การประเมินผลกระทบของปัจจัยที่แตกต่างกันต่อประสิทธิภาพของการหยิบสินค้าในคลังสินค้าที่มีผังแบบหนึ่งบล็อก

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บทคัดย่อ

การดำเนินการในคลังสินค้าเป็นกิจกรรมที่ต้องใช้แรงงานมากและคิดเป็นค่าใช้จ่ายที่สูงเมื่อเทียบกับต้นทุนโลจิสติกส์ทั้งหมด ในบรรดาการดำเนินการต่างๆในคลังสินค้า การหยิบสินค้าถือเป็นหนึ่งในกระบวนการที่สำคัญที่สุด โดยเป็นกระบวนการที่ผู้หยิบสินค้าเดินหยิบสินค้าจากตำแหน่งต่าง ๆ ในคลังสินค้า ซึ่งพบว่าระยะทางรวมที่ผู้หยิบสินค้าเดินหยิบสินค้ามีผลต่อปริมาณงานที่ทำได้ในช่วงเวลาหนึ่งในคลังสินค้า ดังนั้นการลดระยะทางที่ไม่เกิดประโยชน์นี้จึงเป็นหนึ่งในกลไกสำคัญในการเพิ่มประสิทธิภาพของคลังสินค้าได้ งานวิจัยนี้มีวัตถุประสงค์เพื่อประเมินผลกระทบของปัจจัยที่แตกต่างกันต่อระยะทางที่ผู้หยิบสินค้าเดินหยิบสินค้าในคลังสินค้าที่มีผังแบบหนึ่งบล็อก โดยพิจารณาปัจจัยต่าง ๆ ประกอบด้วยขนาดของใบสั่งซื้อ ตำแหน่งของจุดเริ่มต้นและจุดสิ้นสุดการหยิบสินค้า วิธีการเดินหยิบสินค้า และวิธีการเก็บสินค้า ผู้วิจัยจำลองสถานการณ์ที่เป็นไปได้ทั้งหมดของแต่ละระดับของปัจจัยต่างๆ และใช้ผลลัพธ์จากการจำลองไปศึกษาอิทธิพลหลักและอิทธิพลร่วมของปัจจัยต่าง ๆ ต่อระยะทางการเดินหยิบสินค้าโดยใช้การวิเคราะห์ความแปรปรวน ผลการวิเคราะห์ที่ระดับนัยสำคัญ 0.05 พบว่าปัจจัยหลักทุก ๆ ปัจจัยและผลกระทบร่วมระหว่าง 2 ปัจจัยมีอิทธิพลต่อระยะทางการเดินหยิบสินค้าในคลังสินค้าอย่างมีนัยสำคัญทางสถิติ ผลการทดสอบผลกระทบร่วมของ 3 ปัจจัยพบว่าส่วนใหญ่จะไม่มีผลกระทบร่วมกันต่อระยะทางการเดินหยิบสินค้า ยกเว้นผลกระทบร่วมของ 3 ปัจจัยที่ประกอบด้วยขนาดของใบสั่งซื้อ ตำแหน่งของจุดเริ่มต้นและจุดสิ้นสุดการหยิบสินค้า และวิธีการเดินหยิบสินค้า ที่มีผลต่อระยะทางการเดินหยิบสินค้าอย่างมีนัยสำคัญทางสถิติ ส่วนผลการทดสอบของผลกระทบร่วมของ 4 ปัจจัย พบว่าไม่มีผลกระทบร่วมกันต่อระยะทางการเดินหยิบสินค้าในคลังสินค้า

คำสำคัญ: เส้นทางการหยิบสินค้า, การจัดเก็บสินค้า, การหยิบสินค้า, คลังสินค้า

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Evaluating the effects of different factors on the order picking efficiency in the single-block warehouse

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Abstract

Warehouse operations are labor-intensive activities, and they account for the highest share of the total logistics cost. Among the various operations in warehouses, order picking, which is the process of retrieving a set of requested items from specified storage locations in a warehouse, is one of the most critical ones. The picking travel distance required by the order pickers has profound effects on the warehouse throughput. Hence, reducing this unproductive traveling of the order pickers is a significant lever for increasing the total warehouse throughput. The focus of the paper at hand is to evaluate the effects of four main factors, including pick-list sizes, depot location, order picker routing policies, and storage assignment policies on the picking travel distance in a single block warehouse. We simulate all possible combinations of several levels and evaluate the main and interaction effects using the analysis of variance (ANOVA). According to ANOVA analysis, all main single effects and two-way interactions have a statistically significant effect on the picking travel distance at a level of significance α of 0.05. On the other hand, most of the three-way interactions are not statistically significant at an α of 0.05, except the three-way interactions between pick-list sizes, depot location, and storage assignment policies. In terms of four-way interactions, they are not statistically significant at an α of 0.05.

Keywords: picking route, storage assignment, order picking, warehousing

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1. Introduction

Warehouses play a vital role in the supply chain process as they facilitate the shipping of products to the next stage of the supply chain with the highest level of customer service and at the lowest possible cost. As a result, both researchers and practitioners have focused on improving warehouse operations in the past to enhance the efficiency of the supply chain. Among the various warehouse operations, order picking, which is commonly defined as the process of retrieving requested items from storage locations in a warehouse in response to customer orders [1-2], is the most costly activity [3]. Some authors estimated that it accounts for up to 55% of the total warehouse operating costs [4]. In addition, order picking is a critical process for every supply chain because of its direct influence on customer satisfaction [5], which is the main performance factor in e-commerce retail. Underperforming in order picking can cause both unsatisfied customers and high warehouse operating costs. Consequently, improving the efficiency of order picking will lead to lower logistics costs and to an improved performance of the whole supply chain [6-7]. In picker-to-parts systems, order pickers travel through the aisles of the warehouse to pick requested items from storage locations. The time required by the order pickers to travel through the warehouse may account for up to 50% of the total order picking time [8-9]. Hence, reducing this unproductive and non-value adding time is an essential lever for lowering warehouse operating costs. Since the travelling distance is proportional to the travelling time, minimizing the travelling distance of a picking tour is often considered equivalent to reducing the travelling time, and it is seen as a major contributor to the improvement of order picking efficiency. To reduce picking travel distance, previous research has focused on single order picking planning problem, but this research breaks new ground by combining multiple planning problems. Therefore, the main contribution of the paper at hand is to evaluate the effects of four main factors, including pick-list sizes, depot location, order picker routing policies, and storage assignment policies on the picking travel distance in a single block warehouse.

2. Problem description

We assume a single block warehouse, which is a layout that is common in practice and that this is the most frequently used layout in the literature [5],[10]. The warehouse under study is the single-block warehouse with ten aisles. The picking aisles are two-sided with the width of 1 meter. The dimension (width*depth*height) of each storage location is 1*1*1 meter^3 containing a single type of SKU, and 1,000 SKUs (100 in each aisle) are stored in the warehouse in total. This layout is consistent with the warehouse layout literatures of [11-12]. In defining the model, we make the following design assumptions.

1. There is only one depot, where order pickers receive orders and where retrieved items are dropped off for further processing.
2. Order pickers can retrieve the requested items from storage racks arranged on both sides of the picking aisles without having to cross the aisles.
3. Order pickers working in the same area can pass each other, which means that we do not consider picker congestion within aisles.
4. The requested items can be picked directly from the racks without additional vertical travel, which means that in this study we focus on the picker routing problem in a low-level picker-to-parts system.
5. An item is stored in a single location only, which means we consider order picking in a single storage system.

3. Order picker routing

3.1 Exact algorithm

Ratliff and Rosenthal [13] developed exact routing algorithm for routing order pickers through a single-block warehouse as illustrated in Figure 1. The rectangle boxes in Figure 1 represent the storage locations in warehouse, where the black boxes are locations of items to be picked. The order picker receives a pick-list containing a list of items to be picked at the depot, starts retrieving all requested items from storage locations, and then returns to the depot to drop off the retrieved items. Ratliff and Rosenthal [13] defined the picker routing problem as the problem of finding a tour of minimal length on a graph representation of the investigated warehouse.

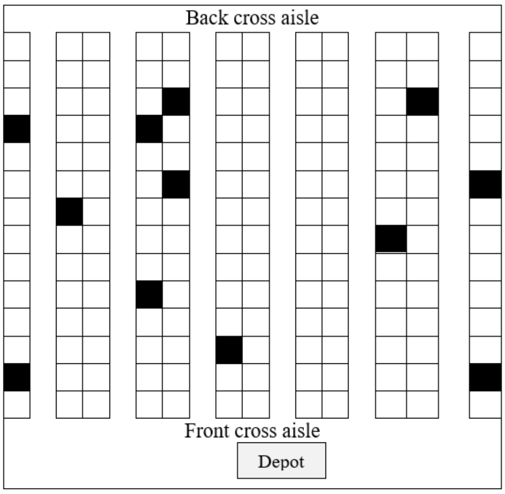

Figure 1 warehouse with a single block [13].

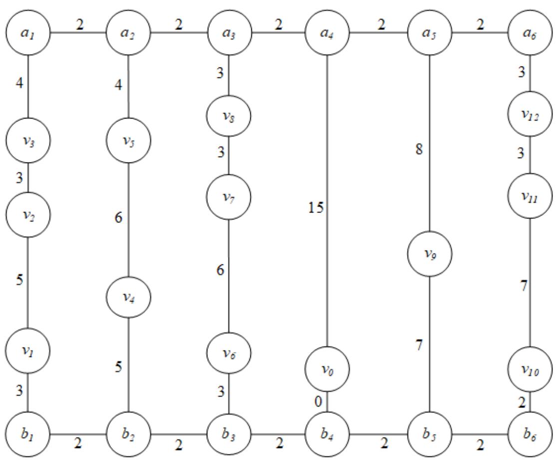

Figure 2 Graph representation G, where $m = 12$ and $n = 6$ [13].

The authors defined a graph G in Figure 2 associated with the picker routing problem in Figure 1, where the vertex v_0 represents the location of the depot and the vertices $v_i, i = 1,2,3, \dots, m$, represent the storage locations of all m requested items. The vertices a_j and b_j are back and front endpoints of each picking aisle $j, j = 1,2,3, \dots, n$. The weight of an edge corresponds to the distance between the endpoints of that edge. The algorithm of Ratliff and Rosenthal [13] aims to find the shortest order picking tour that starts from v_0, determines a sequence of storage locations $v_i, i = 1,2,3, \dots, m$ that have to be visited, and ends at v_0. As can be seen, a tour of an order picker in the warehouse corresponds to a tour on the graph G. So, the problem of finding the shortest order picking tour is identical to the problem of finding a tour on the graph G containing all the required vertices.

3.2 Heuristics

S-shape: The order picker starts in the first aisle that contains requested items and traverses the aisle completely. The picker then moves to the next aisle that contains requested items, traverses this aisle completely, and continues in this fashion until all requested items have been retrieved.

Largest gap: This heuristic divides aisles into two halves using the largest gap between two requested items or between the aisle exits and a requested item for defining the front and back part of each aisle. The order picker enters the aisles in the front part of the warehouse that contain requested items and leaves each aisle on the side where s/he entered it without accessing the back part. Once the front part of the warehouse has been completed, the order picker moves to the back part of the warehouse to complete all aisles in the same fashion.

3.3 Meta-heuristics

Adaptive large neighborhood search (ALNS) is based on the large neighborhood search (LNS), a metaheuristic introduced by Shaw [14]. In an LNS, the neighborhoods are defined by destroy and repair operators. A destroy operator is used to remove a set of vertices to cut the present solution into parts in each iteration of the search. Then, a repair operator is used to re-combine the removed vertices and the remaining parts of the solution to obtain a new feasible solution. A destroy operator that can affect a large portion of a solution, hence the name "large neighborhood search", has potential to help the search navigate different parts of a solution space and lessen a chance of getting stuck at local optima, especially when a problem being tackled has constraints that make it difficult to move from one feasible solution to another by small changes. ALNS has been developed by Ropke and Pisinger [15] and extends the LNS by an adaptive selection mechanism for choosing a destroy and repair operator at each iteration from a "portfolio", i.e. a set of operators. The use of multiple operators and the ability to choose them adaptively in the ALNS allows the search to adjust itself to different instances of the same problem. As it contains a mechanism for choosing operators, ALNS can also be viewed as a hyper-heuristic; it is a heuristic for deciding which heuristic (destroy/repair operators) to use for creating a new feasible solution. ALNS is comprised of four main steps: (1) creating an initial solution; (2) choosing a destroy operator and performing a destroy operator; (3) picking a repair operator and performing a repair operator; and (4) renewing the parameters and the current solution. Such parameters include those that control the probability of choosing each destroy or repair operator. For example, one may adjust the parameters in such a way that an operator that leads to a better solution has a higher probability of being chosen in the next iteration.

A pseudocode of ALNS used in this work is given below, where *N_item* is the pick-list size, and *N_itr* is the number of iterations to be specified.

```
Given: N_item, N_itr.
Generate an initial solution, called S.
Set Best_S = S.
For each destroy operator:
        Set its score = 1.
For itr = 1 to N_itr:
        Randomly choose the number of items to
remove from the route S, called N_to_remove.
        Randomly choose one of the destroy
operators.
        Apply the chosen destroy operator with
N_to_remove to S. Call the result New_S.
        Repair New_S.
        If New_S is accepted
          Set S = New_S.
          Set delta = 1.
        If total distance of New_S is less than Best_S
          Set Best_S = New_S.
          Set delta = 2.
        Increase the score of the chosen destroy
operator by delta.
Return Best_S.
```

In this work, *N_itr* is set to 100×*N_item*, and *N_to_remove* ranges between 1 and min(1, *N_item*/2). An initial solution is generated by randomly permuting items to be picked. Destroy operators are randomly chosen by a process similar to roulette wheel selection in a genetic algorithm [18] with the operators' scores viewed as their "fitness". Destroy operators considered here are "random removal" (randomly removing a given number of items from the route) and "worst removal" (successively removing an item that leads to the highest saving of distance).

4. Storage assignment

Four storage assignment policies are considered in our study, namely (1) random storage with uniform demand, (2) turnover-based storage with 20/40 demand skewness, (3) turnover-based storage with 20/60 demand skewness, and (4) turnover-based storage with 20/80 demand skewness. The notation x/y indicates that x% of the items represents y% of the total demand. For a random storage policy, items are assigned randomly to locations available in the warehouse. In case of turnover-based storage, we implement the turnover-based storage with demand skewness proposed by Çelik and Süral [9] and Pohl et al. [16] by assigning higher demand to items closer to the depot. To do so, we first sort the storage locations in increasing order of their distance from the depot. Secondly, to account for demand skewness, we use the model of Bender [17] as in equation (1) to determine the probability that the item stored in storage location i will be added to a picklist.

$$F(x) = (1 + A)x/(A + x) \qquad (1)$$

The function $F(x)$ is a cumulative distribution function for $x \in [0,1]$. The variable A is a shape factor depending on the demand skewness, where the values of A are 0.60, 0.20, and 0.07 for the demand skewness of 20/40, 20/60, and 20/80, respectively. Assume that the number of items in the warehouse is N. The probability that the item i will be added to the picklist is equal to p_i, as in equation (2):

$$p_i = F(i/N) - F((i-1)/N), \qquad (2)$$
$$i = 1,2,3, \dots N$$

Since the function F is concave down (i.e., F has negative second derivative), an item closer to the depot has higher demand.

5. Experimental design

To investigate the effects of different parameters on the picking travel distance in the single-block warehouse, we use the parameters summarized in Table 1. As can be seen, the experimental design consists of four factors: pick-list sizes (number of items in an order), depot location, order picker routing policies, and storage assignment policies, with some problem sets taken from [11]. This experiment considers five different pick-list sizes with 5, 15, 25, 35, and 45 items. The depot locations considered are central (in the middle of the front cross aisle) (C) and decentral (in the front of the left-most aisle) (D). The order picker routing policies factor investigated here include the exact algorithm (E), the S-shape (S), the largest gap (L), and the adaptive large neighborhood search (ALNS) policy. Four storage assignment policies are considered in our study, namely (1) random storage with uniform demand (R), (2) turnover-based storage with 20/40 demand skewness (TB1), (3) turnover-based storage with 20/60 demand skewness (TB2), and (4) turnover-based storage with 20/80 demand skewness (TB3).

Table 1 Parameters used for evaluating the effect of different parameters on the picking travel distance.

Picklist	5, 15, 25, 35, 45
Depot	C, D
Routing	E, S, L, ALNS
Storage	R, TB1, TB2, TB3

6. Results and statistical analysis

The results of the experiment were analyzed by full factorial design using SPSS software. Table 2 shows the ANOVA results for the picking travel distance. The ANOVA results indicate that the main effect, depot, was found to be statistically significant at a level of significance α of 0.05. The factors, picklist, routing, and storage are also statistically significant; however, these results are not surprising as they are naturally happened. Explaining the effect of the picklist sizes on the picking travel distances is simple and straightforward. An increase in picklist size should be directly translated to an increase in the picking travel distances. Regarding the storage assignment policy, the turnover-based storage policy results in less travel distance than a random storage policy. This result follows from the fact that in the case of higher demand skewness, frequently requested items are assigned closer to the depot, resulting in shorter travel distances. The two-way interactions were found to be statistically significant at a level of significance α of 0.05. On the other hand, most of the three-way interactions are not significant because there is no interaction effect of the three factors on the mean of picking travel distance. The only thing that is significant is the three-way interactions between picklist, depot, and storage. In terms of four-way interactions, they are not significant at a level of significance α of 0.05 for the similar mentioned interaction of four different factors.

Table 2 Full-factorial ANOVA results for picking travel distance.

Tests of Between-Subjects Effects

Dependent Variable: Distance

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	14879157.6[a]	159	93579.607	55.373	.000
Intercept	111216680.8	1	111216680.8	65809.076	.000
Picklist	10585220.68	4	2646305.170	1565.870	.000
Depot	12418.880	1	12418.880	7.348	.007
Routing	1338351.300	3	446117.100	263.976	.000
Storage	2201404.180	3	733801.393	434.205	.000
Picklist * Depot	21077.520	4	5269.380	3.118	.015
Picklist * Routing	116032.000	12	9669.333	5.722	.000
Picklist * Storage	276543.520	12	23045.293	13.636	.000
Depot * Routing	24363.480	3	8121.160	4.805	.003
Depot * Storage	45100.440	3	15033.480	8.896	.000
Routing * Storage	107872.660	9	11985.851	7.092	.000
Picklist * Depot * Routing	5526.120	12	460.510	.272	.993
Picklist * Depot * Storage	40800.360	12	3400.030	2.012	.021
Picklist * Routing * Storage	71810.040	36	1994.723	1.180	.220
Depot * Routing * Storage	25010.800	9	2778.978	1.644	.099
Picklist * Depot * Routing * Storage	7625.600	36	211.822	.125	1.000
Error	1081593.600	640	1689.990		
Total	127177432.0	800			
Corrected Total	15960751.18	799			

a. R Squared = .932 (Adjusted R Squared = .915)

The two main decision problems which are usually solved to increase order picking efficiency include picker routing and storage assignment policies. Table 3 and Figure 3 show the average picking travel distance of the four order picker routing policies in combination with four storage assignment policies. As can be seen, E outperforms ALNS, L, and S for all storage assignment policies. Furthermore, an increase in the skewness of demand reduces the average picking travel distance for all routing policies. In terms of depot location, we summarize the effect of the depot locations on the picking travel distance in Figure 4. It is obvious that the average picking travel distance decreases when the depot location considered is decentralized.

Table 3 Average picking travel distance (meters).

Storage / Routing	R	TB1	TB2	TB3
E	391.64	372.76	320.16	241.52
S	474.76	461.52	424.08	388.88
L	431.36	419.72	371.36	289.76
ALNS	407.44	391.40	331.72	247.60

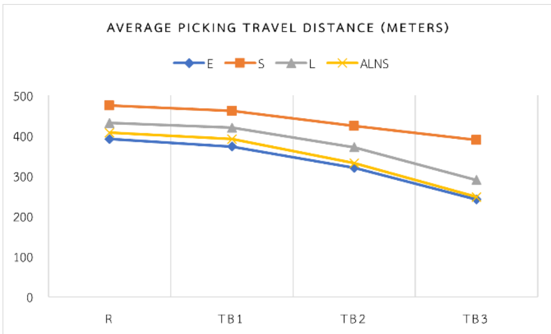

Figure 3 Average picking travel distance (meters) for the order picker routing policies in combination with various storage assignment policies.

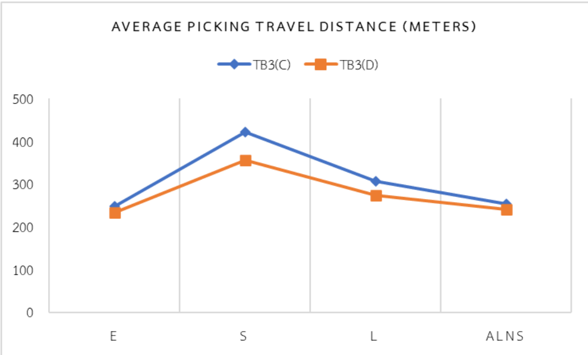

Figure 4 Average picking travel distance (meters) for each routing policy in combination with TB3 under different depot locations.

7. Conclusions and future research

This paper evaluated the effects of four main factors, including pick-list sizes, depot location, order picker routing policies, and storage assignment policies on the picking travel distance in a single block warehouse. The ANOVA results indicated that all the considered parameters and their two-way interactions affect the travel distance. Our computational results showed that the picking travel distance from the combination of exact routing, turnover-based storage with 20/80 demand skewness, and decentralized depot is shorter than the picking travel distance from other combinations. These findings should encourage practitioners to implement the exact routing policy [13] and use decentralized depot together with turnover-based storage assignment. This work could be extended in various directions. For example, future work could also study the effect of order batching on the picking travel distance. Moreover, future research could consider the occurrence of picker blocking in warehouses.

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8. References

[1] C. H. Glock and E. H. Grosse, “Storage policies and order picking strategies in U-shaped order-picking systems with a movable base,” International Journal of Production Research., vol. 50, no. 16, pp. 4344-4357, 2012.

[2] S. Henn, S. Koch, H. Gerking and G. Wäscher, “A U-shaped layout for manual order-picking systems,” *Logistics Research.*, vol. 6, no. 4, pp. 245-261, 2013.

[3] T. Van Gils, K. Ramaekers, A. Caris and R. B. de Koster, "Designing Efficient Order Picking Systems by Combining Planning Problems: State-of-the-art Classification and Review,” *European Journal of Operational Research.*, vol. 267, no. 1, pp. 1-15, 2018.

[4] L. Pansart, N. Catusse and H. Cambazard, “Exact algorithms for the order picking problem,” *Computers & Operations Research.*, vol. 100, pp. 117-127, 2018.

[5] T. Franzke, E. H. Grosse, C. H. Glock and R. Elbert, “An investigation of the effects of storage assignment and picker routing on the occurrence of picker blocking in manual picker-to-parts warehouses,” *The International Journal of Logistics Management.*, vol. 28, no. 3, pp. 841-863, 2017.

[6] F. Chen, G. Xu and Y. Wei, " Heuristic routing methods in multiple-block warehouses with ultra-narrow aisles and access restriction,” *International Journal of Production Research.*, vol. 57, no. 1, pp. 228-249, 2019.

[7] I. Žulj, C. H. Glock, E. H. Grosse and M. Schneider, "Picker routing and storage-

assignment strategies for precedence-constrained order picking," *Computers & Industrial Engineering.*, vol. 123, pp. 338-347, 2018.

[8] R. De Koster, T. Le-Duc and K. J. Roodbergen, "Design and control of warehouse order picking: A literature review," *European Journal of Operational Research.*, vol. 182, no. 2, pp. 481-501, 2007.

[9] M. Çelik and H. Süral, "Order picking under random and turnover-based storage policies in fishbone aisle warehouses," *IIE Transactions.*, vol. 46, no. 3, pp. 283-300, 2014.

[10] M. Masae, C. H. Glock and E. H. Grosse, "Order picker routing in warehouses: A systematic literature review," *International Journal of Production Economics.*, vol. 224, pp. 1-22, 2020.

[11] C. G. Petersen and R. W. Schmenner, "An evaluation of routing and volume based storage policies in an order picking operation," *Decision Sciences.*, vol. 30, no. 2, pp. 481-501, 1999.

[12] C. G. Petersen, G. R. Aase, and D. R. Heiser, "Improving order-picking performance through the implementation of class-based storage," *International Journal of Physical Distribution & Logistics Management.*, vol. 34, no. 7, pp. 534-544, 2004.

[13] H. D. Ratliff and A. S. Rosenthal, "Order-picking in a rectangular warehouse: a solvable case of the traveling salesman problem," *Operations Research.*, vol. 31, no. 3, pp. 507-521, 1983.

[14] P. Shaw, "Using constraint programming and local search methods to solve vehicle routing problems," in *Proceeding of International Conference on Principles and Practice of Constraint Programming*, 1998.

[15] S. Ropke and D. Pisinger, "An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows," *Transportation science.*, vol. 40, no. 4, pp. 455-472, 2006.

[16] L. M. Pohl, R. D. Meller and K. R. Gue, "Turnover-based storage in non-traditional unit-load warehouse designs," *IIE Transactions.*, vol. 43, no. 10, pp. 703-720, 2011.

[17] P. S. Bender, "Mathematical modeling of the 20/80 rule: theory and practice," *Journal of Business Logistics.*, vol. 2, no. 2, pp. 139-157, 1981.

[18] S. Mirjalili, Evolutionary Algorithms and Neural Networks. Studies in Computational Intelligence, Springer, pp. 43-55, 2019.