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Optimizing order picker problem using dynamic programming method

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Abstract

The order picking problem is one of the key elements in warehouse management. The challenge increases during the new norm when orders can be made by going to the shop and also via online that results in high uncertainty in order volume. Despite that, customer expectation remains on fast delivery which requires the selling organizations to be able to provide fast and efficient service to meet the demand from customers. In achieving this, among the contributing factors is efficient warehouse management especially in order picking, storage assignment, sufficient resource allocation, adequate manpower handling and proper tasking allocation. Thus, in this paper, a model for order picking is modified by considering the limited picking capacity of the Order Pickers (OP), the S-shaped route in the warehouse plan and the need for complete order (all demanded items are picked). The modified model is adapted as a Dynamic Programming problem with the objective of minimizing the time taken (through minimizing distance travelled) in picking each order. The results show that testing with a set of secondary data, the modified model shows a reduction of 24.19% in travel distance compared to using Shortest Path Problem (SPP) and Traveling Salesman Problem (TSP). At the same time, the application of the modified model using the real data shows a reduction of 11.6% in the travelled distance as well as more quality task allocation among the OPs.

Keywords: Order picking, dynamic programming, shortest path, warehouse routing, inner warehouse transportation.

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1. Introduction

A critical research area in current warehouse management practice is to find ways in increasing picking productivity and make it work effectively. Typically, a warehouse consists of various areas. These include shipping and receiving areas, bulk storage and order picking areas. Shipping areas or transporting areas is where all the items are ready to be delivered to other locations. Receiving areas sometimes is placed at the same area as the delivery area. Some companies may need a bulk storage if their business involved bulky items and need to be kept longer. Finally, the order picking area consists of retrieving individual items from storage on the basis of customers' orders. According to [20], order picking process is considered as one of the most laborious and costly activities in a warehouse. In a real-life situation, companies are looking forward to minimize production costs and at the same time try to maximize their productivity within their warehouses and distribution centres. The main objective is to be fast, accurate and fulfil 100% of the customers' demand which is uncertain [14]. This has become a key-performance indicator for any warehouse operations. On achieving this, there are many contributing factors to this achievement. Such factors include a warehouse need to have proper handling in order picking, storage assignment, sufficient resource allocation, adequate manpower handling, proper tasking allocation and so on. This is an ongoing process in measuring top productivity of a warehouse.

Other than the facts mentioned, it is aready been widely discussed that 55% of all operating costs in a typical warehouse can be attributed to order picking. This is based on a study done in United Kingdom, as mentioned in [6]. Order picking is defined as the operation of retrieving goods from specified storage locations based on the customer orders [16]. This process may be complex and leads to high budget and an ineffective system could stop or turn down the warehouse from productive operation and further innovation. In spite of many studies have been done in order to improve the order of picking operation, to manage it efficiently have become more complex [8]. As declared in their study, both the demand and supply side arise the complexity in handling order and operating them respectively [19]. [17] also stated that, across many other operations in a warehouse, the most time-consuming operation in general is in order picking.

Therefore, order picking is a benchmark and the highest priority in measuring the performance and productivity improvement of any warehouse management [5]. However, each order-picking requirement may be different from other warehouse operation and one success solution to company A may not necessarily suit company B. [5] stated that more than 80% of all orders in the warehouses are processed and picked manually. According to experts, the order picking techniques can be classified to manual and automated order picking. Thus, there is a need in bridging the gap that may comply to suit all types of order picking in warehouse operation [1, 2, 7]. This statement has also been confirmed in a recent study done by [13]. Even though nowadays robotics and many intelligent automated systems seems to slowly been used in order picking process of a large warehouse, there are still in need of manual order picking by humans in the near future. Using automated system may also incurred cost of maintenance, and small companies may not afford to use this system.

This paper offers an approach to improve real-time management of the order picking system in a warehouse. This can be done by minimizing total travel distance of the warehouse transportation in fulfilling order requests by customers and hence, its response time to a customer may be reduced. Once the customer is satisfied with the order performance, profits may increase and later bring additional rewards to the organization and its workers. Workers may have good sense of motivation and satisfaction when the order picking system going through smooth process in the warehouse. Contribution of this paper includes to manufacturing company and other firms with similar operation process and background. This paper may also contribute to academic literature through contributions in



Figure 1: Six types of routing methods for a single block warehouse as according to [16, 17]

methodological approaches, models, and algorithms.

2. Routing Decision in the warehouse

Due to all these facts, solving order picking problem especially using manual storage system could be a serious call. In addition, it is part of the solution in inner transportation optimization to help reduce the waiting time and response time of a customer in order to receive their demands. Response time in this case refers to the time the moment an order is placed until it is successfully delivered to the customer. This is supported by Mohd Nordin [11], good routing decision contributes towards faster travelling time, thus minimizing response time. This proves routing play an important role in any warehouse. Hence, to have good routing, proper and complete information needed as well as demands are known. Different routing method may result to different outcome of travel time and distance based on a research done by [16, 17, 15]. Mainly, there are six types of routing preferences in a warehouse. Hence, first step is to choose the routing decision.

The illustration of the types of routing is in Figure 1. From the number of routes selections, S-shape routing method will be a basis in this paper later. This type is considered as one of the simplest strategies for order pickers. In this strategy, the picker will enter the aisle from one end and leaves from the other end once the order picker completed the picking part [3]. In this case, the picker will walk along the aisle, identify and collect the type of items requested based on the order lists. For any aisle with no item to be selected, the picker may choose to skip the aisle and go the next respective aisle. If the aisle is a close ended aisle, the picker needs to turn around and return travel. S-shape routing seems to be inefficient if the picking lists are small because they have to travel back and forth and results to a non-productive travel. However, many researches show that this routing policy is efficient when the picking density is large. Furthermore, the S-shape helps to reduce congestion in a warehouse [5]. Thus, for our case study, this routing is more compatible. On the other hand, the midpoint method divides the warehouse into two: front and back, which are identified where fast moving item will be stored at the front aisles and the slow moving items will be stored at the back aisles.

3. Methodology

In this study, optimal order picking process is proposed based on Dynamic programming (DP) algorithm. In order to do that, two sets of data (secondary data from literature) and real life data are compiled and tested using shortest path problem (SPP), Travelling salesman problem (TSP) and DP.

3.1. Secondary data

In this study, a secondary data come from the study done by [4] is used for comparison. They defined the period routing problem as the problem of designing a set of routes of each day to meet the requirement of a customer. They calculate the route cost for each case using two types of subproblem; i) the shortest path problem (SPP) and ii) a traveling salesman problem (TSP). On the basis of this data, demand for 100 customers which is represented in the xy-coordinates (converted into distance between nodes), delivery period, length of days taken to deliver, method of calculation and respective results are compiled. The demand is tested to four different cases; 100a, 100b, 100c and 100d respectively. Each scenario will have different number of vehicles used in completing the delivery in number of days. The details for every delivery process are combined under three situations; one-time delivery, demand within 11 to 25 items and demand for more than 25 items. If the delivery process is more than one day, a series of delivery pattern is followed.

3.2. Real life data

Real time data is collected from an automotive company which then is compared to secondary data in part 3.1 in order to test the effectiveness of the DP method. To suit the situation with the company's data, the number of days, t, in the benchmark data is not varied. The number of vehicles used per day is considered as the number of order pickers (OP) in the company. The total number of OPs used is multiplied by the length of delivery days. The results are explained in depth under the Result and Discussion section further on.

Data was collected from a selected company that manufactures automotive parts including body parts, suspension, engine parts, modular assemblies, engineering plastic parts and lamp assemblies. The data include the complete layout of the warehouse, number of machines or transports used to carry the materials, number of exit and entrance of the warehouse for each transport to collect supplies, number of shelves; and stations for each stop. In this study, the shortest path and distance taken to complete the whole order process, started from picking the order from the shelf, its consolidation, packaging and its delivery documentation at the exit of the warehouse. However, the result may be varied depending on the warehouse size, layout, arrangement and different entrance and exit doors. In this case, the calculation will be up until the transport arrive the exit door. Whereas, for a warehouse with only one door which same door is used for the entrance and exit, the shortest path will be calculated starting from the vehicle enters the warehouse until it arrives at the same starting point. In addition, there are other factors that are considered such as working hours and normal shifts per day, the number of pickers, resting time and their picking capacity. This is to ensure the pickers are able to meet the job requirement within the normal shift without having to do overtime.

4. Models and Algorithms

The proposed algorithm using DP is tested against two previous models from literature which are: shortest path problem (SPP) and travelling salesman problem (TSP).

4.1. Determining shortest path and minimum order picking distance

Basic fundamental of shortest path problem (SPP) is to find the shortest path in a graph from one vertex to another. Given a weighted graph, G = (N, E) where |N| = n are specified nodes (also called as vertices). The vertices between two nodes are connected by edges (arcs), |E| = m with a certain weight from a specified node. Each weight (cost) $w \mapsto \Re$ may be in terms of time, distance, or currency, is add up to the other vertices in increasing order. For instance, w is defined as time, thus the minimum traveling time with the quickest path that starts from a starting node, say O. The algorithm stops when the shortest path with minimum travel time from O to N is obtained and all the nodes are successfully visited. [9] defined this mathematical model also as the network flow problem. The mathematical model of the objective function of SPP is defined as:

$$Minimize \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij}$$

$$(4.1)$$

subject to
$$\sum_{i=1}^{n} x_{ij} = 1, \ i = 1, ..., n$$
 (4.2)

$$\sum_{j=1}^{n} x_{ij} = 1, \ j = 1, ..., n \tag{4.3}$$

such that $c_{ij} = cost involved from node i to node j$ (4.4)

$$x_{ij} = \begin{cases} 1, & \text{path from node i to node j is considered;} \\ 0, & \text{otherwise.} \end{cases}$$
(4.5)

This model is then adjusted to suit the situation in the study and it is hoped to provide better solutions for any warehouse with similar background problem.

4.2. Travelling Sales Problem (TSP)

To further test the objective function of SPP, a mathematical model is adapted from a formulation defined by [10]. In their model, they consider a limited, wall-block layout where the OPs are not able to pass-by through the aisle directly from current location to the next location due to the different picking aisle and barrier of an aisle. Their basic mathematical model is improvised to suits the multi-picker condition in the current paper. The set of edges (arcs) is denoted by E, and the set of a point added during the solution of the geometric optimization problem (also referred to Steiner point) is denoted as P. In addition, V denotes the number of vertices in a graph and w_{ij}^k is the number of product k passing along each vertex from vertex i to j at least once. Then, each edge may be traversed as many times as necessary until all the nodes are visited. The formulation from the Steiner Traveling Salesman Problem (TSP) is defined as follows:

$$Minimize \sum_{(i,j)\in E} c_{ij} x_{ij} \tag{4.6}$$

Subject to
$$\sum_{i=1}^{n} x_{ij}, i = 1, ..., n$$
 (4.7)

$$\sum_{j=1}^{n} x_{ij} = 1, \ j = 1, ..., n \tag{4.8}$$

$$x_{ij} = \begin{cases} 1, & \text{path from node i to node j is considered;} \\ 0, & \text{otherwise.} \end{cases}$$
(4.9)

$$\sum_{j \in V \quad (i,j) \in E} x_{ij} \ge 1 \quad \forall i \in V \setminus P \tag{4.10}$$

$$\sum_{\in V \quad (i,j)\in E} x_{ij} - \sum_{j\in V \quad (i,j)\in E} x_{ij} = 0 \quad \forall i \in V$$

$$(4.11)$$

$$\sum_{j \in V \ (j,1) \in E} w_{i1}^k - \sum_{j \in V \ (1,j) \in E} w_{1k}^k = -1 \quad \forall k \in V \setminus (P \cup \{0\})$$
(4.12)

$$\sum_{j \in V \quad (j,k) \in E} w_{jk}^k - \sum_{j \in V \quad (k,j) \in E} w_{kj}^k = 1 \quad \forall k \in V \setminus (P \cup \{0\})$$

$$(4.13)$$

$$\sum_{j \in V \quad (i,j) \in E} w_{ij}^k - \sum_{j \in V \quad (j,i) \in E} w_{ji}^k = 1 \quad \forall i \in V \setminus 0, k \in V \setminus (P \cup \{0,i\})$$
(4.14)

$$w_{ij}^k \le x_{ij} \quad \forall (i,j) \in E, k \in V \setminus (P \cup \{0\})$$

$$(4.15)$$

$$x_{ij} \in \{0,1\} \quad \forall (i,j) \in E \tag{4.16}$$

$$w_{ij}^k \ge 0 \quad \forall (i,j) \in E, k \in V \setminus (P \cup \{0\})$$

$$(4.17)$$

Expression (4.6) represents the minimization of the total distribution cost, assuming a linear cost structure for shipping. This is subject to the following constraints. Constraint (4.7) ensures that each node not corresponding to a Steiner point is passed through only once, while constraint (4.8) guarantees that number of head ends adjacent to a vertex indegree of each vertex is equal to its tail ends. Constraints (4.9) to (4.12) correspond to the multi service flow restrictions. Finally, constraints (4.13) - (4.14) denote that there exists a path from node *i* to node *j* with the value of 1 and else, 0.

4.3. The Dynamic Programming (DP) Method

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Basically, calculations are easy when those involve small number of orders in the warehouse. However, it becomes tedious and time consuming once the network is expanded. In this situation, the DP method is capable and useful in finding the shortest distance needs to be travelled by the OP while picking orders. The objective of using this model is to determine the shortest path solution with the OPs have equal number of items to be picked. Thus, before presenting the model, the parameters and variables are firstly introduced. Many operations in a warehouse are normally tested in a one-block environment, [15, 18] as deep understanding and detail explanation of the whole procedure with single block warehouse layout is crucial before bigger area of blocks involved.

The basic DP method is adapted from [16], where the detail on the procedure is referred from [12]. The method is now taking into consideration of the limited picking capacity, K which represents the number of order pickers involved in the study. For DP method for one block, only a part of the whole network based on research done by [4] is considered. As in Figure 2, in total, 12 stations need to be visited to collect all the items. The starting node is the Depot (D) and will only stop until the picker completed all the items. There are three subaisles and each aisle has different length. In the current situation, L = 1 and R = 3. Later, for the purpose of calculation, L = l and R = r to suit



Figure 2: Possible nodes and edges based on current layout in the automotive manufacturing company

the method accordingly. Firstly, assuming now the initial point (starting node) as D and node 31 denotes as the terminal point (destination node). The algorithm reads the route from the left-most subaisles (L) which is D, and ends at the right-most subaisles, 31. All the values and distance is transformed to possible nodes and edges. D, 27 and 31 are the nodes from the front of the block while 68, 3 and 81 are the nodes from the back of the block. All these nodes including nodes 28, 76, 77, 69 and 50 denote the locations of the items needed to be picked.

The transition first starts by following Step 1 from [12]. The process starts with selecting the initial node D, and thus to compare between two partial routes L_1^{68} and L_1^D . L_1^{68} means the picker starts at node D and ends at node 68. This process involves transition t_1 with total distance of 25.26. This can also be written as $c(t_1) = 25.26$. On the other hand, L_1^D means we start and ends the same node D and consists of transition t_3 . In this case, the total distance at or $c(t_3) = 40.52$. Calculations for both respective values are done as follows: $L_1^D = 6.71 + 9.43 + 4.12 + 5 = 25.26$ and $L_1^{68} = (6.71 + 9.43 + 4.12) \times 2 = 40.52$ respectively.

Next, Step 2 is to calculate the following shortest route, are used. There are two possibilities of creating L_2^{68} , either:

$$L_1^{68} + t_a + t_4 = 25.26 + 6.08 + ([8.25 + 6.32 + 4.47 + 7.28] \times 2) = 83.98$$

or;

$$L_1^D + t_b + t_1 = 40.52 + 6 + 7.28 + 4.47 + 6.32 + 8.25 = 72.84$$

Thus, the shortest value between the two will be chosen as the next possible shortest path. In this case, the current shortest path is $c(t_1) = 72.84$. Next, the same procedure from Step 1 and Step 2 is used to find L_2^D . The next shortest path for L_2^D is possible to be achieved either between $L_2^D = L_1^{68} + t_a + t_1$ or $L_2^D = L_1^D + t_b + t_3$. The calculation is interpreted in Figure 3 to show how the DP method actually works.

Thus, from Figure 3, the next shortest distance, L_2^D is obtained with the value of $c(t_3) = 57.66$. The same process is followed thoroughly for the whole area of Figure 2 in finding the total travel distance. Finally, the total travel distance for both L_3^{81} and L_2^3 is; $L_2^{27} + t_b + t_1 = 94.39$ and L_2^3 is $L_2^3 + t_a + t_1 = 103.39$ respectively.

Hence, for the last subaisle R, from figure 2, Step 3 from DP method is used. Supposed, the final route L_r^b is calculated in order to complete the order picking process. However, in this layout, the value for L_r^a is not necessary since the items are completely picked in one block. The picker may choose another path, to complete the order picking process. In this scenario, the picker may choose



Figure 3: Procedure of DP method

to traverse from the front of the block to pick the items needed.

On the whole, all these calculations can be transformed into a better mathematical model. As mentioned earlier, the DP method is used to find the shortest distance with all items are completely collected by the OPs. The main objective of using this model is first; to find the shortest travel distance and path and second; to divide equally the number of items need to be picked by all pickers. As discussed in the earlier paragraph, the purpose of adapting this model is to suit the situation of any manufacturing warehouse with the same procedure. Later, this model may help to increase the efficiency of order picking process and hence, reduce the waiting time and response time of customers. Therefore, before presenting the model, the parameters and variables are firstly introduced.

This procedure is used as basis in solving similar SPP problem but by different variations of algorithm. Based on the model, the objective is to find shortest path while ensuring that all items are collected. The procedure of the DP model in finding the shortest path from the packaging point to delivery point is modified here. In this study, an additional constraint on a capacity for each OP in finding the shortest distance is added. This is because, in this current manufacturing warehouse, the shortest path must consider the limited item picking capacity for each OP. Say, the current needed items are 75 and the first OP, A is only able to collect 25 items per round. Thus, OP A needs to travel back and forth from the packaging point O, to the current node i, (item placed) for three times. If the weight (distance) from vertex O to vertex i is c, thus the total distance is 3c. Only when the item collected is 75 then the order picking process by the OP is considered complete. Due to this requirement, the procedure is modified.

4.4. Comparison Analysis

Based on the study done by [4], they tested the TSP onto 100 orders which represents the number of customers. Total number of demands is 1458 items for 100 orders and need to be completed within agreed length number of days. These demands are put into a xy-coordinates and scattered on a graph. Referring to the data in [4], the data is written as x-axis, y-axis and number of demands. These coordinates are then converted to respective distances for every node. Firstly, all the items based on the coordinates were transferred into nodes. From here, the distance from one node to another is calculated based on the Euclidean Distance. A *Depot* is set to be the initial starting point for all pickers. All the distances are placed under the distance matrix and will be calculated using Open Solver in Microsoft Excel (ME) 2013. The help from Open Solver ME will save time and gives accurate result. Open solver is an add-ins tools in ME 2013 and it is used to find minimum or maximum (optimal) value for a formula in a cell. The value obtained is subjected to constraints, or limits of a particular data on a worksheet. Open Solver is capable of handling large sets of data.

OpenSolver - Mo	odel				×
What is AutoMo	del?				AutoModel
AutoModel is a fea structure of the sp	ature of OpenSol preadsheet. It w	ver that tries to automa ill turn its best guess int	atically determine the to a Solver model, wh	problem you are trying to opt ich you can then edit in this wi	imise by observing the indow.
Objective Cell:	\$DA\$1	_	C maximise G	minimise C target value:	0
Variable Cells:	\$B\$5:\$CX\$105				_
Constraints:	,				
<add cons<br="" new="">\$B\$106:\$CX\$10 \$CY\$5:\$CY\$10</add>	traint> 06 <= \$B\$108:\$ 5 = \$DA\$5:\$DA\$	CX\$108 :105			_ = •
				Add constraint	Cancel
				Delete select	ed constraint
				Make unconstrained vo	ariable cells non-negative a constraint list
Sensitivity Ana	lysis ∏ List se	ensitivity analysis on the	e same sheet with top	evious output sheet O on	a new sheet
Solver Engine:			iii	Current Solver Engine: CB	C Solver Engine
Show model at	fter saving	Clear Model	Options	Save Model	Cancel

Figure 4: Interface of the Open Solver

Compared to Excel Solver in ME, the number of data is limited to only 200 cells. As for this case, 100 by 100 nodes are involved and thus, Excel Solver failed to operate. In addition, the straightforward approach by Open Solver is really helpful and save time.

Overall, for this current order of 100 customers, there are 1458 items to be picked. Again, the main objective is to make sure all the items are collected, demands are fulfilled, and every OP has an equal number of items to be picked. The optimal shortest distance is determined using Open solver. Here, we select a cell to determine the objective value. In this situation, we pick the cell and set to find the minimum value. The objective value is to find the optimum path and total travel distance for each picker. Thus, another table is developed later to determine the shortest travel distance and total items to be picked for each OP. Figure 4 depicts the picture of the Open Solver tools defined by user. Here, user will have to give inputs on the constraints involved, the outcome value and save the model. As can be seen, two constraints are added in Figure 4. Firstly, the items to be picked by each OP is set to maximum of 25 items. Secondly, the items picked by OP must meet the customer's demand. Finally, after all constraints are confirmed, 'click' Save Model and 'click' Solve. Hence, the program will calculate the shortest distance travelled objective function as stated by the DP model subject to the listed constraints using the built-in algorithm. The program is run until the optimum solution is achieved.

5. Results and Discussion

The objective of improving the order picking process is modified to add the capacity constraint of the OP in completing the orders required by the customers. At the same time, a requirement that all ordered items must be picked and the routing in the warehouse following the S shape are

		Christofides a	DP method	
Total distance		SSP	TSP	
	100a	839.2	713.60	718.80
	100b	2294.2	1928.40	1462.01
	100c	925	950.20	1425.55
	100d	1819.2	1499.9	1462.01
Total demand	1458 items			

Table 1: Total route cost between TSP, SSP and DP method

considered. The model is run based on three models which are SSP, TSP and DP using two sets of data.

Case I Secondary data

Case II Real life data

5.1. Case I: Secondary data

We test the DP method to the data from [4]. There are four (4) cases of deliveries for 100 customers in the previous study. Under the TSP and one median problem, the number of days is represented by t. Even though the adaptation is made based on their case, however, under this situation, the value t, which represents the number of days in the study does not vary as per scope of our study. Thus, the number of vehicles used per day is transformed to the number of OPs as in the company. Apart from that the combination details are maintained for this comparison test. Table 1 depicts the total route cost for each case based on the three distinctive methods. From the three situations, SSP provides the highest value in most of the total route cost. Resulting this, [4] tested the data again using TSP and obtained the result as shown in Table 1. Final result using TSP shows slight difference with the DP method. Hence, explanations on the results between TSP and DP method are discussed thoroughly in the next paragraph.

Overall, all the data are tested using DP for several times to get the average total route cost. All the results varied depending on the situations. Each case explains different situation. Firstly, in 100a, four vehicles were used to complete the two days order picking tasks. This is equal to eight number of OP involved a day in DP method. Under this scenario, the delivery of demand is completed in one period. Based on the finding, there is an increment in total distance from 713.60 metres to 718.80 metres using TSP and DP respectively.

This is similar to the 100c case where the value obtained using DP is 1425.55 metres which is slightly higher than value obtained using TSP with only 950.20 metres. The only difference is the length of days to deliver demand is 8 days since only one vehicle is used. This shows that, if less manpower is used, the total distance and total picking time is also increased by 1% and 33.35% for respective cases based on results obtained in DP method.

Next, for 100b case, a total of five days is needed to complete demand by customer with the use of five vehicles each day. However, under this situation, there are few conditions need to be satisfied. If the demand made by customer is at most 10, the delivery will be made only once. Next, if the demand of the customers is from 11 to 25, the delivery will be made in two out of the five days. Else, if the demand is more than 25, the supplier will do delivery every day. Results achieved using DP with total number of 25 pickers is 1462.01 metres which is better than using TSP, with 1928.40 metres. The distance is reduced by 24.19%.

100 customers / day	TSP [15]	DP	NOTE	
100a		718.8		
(4 vehicles/day)	713.6	1%	One time delivery	
100b		1462.01	Demand ≤ 10, One time delivery	
(5 vehicles/day)	1928.4		11 ≤ Demand ≤ 25, 2/5 days delivery	
		-24.19%	Demand ≥ 26; every day delivery	
100c		1425.55	One time delivery	
(1 vehicle/day)	950.2	33.35%		
100d		1462.01	Demand ≤ 10, One time delivery	
(4 vehicles/day)	1499.9		11 ≤ Demand ≤ 25, 2/5 days delivery	
		-2.50%	Demand ≥ 26; 3/5 day delivery	

Table 2: Comparison Result between TSP and DP method

Finally, in 100d case, four vehicles were used to complete the five days delivery period according to the TSP. This is equivalent to 20 pickers if tested using DP method. Under this situation, the delivery made is also abide by three different rules. Firstly, a one-time delivery is made if the demand is up to 10. Next, if the demand is from 11 to 25, only two days will be selected for delivery. To end, if the demand is more than 25, delivery will be done in three out of five days. Better results are achieved using DP with total distance of 1462.01 metres while TSP is 1499.9 metres. Similar to the previous scenario, better performance is achieved with total increase of 2.5% with the help of DP method. The percentage changes are as stated in Table 2.

Based on the results for the benchmark or secondary data using the DP method, it is shown that DP does provide shortest path compared to other models. DP is also the best choice in finding optimal solution and is able to handle constraints and multi decision making. In this study, out of the four cases, TSP shows slightly lower route cost in 100a and 100c compared to the DP if the delivery is made only once. However, this follows the nature of how the algorithm or method is solved. In DP method, the path is assumed to go straight from one point to the other while considering the position of aisles that might prevent vehicle from crossing. On the other hand, the TSP works as in a plane where the nodes are plotted randomly. The edges are connected based on the items involved and it does not consider possible obstacles in the warehouse. The nodes are connected by the edges and the algorithm calculates the shortest path as long as the nodes are reachable. Plus, in DP, the results prove to give better value if the case is involved with more deliveries and more OPs. Logically, the more order pickers should result in a better and shorter distance. Number of manpower does play a role in improving delivery services. Even it does not give better result, at least it can be an alternative to the respective user in planning a smooth order picking and delivery system in a warehouse or any similar procedure.

OP	Route	Total Distance (cm)	Number of Items	Total Item
1	$1 \rightarrow 3$	555.13	49 + 180	229
2	$1 \rightarrow 4$	652.14	49 + 180	229
3	$1 \rightarrow 6$	741.20	49 + 180	229
4	$1 \rightarrow 8$	768.80	29 + 200	229
5	$2 \rightarrow 5$	224.72	79 + 150	229
6	$2 \rightarrow 7$	446.00	79 + 150	229
7	$1 \rightarrow 2 \rightarrow 9$	1697.17	4 + 22 + 200	226

Table 3: Shortest path with limited picking capacity for seven pickers

5.2. Case II: Real Life data

In this section, the data is collected from the automotive company with total of 13 orders made per day on average. The total distance for order picking is calculated based on the following assumptions:

- 1. The number of OP is limited to seven pickers.
- 2. Each OP is limited to pick only 25 items per trip.
- 3. The order picking process involved only normal working hours.
- 4. Each OP will pick equal number of items.
- 5. Every OP is familiar to the routes and picking area.
- 6. OP will start their task at the depot.

In this automotive manufacturing company, there are seven OP per shift. For this occasion, only, 13 orders made by customers are selected at random. Following this, the traveling path and distance for each OP from starting node (depot) to destination node (packaging point) is determined. Out of 13 order, 1600 items are needed, nine items station (nodes) and seven pickers are appointed to collect the items. By default, each picker will collect 229 items. The objectives are to make sure all nodes must be visited to complete orders made by customers and to obtain shortest path and distance in picking an order.

Results for order picking exercise by seven pickers are explained in Table 3. The pickers are numbered from 1 to 7. For instance, OP 1 starts at node 1 and will directly go to node 3 and collect 229 items. The picker picks 49 items from node 1 (two trips) and another 180 items (approximately 8 trips) from node 3. Total travel distance for OP 1 is 555.13cm and the respective path is $1 \rightarrow 3$. Next, OP 2 starts at node 1 to collect another 49 items, and the remaining 180 items from node 4 with the total distance is 652.4cm. The remaining pickers will follow the respective route according to the colours and collect all the items needed. Only OP 5 and OP 6 starts to collect items from node 2 while others start at node 1. This route is considered systematic and may help to avoid accident between pickers. Pickers may also plan their routes among them to avoid congestion, delay or longer waiting time to pick items in the similar nodes.

In this modified DP method with limited picking capacity, the shortest path obtained already consider penalties such as humps, turns and stops. In addition, this model also considers the limited picking capacity for pickers. As shown in Table 3, with the use of the modified DP model, the total travel distance for seven pickers is reduced to 5085.16cm. On top of that, pickers also have equal items to be collected. Previously, without the additional of the limited picking capacity constraint is introduced, the total distance is 5776.26cm. This result reduces the total distance by 11.6%. Comparing to the current practice used in the company, the total distance is 6320cm. By introducing this new approach, it is hoped that the response time for the pickers to attend to the customer demand

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and the waiting time is reduced. Apart from that, the workers satisfaction may also increase since they are given equal picking job.

6. Conclusion

The warehouse management system is designed to control the movement and storage of materials within an operation and process the associated transactions. Process of handling and maintaining goods that comes in and out of the warehouse is a costly operation. In addition, the order picking process also contributes more than half time consumption in a warehouse. Thus, to keep the costs as low as possible, it is essential that quantity and placement of the items are accurate. To have efficient warehouse processes, the company must clearly define the warehouse in terms of layout, routing, scheduling, storage assignment as well as internal replenishment information. Thus, in this study, the previous study done by [4] is used in measuring the efficiency of the DP method. The result obtained is to test whether the DP method is reliable in managing the order picking process. Based on the results obtained, the modified DP method provide better results than the TSP. TSP may be able to match results for small nodes, however, for large number of nodes, the TSP is computationally difficult to solve. In general, TSP neglects certain aspects and assumes that the data is in a complete graph. Plus, the algorithm may or may not be used directly to solve optimization problem. In reality, in a warehouse, a wall-block layout is a barrier that stops picker to directly proceed from current location to the next location. This, in reality, the picker may have to choose other path in order to arrive at the stored location. Overall, the study offers an approach to efficient order picking strategy in any warehouse management system with similar scenario. In addition, any parties including both the government and the public will benefit through the proposed model and algorithm which are capable of enhancing the quality of the warehouse management system. Both parties can get the benefits by minimizing the cost of services and maximizing the profit made for a management involved in supply chain management especially in the advance technology where rapid response is vital. Rapid response is important in a decision-making situation because demand is uncertain especially during this new norm with online shopping and such, efficient system helps management to control their stock keeping and storage assignment. If the service of the warehouses can be enhanced, the cost of production can also be minimized while the warehouse management system can be improved.

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