effective problem-solving capabilities and strong pertinence. In addition, LINGO makes use of a standard modeling language that can be utilized to program optimization issues. Users can use some built-in features during modeling because they are available. It uses the branch and bound technique to generate the optimal solution of the designed mixed integer linear programing model.

A numerical experiment was presented to estimate the minimum picking time of the order. The pallets containing the products are unloaded from the inbound vehicles. They are transported to a temporary storage facility where they are sorted based on order type and product type and following a single picker policy, the pallets are picked up by the handling devices to be loaded into the shipping truck destined for a particular location (as shown in Figure 3). The base case of instances (as shown in Table 1) is introduced first which has been derived from the data set [2,47] and modified depending on the need of the model accordingly. Subsequently, further additional instances are generated by varying parameters and its effect on the total picking time and the utilization level of the handling devices is investigated. The data set contains data of a cross-dock center that handles various products, inbound and outgoing vehicles, and order types in a day. In total, four different order types of 1000 kg, 600 kg, 580 kg, and 400 kg were considered apart from four different pallet types. The unloaded product is shipped to outbound trucks for dispatch within 24 h. The inbound trucks are unloaded at the strip door following a particular order, one truck at each door at a time, in each time slot.

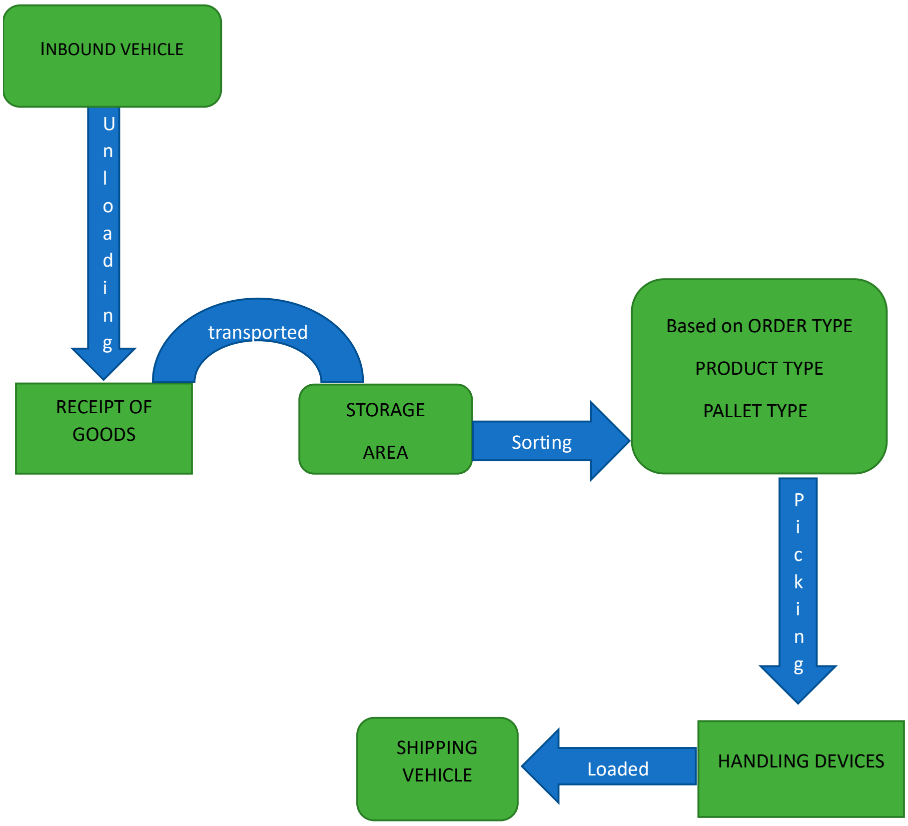

Figure 3. Flowchart to represent the picking process.

Table 1. Parameters of the base case instance.

Parameter	Notation	Value
Total number of pick order pallets	O	160
Number of product type	I	3
Number of pallet type	K	4
Number of order type	J	4
Number of material handling devices or pickers in each time slot	M	4
Daily demand requirement of pallets for each product	a	{70, 55, 35}
Daily demand of products	A	10,000 kg

In addition, medium-size and small-size cross docks for an operation were envisioned rather than large cross docks because large cross-dock facilities have sufficient internal resources of their own as well as proper warehouse management systems. Therefore, they are less motivated to optimize or plan their resources. So, it is reasonable to consider a scaled-down version of our empirical data. According to Jodlbauer [60], the average processing time of the machine should be short. He also mentioned that the average processing time is independent of the scheduling, sequencing, and lot sizing. It is only influenced by the total input and the individual standard processing time. Here, in this proposed model, the processing time of the machine is the same as the picking time of the handling devices. The picking time of the pallets in this model is different for each pallet type and depends on the picker type (i.e., the material handling device used) as well as on each component's height and horizontal distance from the picker.

6. Results and Discussion

For the base case instance, three different types of products were considered. These products are packed in four different pallet types whose quantity is to be determined and all the products are part of the four different order types of customers. The average picking time per component is referred from [49] and modified to suit our model. With the given parameters, the total picking time for the base case is found to be 328.32 min, where the number of pallets of each product type is given in Table 2.

Table 2. Represents the picking time with respect to varying parameters and decision variable.

Decision variable		**Product I** / **Pallet type K**	**i1**	**i2**	**i3**		**Picking Time**
Base case	$(x_{ik}) \geq 0$	K1	6	26	0		328.32 min
		K2	0	29	35		
		K3	32	0	0		
		K4	32	0	0		
Additional instance	$(x_{ik}) \geq 4$	K1	5	4	23		328.32 min
		K2	17	43	4		
		K3	24	4	4		
		K4	24	4	4		
	Parameters	**Product I** / **Pallet type K**	**i1**	**i2**	**i3**		**Picking time**
Base case	K = 4	K1	6	26	0		328.32 min
		K2	0	29	35		
		K3	32	0	0		
		K4	32	0	0		
Additional instance	K = 3	K1	24	22	24		301.44 min
		K2	4	47	4		
		K3	4	27	4		
	K = 5	Exceeds the capacity of the solver					
		Machine / Pallet	M1	M2	M3	M4	Picking time
Base case	M = 4	K1	8	8	8	8	328.32 min
		K2	8	40	8	8	
		K3	8	8	8	8	
		K4	8	8	8	8	
Additional Instance	M = 3	K1	8	8	8		287.2 min
		K2	8	72	8		
		K3	8	8	8		
		K4	8	8	8		
	M = 5	Exceeds the capacity of the solver					

6.1. Base Case Instance

In total, there are 70 pallets of product 1, 55 pallets of product 2, and 35 pallets of product 3. These 70 pallets of product 1 are in a combination of 4 different pallet types, similarly as for product 2 and product 3. Most of the products are packed in pallet type 2 compared to the other three types.

The following pallets are then picked up by the handling devices and shipped to the outbound trucks. (Refer Table 2). The total 32 pallets of each type 1, type 3, and type 4 are being equally carried by 4 different devices while 64 pallets of type 2 are picked by the 4 handling devices where machine 2 carries the maximum number of pallets. In this proposed model, the number of machines available in a particular time slot is four. This led to the utilization of each picker to 40% ($\frac{|O|}{M}$ = $\frac{160}{4}$). However, it was found that machine 2 is overloaded and carrying 64 pallets compared to machines 1, 3, and 4, where each of them is carrying 32 pallets. Thus, the utilization level of machine 2 is $\frac{64}{40} * 100 = 160\%$ compared to the utilization level of other machines which is at $\frac{32}{40} * 100 = 80\%$. This over-utilization of machines may result in machine breakdown and a disruption in services.

6.2. Additional Case Instance

In this section, the emphasis is to know how the change in the parameters affects the picking time of the pallets. In the base case, the total number of pick orders considered is 160 which is a combination of three different product types, packed in four different pallet types.

- Variation in pick order: The optimal result is generated with 70 pallets of product 1, 55 pallets of product 2, and 35 pallets of product 3. An alteration in the number of pallets of the product types brings no noticeable change in the total picking time. However, when the total pick order is varied, the total picking time changes as well. This increase or decrease in the total picking time is only dependent on the total pick order as the number of pallets is increasing. This change in the picking time is irrespective of the change in the number of pallets of each product type;
- Variation in the number of machines: The variation in the number of handling devices affects its utilization level as well as the total picking time. Using three machines for the same order quantity has reduced the total picking time by 41.12 min; however, it has increased the utilization level of machine 2. Even though every machine is bounded by a minimum carrying capacity, the utilization level of the machines is not uniform. Employing three machines will increase the utilization level of each machine to 53.33%. However, the workload on machine 2 seems to further increase to 180%, confirming that machine 2 is over-utilized compared to others and may lead to machine breakdown because of overloading and excessive use (refer to Table 2). Thus, decreasing the number of machines increases the utilization level of machines by 13%. Hence, using four machines is the optimal result;
- Variation in pallet types: A total of four different pallets of varying sizes were considered in the pick order. Decreasing the number of pallet types for the same order quantity affects the total picking time. It was noticed that when three types of pallets are used to accommodate an order of 160, the total picking time is 301.44 min and the variation in the number of pallets of each type is given in Table 2);
- Variation in the number of products: The considered number of products generates a global optimal solution. Decreasing the product types generates infeasible solutions while increasing the product types makes the model unsolvable;
- Variation in picking time. As mentioned earlier the processing time of the machine or the picking time is only influenced by the total input and the individual standard processing/picking time. Figure 4 shows how the 10% variation in the picking time of every component affects the total processing time. We conclude from the obtained result that when the individual picking time of the pallets is less than the overall picking time, it is definitely reduced.

6.3. Pallet Utilization

The decision variable x_{ik} denotes the number of kth pallet types from the ith product type. In the model, it is ensured that the decision variable $x_{ik} \geq 0$ which generates the distribution of products in the pallet types is given by Table 2. The results confirm that pallet type 3 and pallet type 4 are not very much used for the packing of the products. Each pallet type is of a varying size so using bigger pallet sizes to accommodate small loads engulfs more warehouse space. Adding a lower bound on x_{ik} offers better utilization of the pallet types, where products are distributed in all of them. Imposing a lower bound on the decision variable does not bring any change in the total picking time or the number of pallets of each type. It manifolds the distribution of products in all pallet types rather than confiding to selective (Figure 5).

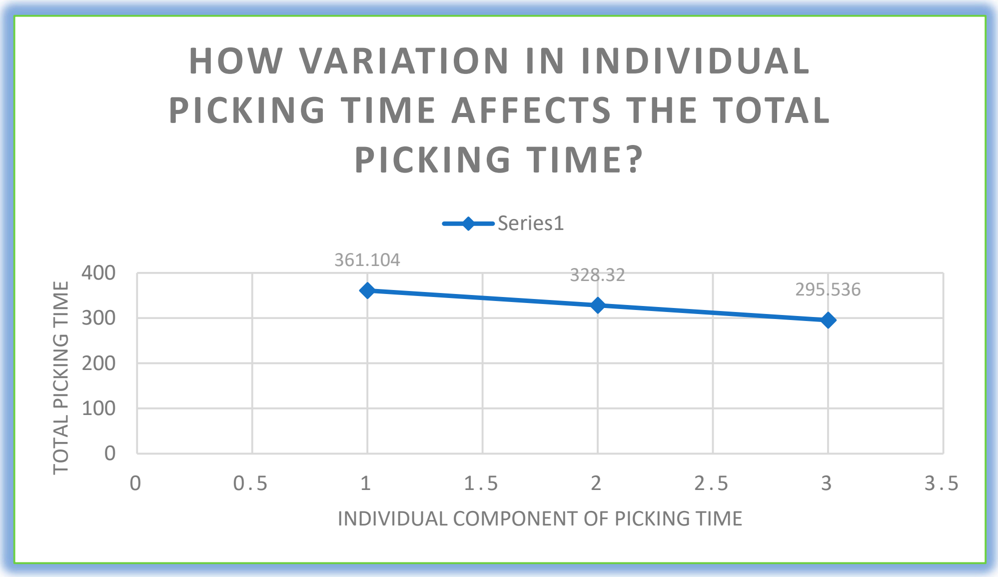

Figure 4. Effect of variation of the individual picking time on the total picking time.

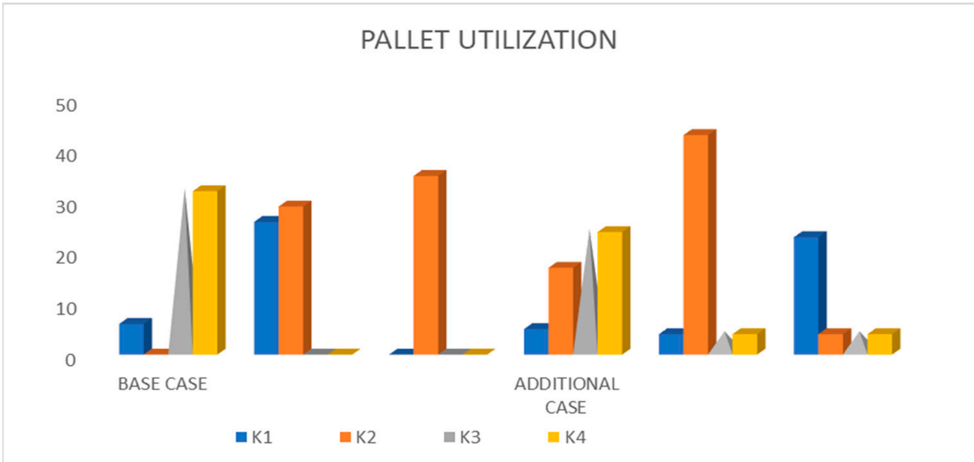

Figure 5. Pallet utilization.

7. Managerial Insights

Money, management, marketing and sales, products and services, people, processes, and systems are the seven pillars on which the base of a successful business stands. A small improvement in any of these above-mentioned factors has the capability of heavily improving a company's performance. Hence, facility managers and business owners are on a constant search for the newest strategies and policies that can improve time, cost, quality, and productivity dimensions [61]. Thus, while selecting a picking method, facility managers and business owners must be cautious because it can make or break the efficiency of warehouse operations. The shortcomings of the decentralized settings impose even greater responsibilities on warehouse managers in maintaining a smooth operation. Through this model, the warehouse managers would be able to draw a clear picture of the number of pallets of each product and can manage the storage and distribution of handling devices as well as warehouse space accordingly. They can predict the type of pickers/handling devices required for order picking and regulate the cost and time to finish the operation. Those companies which prefer the pre-picking process and organize the customer order packed in boxes or pallets, for them knowing the pallet quantity of each product will smooth their task.

8. Conclusions and Future Research

A careful review of the literature related to modern warehouses and traditional warehouses reveals a significant difference in their operational level, demanding that the majority of models and frameworks must undergo significant modifications in order to be applied to contemporary warehouse operations on a dynamic scale and current size and application. Warehouse operations are intricate and interconnected, and when dealt with or optimized in isolation, they fail to produce results that are globally ideal. Hence, the necessity of coordinated strategies for operational issues and multiple decision making within warehouses, cross-dock centers, or distribution centers that are strongly connected is one point that is highlighted, making it necessary to group pertinent issues that must be resolved at the same time [62].

Through this study, it is discovered that most warehouse operations have some degree of uniqueness based on the sector in which they operate and organizational policies. Apart from picking or retrieval functions of warehouse operations, some other factors like the homogeneity or heterogeneity, size, number of the items stored, handling characteristics of products or their product carriers [63], etc., are vital in warehouse operational decision making. As a result, it is clear that the range of potential research areas has been reduced to results regarding problem-specific solutions.

In order to make the best use of warehouse resources through proper palletizing, this article offers a straightforward and practical MILP model. The total picking time is calculated based on the number of pallets carried by each handling device. The number of pallets for each product is calculated based on the daily demand for each product as well as on other warehouse operational constraints. Though increasing the number of material handling devices used for order picking reduces the picking time, it increases the utilization level of the machines by 13% and increases the chances of machine damage. The use of three different pallet types for managing four different product types reduces the picking time but it increases the possibilities of product congestion within the pallets leading to product damage. The model was able to produce optimal answers for almost all the investigated situations with minimal computational time and effort. This shows that the suggested MILP model offers a good approach to the issue of pallet distribution and picker utilization by optimizing the number of pallets required to satisfy the demand from each product category and the number of pallets carried by each handling device. In a real-world setting where the labor cost is exponentially huge, the methodology suggested in this work can be utilized as a starting point for the further optimization of fundamental warehousing functions.

For future research, there are various other aspects that can be incorporated into the model and further explored.

- The proposed model for this study takes into account the homogeneity of the items that are placed on a pallet. Future research could explore the possibility of testing and enhancing the model to function when the items to be piled on the pallet are heterogeneous;
- The proposed model is based on the fact that the daily demand and order quantity are deterministic. The model can be further explored with stochastic demands or alternatively, the study could be expanded further to include forecasted order quantities as model inputs;
- In this model, a particular order in a planning horizon concentrated in a decentralized small-sized cross dock is considered and the pallet distribution and machine's workload are suggested accordingly to attain the minimized total picking time. The effect of multiple orders and its effects on the total picking time can be further investigated within the premises of a large-sized cross dock;
- The allocation of material handling devices for this model was random. However, the model can be explored by setting the allocation of machines to pallet picking on the criteria of the shortest processing or picking time.

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Abbreviations

Indices, decision variables, and parameters were included in the following subsection of notation to formulate the mathematical model:

Indices

K	Number of pallet types
J	Number of order types
I	Number of product types.
M	Number of available material handling machines
A	Daily demand requirement of products in Kg
a	Daily demand requirement of pallets of each product

Parameters

Y_{ij}	Order Quantity of ith product in jth order where i = 1,2,3, . . . , I and J = 1,2,3, . . . , J
p_{ij}	Number of pallets of ith product in jth order
P_{km}	Processing time of kth pallet in mth machine, where k = 1,2,3, . . . , K and m = 1,2,3, . . . , M.

Decision variables

Z_{km}	Number of pallets k carried by machine m, where k = 1, 2,3, . . . , K, m = 1,2,3, . . . , M.
X_{ik}	Number of kth pallet type from ith product type, where i = 1,2,3, . . . , *I, and* k = 1,2,3, . . . , K

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