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DYNAMIC SIMULATION ANALYSIS FOR VARIOUS NUMBERS OF ORDERS IN AN INTEGRATED CAR-MANUFACTURING WAREHOUSE

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The order-picking process in a warehouse is critical in managing customer orders, especially in retail stores. It is expensive because fulfilling online orders takes up to 70% of all warehouse activities. Procedures in order picking, including different route selection schemes, can significantly increase yield and reduce costs. The research shows that a suitable routing method can reduce the travel time of the order picker to fulfill the order. However, the number of orders may vary. This paper presented a dynamic simulation analysis based on a real scenario of a various number of orders in an integrated car manufacturing warehouse. The simulation reduced the travel time of the voters by about 44.89%. This simulation model helps to visualize the potential reduction in customer waiting times, leading to increased customer satisfaction.

Keywords: Dynamic Simulation, Order Picking, Shortest Path.

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1. INTRODUCTION

Order picking is an important process in warehouse management practice, and finding ways to increase picking productivity and make it work effectively is a critical research area. The research objective is to have an optimal order-picking process to improve warehouse operational efficiency. Many studies show that order picking is one of the most critical processes in a warehouse. Petersen and Aase (2017) stated that the order-picking process accounts for 50%–75% of the total operating cost of a typical warehouse. Reports show that 55% of all operating costs in a typical warehouse can be attributed to order picking, and the process takes up to 70% of operation time (Habazin *et al*., 2017; Bartholdi and Hackman, 2011; Dharmapriya and Kulatunga, 2011). Order picking remains a very capital-intensive operation even in automated warehouses (Goetschalckx and Ashayeri, 1989) because there are many sub-processes in the order picking stage. It includes batching, routing, and sorting processes; hence the performance of the order-picking process in a warehouse or distribution center can be measured based on the order fulfillment lead time (Mercedes *et al*., 2019). It highlights the importance of performance analysis and improvement of order-picking process systems as it directly impacts achieving most companies' objective of the shortest order fulfillment lead time.

Order picking is retrieving products from specified storage locations based on customer orders. However, the warehouse design can result in more complex order-picking processes. Therefore, ensuring the order-picking process is smooth is vital to avoid interruption or discomfort in delivering the goods to the customers. This study focused on an order-picking process with limited picking quantity by an order picker.

According to the job description by most human resource departments in the United States, the order picker task is not limited to picking items and getting them ready for shipment (Order Picker, 2022). An order picker also loads and unloads goods from containers and updates the inventory systems. Sometimes, an order picker is also responsible for product assembly. Formally, the job of an order picker starts when he receives an order note at the depot, goes to identified locations

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to retrieve items according to the order list, and delivers them to the packaging point for distribution to the customers (Chan and Chan, 2011). Bhavin and Vivek (2017) and many other researchers confirmed that the main objective of warehouse management is to fulfill 100% of the customers' demand. It is done by ensuring that the customers are satisfied with effective resource utilization when the product is delivered correctly, on time, at the right place, and in good condition. Therefore, a warehouse needs a proper system for its order-picking process and related subprocesses, such as storage assignment, resource allocation, workforce handling, and task allocation (Kusrini *et al*., 2018; Sahin-Arslan and Erkem, 2019).

Different warehouses have different priorities that make choosing the order-picking process challenging. Therefore, the study aimed to evaluate whether specific strategies in order picking could reduce operating costs while keeping the service level as high as possible. It will affect the demand-supply system, the order pickers, and the staff. Therefore, optimizing the order-picking process is crucial in inner warehouse movement and transportation.

A good strategy to find the shortest path and time to complete orders according to the customers' needs is highly needed. Furthermore, the order picker must ensure the order is completed successfully within regular working hours. James and Dale (2004) mentioned that order fulfillment models should include basic procedures for picking orders: picker-to-part, zone picking, wave picking, and sorting systems. In the picker-to-part process, the picker moves to the storage area that contains the items based on the order. The warehouse is divided into distinct zones in zone picking, with one picker assigned to each zone. Each order picker is in charge of a zone, and each item is divided into several picking lists. In the wave-picking process, the order picker moves to collect the items for several orders. The process performance is measured by how fast all the items in the order list are picked. In contrast, the sorting systems process has no movement of the order picker. Instead, the products are brought to the picker by an automated system.

Simulation is an analysis process for warehouse performance evaluation (Verriet *et al*., 2013). It presents a warehouse simulation model that is applied in the early stage of the development process. Gagliardi *et al*. (2007) used a discrete event simulation model to improve warehouse operations to evaluate strategies for handling stock-keeping units (SKUs) and allocating space needed for each item. The results showed reduced operation costs and maintained a high-level service for the warehouse. Hrihorkiv *et al.* (2010) focused on the warehouse' order-picking process. The results showed that by choosing an appropriate combination of optimization methods, the picker travel distance could be reduced by about 50%. Andriansyah *et al*. (2009) proposed a simulation modeling approach based on aggregate process times for the performance analysis of order-picking workstations in automated warehouses. The simulation was not limited to a single warehouse (Andriansyah *et al*., 2011). A layered warehouse simulation model was built from reusable components, which allowed varying the number of storage aisles and workstations in a mini load-workstation order-picking system. Although the proposed model could handle more than one warehouse, it was limited to one type of warehouse topology.

Li *et al*. (2020) proposed a four-door dangerous goods warehouse and a route planning method for forklifts to ensure safety and increase the operational efficiency of the warehouse. The study revolutionized the warehouse design by elevating the routing optimization of two forklifts operating in the four-door warehouse. Jorge *et al*. (2012) simulated an order-picking system in a pharmaceutical warehouse to increase operational efficiency. The study highlighted the optimal number of order pickers required for the picking activities. Consequently, the improvement in the service and an optimal number of order pickers reduced total operating costs. Furthermore, a suitable number of order pickers can lead to higher staff motivation and customer service satisfaction. Other simulation research related to order picking process, warehouse layout, and methods was conducted by Renaud and Ruiz (2008), Wu *et al*. (2010), Gu *et al*. (2010), Chawla *et al*. (2019), and Hashemi *et al*. (2020).

Order-picking practices combine the basic procedures mentioned earlier. Furthermore, they require proper coordination and thoroughness (Chin, 2018). Choosing an order-picking system depends on cost, movement complexity, number of customer orders, size, and number of items. This study of the automotive manufacturing company focused on the most common practice of picker-to-part. In this approach, an order picker picks all the ordered items from the racks at once to minimize time. However, some companies limit the number of items collected at once due to the picking vehicle's limited capacity. In addition, increment in order volume also affects the performance. Minimizing the travel time of the pickers and optimizing the staff working hours and loads without additional cost is critically important to reduce the waiting time for customers involved in the order system. Therefore, this study considered the potential increase and variation in order volume (characterized by the number of orders) while having a fixed number of order-pickers in the system. The problem was analyzed using simulation models as it does not affect the actual system (Hwang and Cho, 2006; Petersen and Aase, 2004; Kostrzerovski, 2020; Wilkenhaus *et al*., 2022). The study setting is described in Section 2, details on the simulation part are explained in Section 3, and results and discussion are illustrated in Section 4.

2. CURRENT SCENARIO

2.1 Demand and order patterns

The major input for the simulation model is the expected demand (number of items ordered) to be handled by the order-picking operation. This study's setting was the manufacturing company in which the order made per day was identical and small. Figure 1 shows the average number of items ordered by customers per month. The demand was high for the first quarter as the number of items delivered to customers was almost 40000. However, the demand fell in the second and third quarters. Furthermore, the number of working days was less due to technical issues in the warehouse. The number of orders per month in 2015 during the day shift was 25000–38000 items. The maximum and the minimum number of items ordered daily were approximately 2520 and 470, respectively.

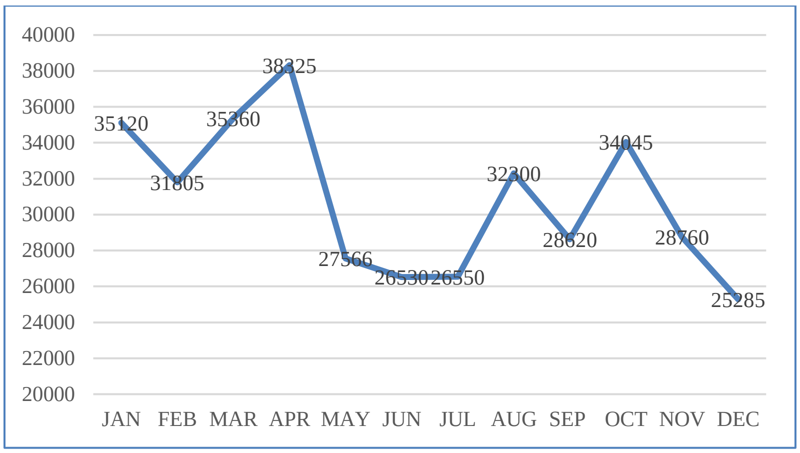

Figure 1. Total items ordered per month in 2015.

Based on the number of orders and items (Figure 1), the order-picking process could be completed within the designated time of normal working hours. However, as the company is predicted to future growth in the demand for local cars, the limited number of order-pickers with limited picking capacity is concerning. Therefore, this study simulated bigger orders to test the model's stability in reacting to various demand patterns. The main elements in the simulation model were the daily order volume, the order size, the number of items in the order, and the quantity ordered of each item.

The process of order-picking start depends on the warehouse layout. The layout plan for the warehouse under study had four shelves with four front (A, B, C, D) and four end sub-aisles (E, F, G, H) (Figure 2). Each aisle was an open-ended route. Each shelf was loaded with items ready to be picked. In this case, an order-picker (OP) was free to go to any side of the shelves and may return to the same point. Order-pickers started their working operation by collecting information on the number of customer orders. They gathered at the main platform in each zone to receive a delivery order (DO). DO form was based on orders made online by the customers. Once the form was received, the items were identified. Next, the OP started moving from the platform to the ordered items area.

The study analyzed the current demand based on order patterns. The objective was to pick all items in the order form in the shortest path or minimum order-picking time. The capacity and volume to be picked for each OP were considered in this situation. Each OP could pick a maximum of 25 items at a time, and they were free to use any route as long as all the items were fully collected. There were nine nodes (where the items were stationed) and seven OPs who picked the items based on the test run using Excel Solver. The OP started at node *1*. Each OP continued to pick at the remaining eight nodes. At the end of the process, all the items collected were gathered at the packaging point (destination point).

Considering the highest number of items of 68,265 picked in a month in 2015, each OP needed to pick 9752 items. For example, OP 1 was expected to collect 9752 items from node *1*. Next, OP 2 had to go directly to Node *7* and collect 5905 items. After finishing the job at Node *7*, OP 2 needed to move to Node *8* to collect the remaining 3847 items to complete the total items picked of 9752. Therefore, the OP had to travel the same route back and forth to collect all the items. The shortest path for OP 1 was ***1* → *8***. Meanwhile, the path for OP 2 was ***1* → *7* → *8***. The full results of the total items picked for all OPs are summarized in Table 1.

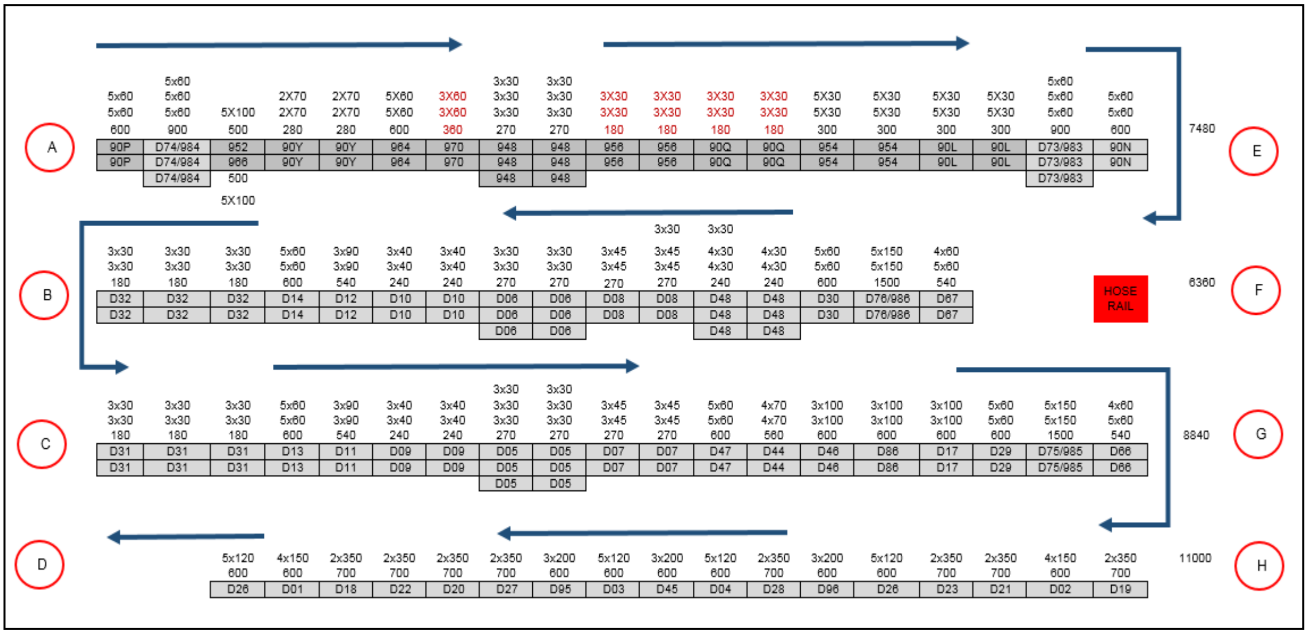

Figure 2. Layout plan for Zone 1.

Table 1. Total items to be picked by each OP – initial results.

From (Node)	OP1	OP2	OP3	OP4	OP5	OP6	OP7	Limit
1	0	0	0	0	0	3780	0	3780
2	0	0	0	0	2701	1124	0	3825
3	0	0	0	0	2670	0	0	2670
4	0	0	0	0	4200	0	0	4200
5	0	0	0	3659	181	0	0	3840
6	0	0	4557	6093	0	0	0	10650
7	0	5905	5195	0	0	0	0	11100
8	9752	3847	0	0	0	0	0	13600
9	0	0	0	0	0	4848	9752	14600
Limit	9752	9752	9752	9752	9752	9752	9752	68265

Based on Figures 1, 2, and Table 1, the limited number of OPs might not be able to complete the total pick within the stipulated timeframe, given a potential increase in demand. Therefore, a simulation analysis on the potential increase in the number of items to be picked was proposed to support the potential increment.

3. SYSTEM DESCRIPTION

3.1 Description of the order-picking process

Order picking is the process of picking up goods or items requested by customers from the storage and preparing them for delivery within a targeted time. This study was done in a warehouse that stores small parts in bins, shelves, and aisles. Under this situation, the OPs started collecting order forms from the depot or the first point. The OPs needed to move between aisles toward the closest cross-aisle. Therefore, the proposed routing algorithm chose the shortest way for each aisle in which the individual OP needed to return to the front cross-aisle or to cross the aisle through its entire length to the rear cross-aisle. Since the items were placed on both sides of the storage rack, the OPs could take items closest to the following consecutive items. Every item collected was placed in the packaging point. The items were organized according to the order form and were ready to be delivered to the respective customers.

3.2 Model and simulation algorithm

A dynamic programming (DP) method was used to find the shortest path and the optimal number of items to be picked by each OP. Roodbergen (2001) introduced this method in which numerous operations in a warehouse were tested in a one-block environment. Therefore, a complete understanding of the procedure of one-block operation was essential before the procedure could be applied when a greater number of blocks were involved. Routing policies in one block layout include optimal algorithms, not heuristics. This DP method was used to find the shortest time with all items collected by the OPs. This model was adjusted to suit the situation in the study.

The basic model, the shortest path problem (SPP), can be defined as an undirected graph, $G = (\mathrm{N}, \mathrm{E})$ where $|N| = n$nodes are connected by edges (arcs), $|E| = m$from a specified node *S*, the source. Each arc is numbered sequentially and is given a cost function$c \mapsto \Re$. This *c* can be in terms of time, distance, or currency. For example, c_{ij} represents the distance traveled from any node *i* to *j*; thus, the distance and the shortest path that starts from a given node *S* can be calculated. The main objective of SPP is to find the minimum cost of all paths from *S* to all nodes in *N*.

The mathematical model for the objective function of SPP is adapted from a formulation by Letchford *et al*. (2013). In the model, a block layout is considered where the OP cannot proceed directly from the current location to the next location due to the different picking aisle and barrier of an aisle. This basic model was modified to suit the multi-picker situation in the current study. The set of edges (arcs) is denoted by *E*, and the set of Steiner points is defined by *P*. In addition, *V* denotes the number of vertices in a graph, W_{ij}^{k} is the number of units of commodity *k* passed on directly from vertex *i* to *j*, and *Cap* represents the capacity of each picker. The formulation from the Steiner Traveling Salesman Problem (TSP) was written as follows:

$$\text{Minimize } \sum_{(i,j)\in E} c_{ij}x_{ij} \qquad \text{Equation (1)}$$

$$\text{subject to} \sum_{i=1}^{n} x_{ij} = 1, i = 1,\ldots,n \qquad \text{Constraint (2)}$$

$$\sum_{j=1}^{n} x_{ij} = 1, j = 1,\ldots,n \qquad \text{Constraint (3)}$$

$$x_{ij} = \begin{cases} 1 & \text{path from node } i \text{ to node } j \text{ is considered} \\ 0 & \text{otherwise} \end{cases}$$

$$\sum_{\substack{j\in V \\ (i,j)\in E}} x_{ij} \geq 1 \qquad \forall\ i \in V\backslash P \qquad \text{Constraint (4)}$$

$$\sum_{\substack{j\in V \\ (i,j)\in E}} x_{ij} - \sum_{\substack{j\in V \\ (i,j+1)\in E}} x_{i,j+1} = 0 \qquad \forall \quad i \in V \qquad \text{Constraint (5)}$$

$$\sum_{\substack{j\in V \\ (j,1)\in E}} W_{i1}{}^{k} - \sum_{\substack{j\in V \\ (j,1)\in E}} W_{1k}{}^{k} = -1 \qquad \forall\ \kappa \in \mathrm{V} \setminus (P \cup \{0\}) \qquad \text{Constraint (6)}$$

$$\sum_{\substack{j\in V \\ (j,k)\in E}} W_{jk}{}^{k} - \sum_{\substack{j\in V \\ (k,j)\in E}} W_{kj}{}^{k} = 1 \qquad \forall\ \kappa \in \mathrm{V} \setminus (P \cup \{0\}) \qquad \text{Constraint (7)}$$

$$\sum_{\substack{j\in V \\ (i,j)\in E}} W_{ij}{}^{k} - \sum_{\substack{j\in V \\ (j,i)\in E}} W_{ji}{}^{k} = 1 \qquad \forall\ i \in V \setminus (P \cup \{0, i\}) \qquad \text{Constraint (8)}$$

$$w_{ij}^{k} \leq Cap * x_{ij} \qquad \forall (i,j) \in V\backslash(P \cup \{0\}) \qquad \text{Constraint (9)}$$

$$x_{ij} \in \{0,1\} \qquad \forall (i,j) \in E \qquad \text{Constraint (10)}$$

$$W_{ij}{}^{k} \geq 0 \qquad \forall (\, i,j) \in E, k \in V \setminus (P \cup \{0\}) \qquad \text{Constraint (11)}$$

Equation (1) minimized the total distance traveled, assuming a linear cost structure for the movement. It was subject to the following constraints. Constraints (2) and (3) showed whether the items were available to be picked or not at the current node (*i*, *j*). Constraint (4) ensured that each vertex not corresponding to a Steiner point was visited only once, while Constraint (5) guaranteed that the starting point for the next move equaled the next starting point. Constraints (6)–(9) corresponded to the multi-commodity flow constraints based on Claus (1984). Constraints (10) - (11) denoted that the path from node *i* to node *j* existed (but may not be considered).

This study added a capacity constraint for each OP so that each OP could collect only 25 items per round. For example, if the total number of items to be collected was 75, the OP needed to travel back and forth from the packaging point *O* to the current node *i* (item placed) thrice. If the distance from *O* to *i* is *d*, the total distance is 3*d*; hence 75 items were collected. Due to this requirement, the procedure was modified to suit the current situation in this manufacturing company and later for other manufacturers with the same procedure.

4. RESULTS AND DISCUSSION

The model was solved using the DP method (Nordin *et al*., 2019). This section discusses the simulation algorithm.

4.1 Real-Life Application

This study selected an automobile part-manufacturing company as its case study. The parts included body parts, suspension, engine parts, modular assemblies, engineering plastic parts, and car lamp assemblies. The company had contract customers who ordered items in large quantities and various sizes. The order-picking process was based on the item sizes. If the orders were big items, the orders were assembled using a pallet-picking strategy, with forklifts moving back and forth within the warehouse. On the other hand, if the order involved small items, seven OPs were assigned to assemble the items and gather them at the packaging point before the order was passed to the delivery point. This study considered the order-picking process for small items due to its nature of being manually picked in several manufacturing companies in Malaysia.

4.2 Simulation process for order-picking in a warehouse

A few assumptions were made to map the warehouse layout to run the simulation task:

1. The number of OP was limited to seven.
2. Each OP could pick only 25 items per trip (from previous studies).
3. The order-picking process was within normal working hours only.
4. The number of items to be picked by each OP was divided equally.
5. Every OP was familiar with the routes and picking area.
6. OP started their task at the depot.
7. The time of lifting and disembarking items was added to the time travel between two consecutive nodes.
8. The OP followed the S-shape routing method (Roodbergen, 2001).

The simulation process was divided into four steps:

STEP 1. The order size was generated using excel random numbers with minimum and maximum order sizes of 50 and 150 items, depending on the item type. This distribution was based on current data obtained from the customer demand to the manufacturing company.

STEP 2. Five similar data sets were simulated based on the demand patterns discussed in Section 3.

STEP 3. The shortest path and distance for seven OPs were simulated, whereby each serving time was limited to 25 items. For every maximum number of items collected, the current OP continued to pick the remaining items from the previous nodes.

STEP 4. The total distances for each simulated order were converted to equivalent travel times to suit the second objective of finding the minimum travel time for the OP to collect simulated items.

Based on the company’s current data, a simulation was done for 50 and 150 orders per day. This model applied a Monte Carlo simulation technique based on the order data dated 30th October 2015. Nine items were involved in the order forms, and 13 orders were made for the items. The nine items were named Item A, Item B, Item C, Item D, Item E, Item F, Item G, Item H, and Item I. The number of occurrences for each item is displayed in Table 2.

Based on these values, a simulation for nine items was generated to obtain the expected number of items ordered for 50 orders and 150 orders made by a customer in a day. These data were simulated using Microsoft Excel (2007). The total number of items needed for a day for 50 orders in the first iteration was 11380 for nine nodes. Meanwhile, for 150 orders, the total number of items needed to be collected at nine different stations for the first iteration was 38415. These numbers were generated using random numbers based on current data in the company and assumed to be uniformly distributed.

Table 2. Probability of occurrence for each item.

	Current (Small)		Simulated Data			
	13 orders		50 orders (medium)		150 orders (large)	
	Item occurrence	Probability of occurrence	Item occurrence	Probability of occurrence	Item occurrence	Probability of occurrence
Item A	4	0.3077	15	0.3077	46	0.3077
Item B	4	0.3077	15	0.3077	46	0.3077
Item C	6	0.4615	23	0.4615	69	0.4615
Item D	2	0.1538	8	0.1538	23	0.1538
Item E	1	0.0769	4	0.0769	12	0.0769
Item F	1	0.0769	4	0.0769	12	0.0769
Item G	1	0.0769	4	0.0769	12	0.0769
Item H	1	0.0769	4	0.0769	12	0.0769
Item I	1	0.0769	4	0.0769	12	0.0769
Total	21		81		244	

4.2 Simulation model

The simulation for 50 orders is shown in Table 3. The simulation for 150 orders followed the same procedure as the 50 orders. For each simulation, the data was generated up to 50 orders until five consecutive iterations. The first simulated data set is shown in Table 3.

Table 3. First iteration for 50 orders.

Order Number (n=1, …, 50)	Random Number	Number of Items in an Order	Random Number of Items (i=1, …, 6)	Items Involved	Total Number of Items
1	94	1	92	H=200	200
2	17	4	36, 16, 59, 13	B=45, A=45, C=30, A=45	165
3	14	4	57, 86, 87, 45	C=30, F=150, F=150, C=30	360
4	15	4	64, 96, 85, 1	C=30, I=200, F=150, A=45	425
5	9	4	25, 91, 42, 9	B=45, H=200, C=30, A=45	320
⋮	⋮	⋮	⋮	⋮	⋮
46	100	1	15	A=45	45
47	94	1	1	A=45	45
48	18	4	63, 94, 18, 71	C=30, H=200, A=45, D=60	335
49	20	4	13, 67, 81, 77	A=45, C=30, E=60, E=60	195
50	50	6	66, 25, 66, 46, 53, 80	C=30, B=45, C=30, C=30, C=30, E=60	225
Total number of orders for the first iteration: 11380 items					

The simulation processes for large and medium orders (Figure 3) show that for the first order number, n = 1, the first random number was 94. This number represented the number of orders expected to occur based on the customer's demand. Based on the number 94, the order demand from the customer was only one item. Next, another random number was created in the first order to identify the type of items ordered. The number of items can be up to six per order for each customer. Therefore, for the second random number, 92, item *i* was classified under item H with a total of 200 items. For the first order, the total number of items was 200. For this first iteration, the total number of items involved for 50 orders was 11380.

The remaining iterations followed the same procedure as in Figure 3 and Table 3. After five iterations and simulated data set, 60365 items were to be picked for 50 orders (Table 4). The breakdown total for each item (Item A to Item I) is listed in the final row. For instance, for item A, the total number of items ordered after the first iterations were 11380 items. The average and standard deviation for each item showed that the data was spread in a normal distribution. Therefore, the simulation was stopped after five trials.

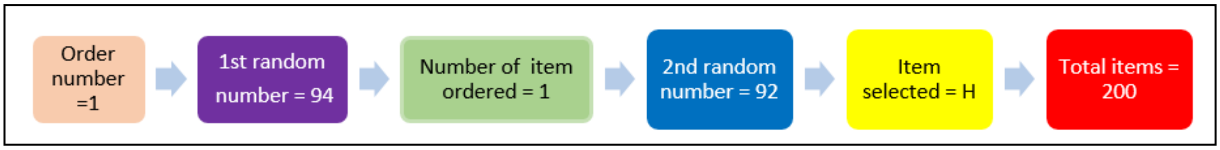

Figure 3. Process of retrieving items using simulation process.

Table 4. Simulated data for 50 orders for five consecutive simulations.

	Simulated Data: 50 Orders (Medium)						
	First data set	Second data set	Third data set	Fourth data set	Fifth data set	Average	Standard deviation
Item A	1620	1350	1845	1530	1890	1647	224.10
Item B	1170	1440	1710	1665	1845	1566	265.08
Item C	1800	1530	1440	2040	1230	1608	316.50
Item D	780	840	960	1200	1500	1056	295.77
Item E	660	840	540	780	660	696	116.96
Item F	1200	1200	1500	1050	1050	1200	183.71
Item G	1350	450	1500	900	300	900	530.33
Item H	1800	1400	1800	1600	2200	1760	296.65
Item I	1000	1000	1400	2200	2600	1640	726.64
Total	11380	10050	12695	12965	13275	12073	1341.65

Simulation carried out five times (Table 5) showed that the numbers tripled for large order (Table 6) compared to the medium order. The simulated data for 150 orders also followed a normal distribution.

Table 5. Total number of items ordered for large, medium, and current orders.

Data Set	**13 Orders (Current/Small)**	**50 Orders (Medium)**	**150 Orders (Large)**
Total items for the first data set	1550	11380	38415
Total items for the second data set	1280	10050	36400
Total items for the third data set	1600	12695	34050
Total items for the fourth data set	1630	12965	40210
Total items for the fifth data set	1585	13275	38605

Table 6. Simulated data for 150 orders for five iterations.

	Simulated Data: 150 Orders (Large)						
	First data set	Second data set	Third data set	Fourth data set	Fifth data set	Average	Standard deviation
Item A	4500	4860	4680	4995	4680	4743	189.86
Item B	4320	4770	5040	5265	5445	4968	441.60
Item C	4875	4650	4560	5520	4380	4797	441.72
Item D	3600	2640	2520	2760	3240	2952	453.78
Item E	1920	2280	1800	1620	1860	1896	242.24
Item F	5550	3900	3900	3300	1950	3720	1296.44
Item G	3450	3300	3150	3750	2250	3180	565.24
Item H	6000	4800	4000	6600	8600	6000	1772.01
Item I	4200	5200	4400	6400	6200	5280	1005.98
Total	38415	36400	34050	40210	38605	37536	6408.87

The spread of the number of items between large, medium, and current orders (Figure 4) in the current scenario showed that the company could complete picking items within the designated time. The OPs had to work during normal hours with daily and night shifts without extra working hours to test whether the company could manage various numbers of orders within normal working time. The results showed that the demand fluctuated widely for large orders. The difference between the number of items ordered large, and medium was larger than that of current and medium orders. Furthermore, the trend for the current order was stable almost every day, unlike large orders.

Figure 4. Comparison between large, medium, and current order.

Based on these data, the total travel time for the seven OPs in collecting the items for a day was calculated instead of the total distance traveled because, in real-time and real-life situations, time is more reliable in finding the shortest path. Therefore, all items and the measured distances were converted accordingly to the travel time.

4.3 Part A: Finding total distance and total travel time for limited-picking capacity

The model was solved by additional picker constraints in DP (Table 5) and computed using the Excel Solver. Results obtained for each case showed an optimal solution. The shortest path was calculated by considering the current/small, medium, and large numbers of items to be picked and every turn (penalty). In the previous studies by Nordin *et al*. (2018) and Nordin *et al*. (2019), the total distance was 5776.26 cm without adding the capacity constraint. The total distance was 6320 cm in the current practice used in the warehouse company. When the capacity constraint was added to the model, the total distance for each picker could be reduced by 12.33%. Next, the model's reliability and stability were tested by simulating data to represent the current scenario of the picking system. This simulated data for the study considered the limited picking capacity of each OP.

In the first result for 13 orders, the total distance for the pickers was reduced to 5712.69 cm when this capacity constraint was added. However, when the order was increased to 50 orders (almost 74%), the distance for the picker was increased to 5509.79 cm. It was observed that the larger number of orders to be fulfilled led to fewer router-picking choices. On the other hand, for the third case of 150 orders, the distance for the picker was reduced to 5023.6 cm. It was a surprising finding because, by logic, larger order leads to bigger items to be picked and, thus, longer picking times. However, the choices of routes became more stable, and the pickers stopped at fewer nodes.

Furthermore, time is more reliable in determining whether the model can handle such a big task with limited resources in real-world situations. In this case, the resources were the number of OPs. Only seven OPs were assigned in the warehouse to complete the current order within the normal working hours a day. With 13 orders, the total distance for the pickers was 5712.69 cm, equivalent to almost five normal working hours to complete the picking task. It complied with the current scenario where the warehouse provided two shifts (day and night) to collect items to fulfill the customer's demand.

The simulations for data of 50 and 150 orders were conducted to check whether the pickers could meet customers' demands within eight working hours a day. The tests showed that OPs could meet the demands set by customers in 4.64 hours (278.55 minutes) for 13 orders. The converting method from centimeters to minutes followed the concept introduced by Clarence Perry (1920). The neighborhood unit, 'pedestrian shed,' is a community model that considers the distance people are willing to walk before opting to drive (Morphocode, 2018). A 5-minute walk is about 400 meters based on the average walking speed of a normal person. Following this benchmark, the total travel times obtained were based on the equivalent conversion in the following procedure. The calculation is shown for the 50 orders, and the remaining orders follow the same procedure.

All OPs except OP7 picked an equal number of items, and the optimal solution was obtained using Microsoft Excel. The process used the current manpower and sources from the manufacturing company (Table 7). Then, the total distances were converted to total time using Morphocode (Figure 5).

Table 7. Shortest route(s) obtained for each OP (50 orders) based on the third iteration.

Order Picker	Total No. of Item	No. of Stop(s) and route	Total Distance (cm)	Total time (minutes)
OP 1	1814	2: Nodes 1 and 3	555.13	5.04
OP 2	1814	2: Nodes 1 and 4	652.14	5.91
OP 3	1814	2: Nodes 2 and 5	224.72	2.04
OP 4	1814	2: Nodes 1 and 6	741.20	6.72
OP 5	1814	2: Nodes 2 and 7	446.00	4.05
OP 6	1814	2: Nodes 1 and 8	768.80	6.97
OP 7	1811	3: Nodes 1, 2, and 9	1697.17	15.39
Total Items: 12695			5085.16	46.12

Given,

k	=	Total item can be picked by order picker per trip
TI	=	Total average item to be picked with respect to number of orders
p	=	Number of item to be picked by each picker
i	=	Number of order picker by turn where $i = 1, 2, 3, \ldots, 7$
d_i	=	Distance for every picker *i*
x_i	=	Number of trips needed for every *i* based on *p* per *k*
y_i	=	Total distance for each picker *i* in centimetres
z_i	=	Total distance for each picker *i* in metres
m_i	=	Travel time for each picker *i* in minutes
t_i	=	Travel time for each picker *i* in hours

Figure 5. Parameters for conversion from distance (cm) to time (hours) using Morphocode (2018).

The total travel time, *t*, can be calculated as follows:

Say, with 50 orders in the third simulation,

$TI = 12695\ items$

$p = \frac{TI}{7}; where\ \frac{12695}{7} \approx 1814 items$

Then for $i = 1$,

$x_1 = \frac{p}{k}$; such that $x_1 = \frac{1814}{25} \approx 72.56 trips$

For $y_1 = x_1 \times d_1$, thus $y_1 = 72.56 \times 555.13 \approx 40280.2cm$

Hence, $z_1 = 402.802m$

By referring to Morphocode (2018), a 5-minute walk was equivalent to 400 m. The mathematical expression can be written as:

$m_1 = \frac{402.802m}{400m} \times 5min$; therefore $m_1 = 5.04min\ or\ t_1 = 0.09$ hours

Therefore, the travel time needed by the first OP to collect 1814 items was five minutes. This formula was used to calculate the travel times of the remaining six OPs with respect to their total distances. Finally, the total travel time to complete 12695 items was 46 minutes. The time taken was faster than the actual 13 orders made by the customer.

Table 8. Shortest route(s) obtained for each order picker (150 orders) based on the third iteration.

Order Picker	Total No. of Item	No. of Stop(s) and route	Total Distance	Total time (minutes)
OP 1	4865	2: Nodes 2 and 4	409.00	9.95
OP 2	4865	3: Nodes 2, 3, and 5	804.48	19.57
OP 3	4865	2: Nodes 3 and 6	329.81	8.02
OP 4	4865	2: Nodes 2 and 7	446.00	10.85
OP 5	4865	2: Nodes 3 and 8	502.73	12.23
OP 6	4865	2: Nodes 2 and 9	665.17	16.18
OP 7	4860	2: Nodes 1 and 3	555.13	13.50
Total Items: 34050			3712.32	90.30

In this scenario, the choice of routes for each OP was similar to the routes in Table 7. However, OP 2 traveled the longest distance since the OP needed to stop over three different nodes. For this purpose, the company could adjust or provide a suitable mechanism for this OP since he had to travel more than others. The potential mechanism could be alternate schedules for the pickers. The total travel time for 150 orders was calculated Using the same procedure based on the shortest route obtained for large order sizes (Table 8). In this scenario, the total travel time to complete 34050 items was 90.30 minutes (almost 1.5 hours). It shows that the company may need to reorganize or restructure the current warehouse if they want to increase customer orders within the normal working hours of eight hours a day.

Table 9. Total time and distance for each large and medium order.

	First Simulation		Second Simulation		Third Simulation		Fourth Simulation		Fifth Simulation	
	Total distance (cm)	Total time (minutes)	Total distance (cm)	Total time (minutes)	Total distance (cm)	Total time (minutes)	Total distance (cm)	Total time (minutes)	Total distance (cm)	Total time (minutes)
150 Orders	5035.05	138.16	4041.84	105.09	3712.32	90.30	5856.73	168.24	5522.4	152.28
50 Orders	4052.83	32.93	4018.4	28.85	5085.16	46.12	5719.82	52.97	5933.06	56.28

The total distance and time for each large and medium order based on the five simulations are shown in Table 5. The values obtained showed that the manufacturing company could handle the situation if there is an increase or variety in the number of orders with the current capacity constrained by the limited number of OPs. The company may cut costs by providing single shifts to the workers. However, the OP's capability and strength in picking orders need to be considered for real-life situations.

A comparison was carried out for each category's total number of items and the possible percentage reduction in total traveling time by each OP. The percentage reduction in total distance per picker per trip was calculated to be 12.1% (from 5712.69 cm to 5023.60 cm).

Table 10. Comparison between small, medium, and large order sizes.

Description	Current Data	Simulated Data	
	13 orders (small)	50 orders (medium)	150 orders (large)
Number of nodes (items)	9	9	9
Number of OP	7	7	7
Total distance per picker per trip (cm)	5712.69	5509.79	5023.60
Total travel time per picker per trip (minutes)	278.551	237.582	673.391
Total demand volume	7645	60365	187680
Average demand per order	1529	12073	37536

In this case, the company might be able to maintain the operating expenses as there is no need to increase the manpower, and the company's aim to complete the orders can be achieved. These results can be a new benchmark for this model, and the system can manage big data (if needed). This new approach will reduce the waiting time at the customers' end and increase customer satisfaction.

4.4 Part B: Finding total distance and total travel time for unlimited picking capacity

The number of items to be picked was simulated based on the unlimited picking capacity to check whether the total distance for the pickers was reduced for all three order types. Based on the new capacity constraint (*Cap* = 25) where *w* was the number of items to be picked for every trip by each picker, the total distances for 13 orders, 50 orders, and 150 orders were calculated (Table 8). The total percentages reduced for each number of orders were calculated using Equation (2):

$$\frac{Oldvalue-Newvalue}{Oldvalue} \times 100\% \tag{2}$$

The old value was the total distance before the capacity constraint was added to the model, while the new value was the *distance + capacity constraint* for each order picker. Therefore, the percentage reduced in the total distance for each OP when the value of *Cap* was added into the current mathematical model for the first actual data was calculated using Equation (3):

$$\frac{5776.26-5712.69}{5776.26} \times 100\% = 1.1\% \tag{3}$$

The other respective values for each simulated data are shown in Table 8.

The total travel time between the limited and unlimited picking capacities was calculated, and it was found that the time travel using the newly modified model was lesser (Table 11). Furthermore, the new constraint added to the model was more reliable and reduced to more than 50% of the travel time for each OP. For example, for 150 orders, it took almost a day to complete the customer demand with a total travel time of 23.16 hours (1389.55 minutes).

Table 11. Comparison between limited and unlimited picking capacities based on small, medium, and large order sizes.

Description	Current Data (Small Order)		Simulated Data (Medium and Large Data)			
	13 orders (cm)	13 orders (minutes)	50 orders (cm)	50 orders (minutes)	150 orders (cm)	150 orders (minutes)
Limited picking capacity (*New*)	5712.69	278.55	5509.79	237.58	5023.60	673.39
Unlimited picking capacity (*Old*)	5776.26	505.42	5793.18	506.90	15880.59	1389.55
Percentage reduced	1.10%	44.89%	4.89%	53.13%	68.37%	51.54%

However, once the capacity constraint is added to the model, the total travel time is reduced to only 11.22 hours (673.39 minutes). It should help the industry recalculate and reorganize its warehouse operation for potential business growth. For example, if they have limited manpower, the company may limit their order to fewer than 150 orders a day. On the other hand, if they have a higher monetary budget, they may want to increase the manpower to comply with the large number of orders made within a day. This model may be helpful for any industry with similar operations and constraints to this selected case study.

5. CONCLUSION

This paper presented the modified DP method for the order-picking process in the warehouse with limited picking capacity as the constraint for OPs. The main objective of this paper was achieved when all the items in every node were well-visited and fully picked. In addition, the second objective of obtaining the shortest path and minimum travel time for each OP was also achieved. The model could cater to a case of larger sets of data with the number of order pickers maintained. Results showed that total operation time could be optimized with proper routing and order-picking tasks, despite the increase in the number of orders picked and completed. Furthermore, each OP could optimize its picking capacity.

By selecting the optimum path, the OPs had more time to collect more orders, and the waiting time for the customer was also reduced, leading to customer satisfaction. Future research can relate to the OPs' motivation since everybody has an equal load while picking orders. The whole study demonstrated that the efficiency of the order-picking process could be improved by considering the situation. This study's procedure can be applied to other areas with a similar situation.

REFERENCES

Andriansyah, R. W., De Koning, W., Jordan R. M., Etman L. F., and Rooda J. E. (2011). A Process Algebra Based Simulation Model of A Miniload-Workstation Order Picking System. *Computers in Industry 2011*, 62(3): 292–300.

Andriansyah, R., Etman, L. F. P., and Rood, J. E. (2009). Simulation Model of A Single-Server Order Picking Workstation Using Aggregate Process Times. *1st International Conference on Advances in System Simulation (SIMUL 2009)*, Porto, Portugal.

Bartholdi, J. J. and Hackman, S. T. (2016). *Warehouse and Distribution Science*. In *E-Book 0.97*.

Bhavin, S. and Vivek, K. (2017). A Comprehensive Review of Warehouse Operational Issues. *International Journal of Logistics Systems and Management 2017*, 26(3): 346–378.

Chan, F. T., and Chan, H. K. (2011). Improving The Productivity of Order Picking of A Manual-Pick and Multi-Level Rack Distribution Warehouse Through The Implementation of Class-Based Storage. *Expert Systems with Applications*, 38(3): 2686–2700.

Chawla, V. K., Chanda, A. K., and Angra, S. (2019). Automatic Guided Vehicle Systems in Flexible Manufacturing System–A Review. *International Journal of Industrial Engineering: Theory, Applications and Practice*, *26*(5).

Chin, L. Y. (2018). Techniques of Order Picking for Warehouse Productivity, *Singapore Institute of Purchasing and Materials Management (SIPMM)*, (Accessed on July 2018).

Claus, A. (1984). A New Formulation for The Traveling Salesman Problem. *SIAM Journal on Algebraic and Discrete Methods*, (5): 21–25.

Dharmapriya, U. S. S. and Kulatunga, A. K. (2011). *Proceedings of The 2011 International Conference on Industrial Engineering and Operations Management*, Kuala Lumpur, Malaysia, 513–519.

Gagliardi, J. P., Renaud, J., and Ruiz, A. (2007). A Simulation Model to Improve Warehouse Operations. *Proceedings of The Winter Simulation Conference*, Washington, DC, USA.

Goetschalckx, M. and Ashayeri, J. (1989). Classification and Design of Order Picking. *Emerald Backfiles (2007).*

Gu, J., Goetschalckx, M., and Mcginnis, L. F. (2010). Research on Warehouse Design and Performance Evaluation: A Comprehensive Review. *European Journal of Operational Research*, 203(3): 539–549.

Habazin, J., Glasnović, A., and Bajor, I. (2017). Order Picking Process in Warehouse: Case Study of Dairy Industry in Croatia. *Promet – Traffic&Transportation*, 29(1): 57–65.

Hashemi, S., Salari, M., and Ranjbar, M. (2020). Multi-Trip Open Vehicle Routing Problem with Time Windows: A Case Study. *International Journal of Industrial Engineering*, *27*(1).

Hrihorkiv, V., Vodianytskyi, D., Verstiak, A., and Hrihorkiv, M. (2010). Simulation Model Research of Warehouse Order Picking Process. *Proceedings of The 1st Olympus International Conference on Supply Chains (ICSC2010)*, Katerini, Greece.

Hwang, H. S. and Cho, G. S. (2006). A Performance Evaluation Model for Order Picking Warehouse Design. *Computers & Industrial Engineering*, *51*(2): 335–342.

James, A. T. and Dale, H. (2004). *Warehouse Operations*. In The Supply Chain Handbook. Tompkins Press.

Jorge, J. P., Kokkinogenis, Z., Rossetti, R., and Marques, A. P. (2012). Simulation of An Order Picking System in A Pharmaceutical Warehouse. *The Fourth International Conference on Advances in System Simulation (SIMUL 2012)*, Lisbon, Portugal.

Kostrzewski, M. (2020). Sensitivity Analysis of Selected Parameters in The Order Picking Process Simulation Model, with Randomly Generated Orders. *Entropy*, *22*(4): 423.

Kusrini, E., Asmarawati, C., Sari, I. G. M., Nurjanah, A. Kisanjani, A., Wibowo, S. A., and Prakoso, I. (2017). Warehousing Performance Improvement Using Frazelle Model and Per Group Benchmarking: A Case Study in Retail Warehouse in Yogyakarta and Central Java. *MATEC Web of Conferences (ICET4SD 2017)*, Indonesia, 2017.

Letchford, A. N., Nasiri, S. D., and Theis D. O (2013). Compact Formulations of The Steiner Traveling Salesman Problem and Related Problems. *European Journal of Operational Research*, 228: 83–92.

Li, J., Zhang, F., Wan, Z., Sun, J., Ke, L. G., Zuo, J., and Li, K. (2020). Design of An Optimized Forklift Routes for A Four-Door Dangerous Goods Monolayer Warehouse Through Genetic Particle Swarm Optimization Algorithm. *International Journal of Industrial Engineering*, 27(2).

Mercedes, U., Mendoza, A., and Gonzalez, A. (2019). Evaluating The Impact of Order Picking Strategies on The Order Fulfilment Time: A Simulation Study. *International Scientific Journal About Logistics 2019*, 6(4): 103–114. DOI: 10.22306/Al.V6i4.129

Morphocode Academy. (2018). Featured Story: The 5-Minutes Walk, *Blog: Morphocode*, (Accessed on September 2020).

Nordin, N. A. M., Omar, M., and Shariff, S. S. R. (2018). The Application of Dynamic Programming Method in Finding Shortest Path for Order Picker with Limited Picking Capacity. *Management Review: An International Journal*, 13(1): 20–48.

Nordin, N. A. M., Shariff, S. S. R., and Omar, M. (2020, March). Sensitivity Analysis in Finding Shortest Path for Order Picker with Limited Picking Capacity. in *Journal of Physics: Conference Series*, 1496(1): 012021. IOP Publishing.

Order Picker Job Description: Top Duties and Qualifications. (2022). Retrieved from https://www.indeed.com/employers/job-description/order-picker on 20th May 2022.

Perry, C. A. (1926). *The Rehabilitation of The Local Community*. in Social Forces 4, 3: 558–562.

Petersen, C. G. and Aase, G. (2004). A Comparison of Picking, Storage, and Routing Policies in Manual Order Picking. *International Journal of Production Economics*, *92*(1): 11–19.

Petersen, C. G. and Aase, G. R. (2017). Improving Order Picking Efficiency with The Use of Cross Aisles and Storage Policies. *Open Journal of Business and Management 2017*, 5: 95–104. DOI: http://dx.doi.org/10.4236/ojbm.2017.51009

Renaud, J. and Ruiz, A. (2008). Improving Product Location and Order Picking Activities in A Distribution Centre. *Journal of The Operational Research Society*, 59(12): 1603–1613.

Roodbergen, K. J. and De Koster, R. (2001). Routing Order Pickers in A Warehouse with A Middle Aisle. European Journal of Operational Research, 133(1): 32–43.

Sahin-Arslan, A. and Ertem, M. A. (2019). A Warehouse Design with Containers for Humanitarian Logistics: A Real-Life Implementation from Turkey. *International Journal of Industrial Engineering*, 26(2).

Verriet, J., Caarls, J., and Wijngaarden, B.V. (2013). Warehouse Simulation Through Model Configuration. *Conference: 27th Conference on Modelling and Simulation*, Alesund, Norway.

Winkelhaus, S., Zhang, M., Grosse, E. H., and Glock, C. H. (2022). Hybrid Order Picking: A Simulation Model of A Joint Manual and Autonomous Order Picking System. *Computers & Industrial Engineering*, 167: 107981.

Wu, F. C., Wang, H. M., and Fan, T. Y. (2010). Quality Design of Taguchi's Digital Dynamic Systems. *International Journal of Industrial Engineering: Theory, Applications and Practice*, *17*(1).