International Journal of Industrial Engineering and Management (IJIEM), Vol.8 No 4, Month 2017, pp. 229-238
Available online at www.iim.ftn.uns.ac.rs/ijiem_journal.php
ISSN 2217-2661

**UDK 658.286 005.93**

# An Evaluation of Picking Routing Policies to Improve Warehouse Efficiency

**Jose Alejandro Cano**
Universidad de Medellín, Cra. 87 # 30 - 65, Colombia, jacano@udem.edu.co
**Alexander Alberto Correa-Espinal**
Universidad Nacional de Colombia, Calle 80 # 65 - 223, Colombia, alcorrea@unal.edu.co
**Rodrigo Andrés Gómez-Montoya**
ESACS – Escuela Superior en Administración de Cadena de Suministro, Calle 4 # 18 - 51, Colombia, rodrigomezm1986@gmail.com

Received (08.06.2017.); Revised (20.09.2017.); Accepted (03.11.2017.)

**Abstract**

*This paper evaluates various routing policies (s-shape, largest gap, return and composite policies) and introduces a novel heuristic called Minimum Heuristic (MinH) to solve the picker routing problem. The performance of the routing policies and the MinH heuristic is validated by an experimental design, varying the number of aisles, locations per aisle and pick list size. The experimental results show the travel distance savings of MinH heuristic over routing policies, highlighting that for all of the instances, the MinH heuristic performs 14,3% better than the existing routing policies.*

**Key words:** *Experimental design; Heuristics; Order picking; Routing; Warehousing.*

## 1. INTRODUCTION

Warehouses and distribution centres are important components in the supply chain because they link suppliers with production plants, and production plants with distribution systems [1], and the performance of warehouse operations and distribution centres significantly affect the efficiency of the entire supply chain to which they belong [2], [3]. In their operation, warehouses store and retrieve products to meet customer orders [4], in terms of accuracy, response times, the frequency of deliveries, number and sizes of orders [5]. Therefore, the success of managing a warehouse in a supply chain depends to a large extent on an efficient and effective retrieve of customer orders [3], [6].

Warehouse management has a large influence on total logistical costs [7], because most warehouse operations are labour intensive or capital intensive, so it is necessary to improve productivity and reduce warehouse costs to improve supply chain efficiency [1]. In this sense, warehouse management can account for about 20% of the operational costs a supply chain [8], which means that a better warehouse performance is required [9], thus increasing the ability to process large quantities of orders daily with a wide range of items.

Within warehouses, operations such as reception, accommodation, storage, order picking, sorting, packing, and dispatching are carried out [10], [11]; and from these activities order picking deals with the recovery of items to satisfy customer orders [12], and is considered the most labour-intensive function [13], up to the point of generating about 50% - 75% of the operating costs of a warehouse [14].

Due to this, an efficient picking operation can lead to great reductions in warehouse management costs as well as an increase in service level [15]. Within the picking operations, transport and travel time consumes at least 50% of the total order processing time [14], whereby storage costs can be reduced with small reductions of the picking travelled distance [6], and this is achieved through a proper picker routing planning [16]. In the picker routing, the optimum sequence is determined to visit storage positions by the picking operator [17], seeking to minimize the total travelled distance [18]. As a result, picker routing generates tours with which operators are guided to retrieve products from storage locations [19]. To address picking routing problem, different solution approaches are often used. Among these approaches are the use of policies or routing strategies, heuristics, metaheuristics and optimal solutions. Some of these approaches are the routing policies or strategies, heuristics, metaheuristics and optimal solutions.

There are several routing policies that are used in practice, whose performance usually depends on the particular conditions of the storage system for which they are applied [20]. These policies determine the picking sequence of SKUs (stock keeping units) on the pick list [12] and have the benefit of being simple and familiar to pickers [21]. The most commonly used picking routing policies in the literature are s-shape, return, midpoint, largest gap, combined and composite schemes [22], [23].

Some of the proposed heuristics in the literature to solve the picker routing problem proposed are the 2-opt heuristic [24], Largest Gap with Simulated Annealing (LG+SA) method [25], Nearest Neighbor+Or-opt and Savings+2-Opt heuristics [26], travelling salesman and weight heuristics [27], LKH (Lin–Kernighan–Helsgaun) TSP heuristics with 2-opt local search phase [22]. In order to identify the most effective traveling path, some metaheuristics have been proposed such as genetic algorithms [28], ant colony optimization [29], particle swarm optimization [30], tabu search [31], among others.

With regard to routing methods that ensure an optimal picking route, [32] proposed one of the first algorithms to find an optimal picking route in rectangular warehouses, combining the graph theory and dynamic programming; this procedure is fast and can be run on a personal computer [33] and solved optimally with commercial software [34]. Furthermore, [35] propose a solution method for the TSP through a graphs system, and [36] propose a branch-and-cut algorithm. However, [37] states that the results of these optimal routing methods are usually the hybrid between s-shape and largest gap policies, hence that different routing policies can generate close-to-optimal solutions, avoiding confusion generated by the optimal solutions in the picking operators and facilitating their use [21]. Hence, the use of routing policies is prevalent in real world applications due to the convenience of their implementation [38], because they are easy to understand and implement, and tend to form similar routes [33]. Likewise, as picking aisles or the pick list size increases, the complexity and probability of errors in the picking time increases [20], as well as the computation times increase, whereby routing policies are an alternative to the optimal route [39].

According to the abovementioned, heuristic strategies are commonly used in practice, and they need to be studied [33], especially because routing policies could, in some situations result in a near-optimal route, but in some other situations could perform badly [20]. Therefore, it is important to develop a method that generates the results of the most used routing policies, and based on these results, propose for each situation the routing policy to be applied in order to obtain the shortest distance. Similarly, it becomes necessary to perform an extensive number of experiments to know which routing policies are better than others, and under what configurations this occurs.

In the literature, there are some studies on the distance of travel or picking time of routing policies. Petersen [33] performed an investigation with four factors: routing heuristic factor, depot factor, warehouse shape, and pick list size factor, testing 240 treatments and 30 replications per treatment. Dukic & Oluic [20] compared routing methods and their interactions with storage methods, using three factors: pick list size, warehouse sizes, and warehouse layouts, examining 48 different situations using volume-based storage and random storage. Petersen & Aase [12] evaluated several picking, routing, and storage policies to determine which policy or combination of policies will provide the greatest reduction in total travel and picking time through three factors: picking policy, routing policy, storage policy, average order size, in a warehouse layout with 10 picking aisles and a total storage capacity of 1000 SKUs. Petersen & Schmenner [40] presented four factors to study the total distance travelled by the picker to pick all items on a pick list: Routing heuristic, storage policy, pick list size, demand skewness, for a total of 720 treatments and 30 replications per treatment. Hwang et al. [38] examined the effects of order size, popularity skewness, and the ratio of the length to the width of the warehouse on total expected travel distance, for 160 different cases. van Gils et al. [39] performed a simulation experiment with four factors: storage assignment policies, batching policies, zone-picking policies, routing policies, and 30 replications per policy combination, resulting in 7.500 observations.

These studies have analysed factors such as routing policies, depot position, pick list size, warehouse size, picking policy, storage policy, popularity skewness, batching policies; however, to the best of our knowledge, the number of aisles, picking positions per aisle side (length of corridor), and pick list size have not yet been considered as independent factors in order to establish the warehouse configuration and operation volume in which each routing policy performs well in relation to the total travelled distance. Likewise, it has not been identified a simple and fast routing policy that adapts with the ability to adapt to different warehouse configurations and operating volumes to provide a satisfactory solution with respect to total travelled distance.

Based on the above, this article aims to perform an extensive study to analyse the performance of various routing policies under different warehouse configurations (number of aisles, aisles depth) and operating volumes (pick list size), and propose a simple routing heuristic that offers a global solution based on the routing policies analysed. The remainder of the paper is organized as follows. In Section 2, we provide a background and assumptions of the routing policies. In Section 3, we present a novel picking strategy named Minimum Heuristic with a global solution of several routing policies. In Section 4, we present the experimental design to validate routing policies and the proposed heuristic. The results and managerial implications, and conclusions obtained with the experimental design are presented in Sections 5 and 6, respectively.

## 2. BACKGROUND AND ASSUMPTIONS OF THE ROUTING POLICIES

Some of the most used routing policies in real warehouses are the s-shape and the largest gap heuristic since order pickers seem to accept only straightforward and non-confusing routing schemes [41]. Likewise, the return and midpoint heuristics are prevalent in practice due to ease of use and very low error rates during routing and picking [23]. However, largest gap policy is preferred than midpoint policy due to the largest gap policy is similar to the midpoint policy, with the difference that the point of return is determined by the largest gap instead of the middle point of the pick aisle [42], [43], and due to the largest gap policy at least equal to or improves the route defined by the midpoint policy in all possible situations [20]. Also, the composite routing policy is one of the best heuristics procedures, especially when the pick list size is large [33], combining features of the s-shape and return policies. Although largest gap routing and composite routing are not as easy as s-shape routing, they are still used in some warehouses due to the shorter walking distances that are often obtained [42], [44].

According to the above, the s-shape, largest gap, return and composite routing policies, which are presented in Figure 1, will be considered in this study and are described below in depth.

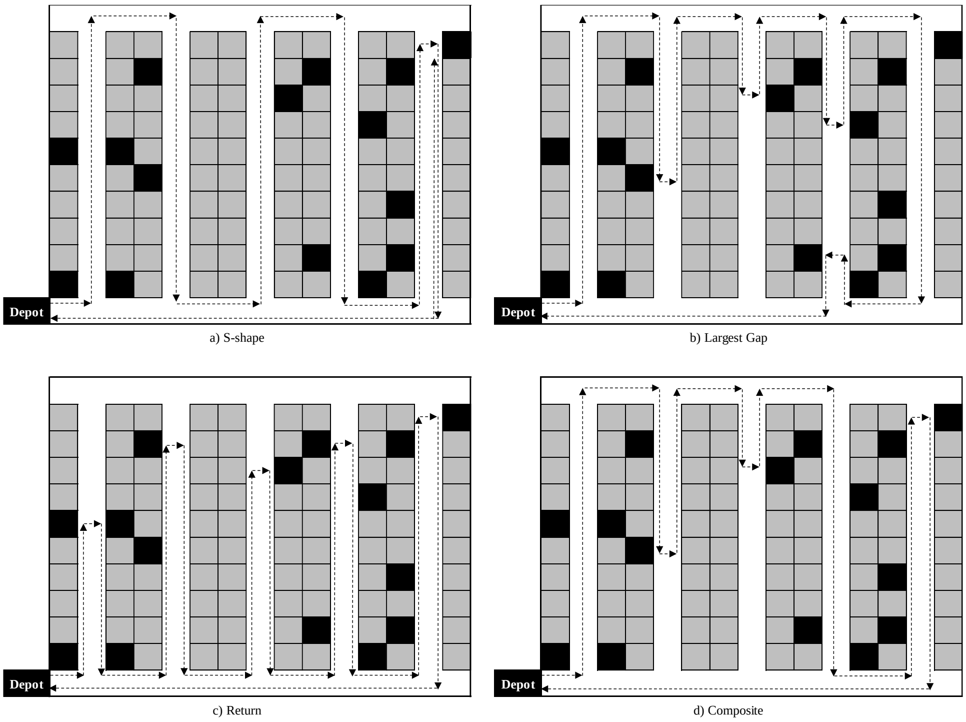


**Figure 1**. Routing policies considered to retrieve items of a pick list

## 2.1 **S-shape routing policy**

S-shape or Traversal policy was introduced by Goetschalckx & Ratliff [45], and is one of the simplest strategies for routing pickers, where a picker enters an aisle from one end and leaves from the other [33]. Therefore, the order picker enters an aisle if at least one requested item is located in that aisle and traverses it completely, and then the order picker proceeds to the next aisle which contains a requested item [41]. Aisles without locations to be visited are skipped, and if the number of the last aisle containing an item to be picked is odd, a return travel is performed in the last aisle visited [20]. Several studies has shown that the s-shape routing policy performs better when the pick density per picking aisle is large [12], providing smaller across-aisles travel distance; but when the pick list size is small the inefficiency becomes more prominent [20], [38]. This is because, with s-shape policy, the order picker has to traverse the aisle once he/she enters a picking aisle, resulting in a non-productive travel. However, this condition can help reduce congestion [14].

## 2.2 **Largest Gap routing policy**

The largest gap policy was developed by Hall [37]. This routing policy compares the distances between items to be collected in an aisle and both ends of the corridors, choosing the shortest distance [7]. The gap refers to the separation between any pair of adjacent items, between the first item and the front aisle, or between the last item and the back aisle; whereby the largest gap is the portion of the aisle that the order picker does not traverse [43], or the longest segment that does not contain items, either the segment between two adjacent items, between the front aisle and lower item, or between the back aisle and the last item [46]. The picker travels in an aisle only to the largest gap between two items to be recovered, since the largest gap between two items is used as a reference point to return to the cross-aisle for which the picker entered [42]. Therefore, each aisle except the first and last visited aisle is abandoned on the side where the entrance was made, while the first and last aisle to be visited are completely traversed [47]. It is expected that the largest gap policy performs well in the case of small pick sizes [33], especially in situations with a very small number of picks in a warehouse with long aisles; while it is inefficient in the case of large number of picks [20].

## 2.3 **Return routing policy**

The return policy is a simple straightforward heuristic, where a picker enters and leaves every pick aisle from the front cross-aisle [39]. Within an aisle, the picker travels as far as the farthest pick location and then returns to the front cross-aisle [48]. It was observed by [38] that for very small order size (4 or 5 items), the return policy shows better performance due to shorter within-aisle travel distance, while for large order sizes, it appears to be ineffective [33]. When implementing the return policy, the use of an across-aisle is recommended in order to minimize the within aisle travel distance, as long as it does not increase much the number of picks per visited aisle, that is, do not increase much the distance travel per visited aisle [48].

## 2.4 **Composite routing policy**

The composite routing policy was introduced by Petersen [49], combining the best features of the S-shape and Return heuristics [26] and minimizing the travel distance between the farthest picks in two adjacent aisles for each aisle individually [33], [42]. The composite routing policy is straightforward and easy to follow [40], the picker will not traverse every aisle [21], in fact, to decide the shortest way to each aisle individually, the picker needs to return back to the front cross-aisle or through the entire length to the back cross-aisle [50]. At every aisle, the picker has to determine whether use a return strategy or use a transversal strategy depending on the location of the items to be retrieved in the next pick aisle [40]. Petersen [33] showed that the performance of the composite policy seems to be similar or even better than to the optimal procedure, especially for larger pick list sizes.

# 3. PROPOSED MODEL

Warehouses and distribution centres are interested in finding the most economical way to retrieve customer orders, which means minimizing operating costs, i.e. reducing total travelled distance or travel time [4], [6]. Most studies focus on reducing total travel distance [19], [26], [51], transport time, search time, and operating time [52], [53]. Therefore, we aim to minimize the total travelled distance for the picker routing problem.

Picker routing problem is a traditional traveling salesman problem (TSP) [19], [54], where it is assumed that there are n storage positions, the distances between each storage position are known, each storage position must be visited only once to retrieve the products [7], [52]. However, an order picker cannot proceed directly from one location of a requested item to another one if these items are located in different picking aisles, for which a cross aisle has to be used for switching over from one picking aisle to the other [35]. To deal with this situation, the problem of sequencing and routing order pickers in conventional multi-parallel-aisle systems classifies as Steiner TSP [26], due to some of the nodes do not have to be visited and that the other nodes can be visited at least once, since they are either an order item or the depot [14], [22].

To solve the STSP it can be reformulated into the classic TSP by computing the shortest paths between every pair of required nodes, or it can be solved by using exact (dedicated) algorithms [55]. In this case, to solve the picker routing problem, a TSP with Manhattan distances will be formulated. The set of parameters, indexes and decision variables are represented below.

In order to reduce computation times of the solution algorithm, the Manhattan distance between storage locations i and j ($d_{ij}$) must be calculated previously in a matrix according to the warehouse configuration. In this case, the algorithm simply queries in the distance matrix the $d_{ij}$ value, avoiding the calculation of each $d_{ij}$ at each iteration of the routing process. If the coordinate of the lower left corner of the warehouse is considered as $(0, L)$ and the coordinate of the upper left corner of the warehouse is considered as $(0, U)$, the Manhattan distance $d_{ij}$ between two picking positions $i = (x_1, y_1)$ and $j = (x_2, y_2)$ is computed as shown in Eq. (1).

$$d_{ij} = \begin{cases} |x_1 - x_2| + |y_1 - y_2| \\ \text{if } (x_1, y_1) \text{ and } (x_2, y_2) \text{ belongs to the same aisle} \\ |x_1 - x_2| + min\{|y_1 - U| + |U - y_2|, |y_1 - L| + |L - y_2|\} \\ \text{otherwise} \end{cases} \quad (1)$$

Decision variables are defined as $y_{ij}$ and $z_i$. The variables $y_{ij}$ take the value of 1 if location $i$ is visited immediately after location $j$ in a picking route, and 0 otherwise; and the variables $z_i$ take the value of 1 if location $i$ is visited to pick an item in a picking route, and 0 otherwise. The formulation of the TSP for the picker routing is as follow in Eq. (2-6):

$$Min\ D = \sum_{i=1}^{L} \sum_{j=1}^{L} d_{ij} * y_{ij} \quad i \neq j \quad (2)$$

$$\sum_{j=1}^{L} y_{ij} = z_i \quad \forall i,\ i \neq j \quad (3)$$

$$\sum_{i=1}^{L} y_{ij} = z_j \quad \forall j,\ i \neq j \quad (4)$$

$$\sum_{i=1}^{L} y_{ij} \geq z_j \quad \forall j,\ i \neq j \quad (5)$$

$$y_{ij}, Z_i \in \{0,1\} \quad (6)$$

Model formulation is formed by an objective function and constraints. The function objective in Eq. (2) minimizes the total travel distance of a picking route. Constraints in Eq. (3) and Eq. (4) ensure that in a picking route each storage location can be visited only once and that each storage location has only one predecessor and one successor. Constraints in Eq. (5) guarantee to avoid sub-tours of the TSP ensuring a complete picking route where all the storage locations with items to be picked are connected in a single tour. Constraints in Eq. (6) ensure decision variables as binary.

## 3.1 **Minimum heuristic routing policy**

In previous studies, Petersen [33] determined that as the number of aisles increases and the warehouse becomes wider, the performance of the routing policies is more consistent and similar. Caron et al. [56] compared the s-shape and return policies and suggested that the choice of a routing policy should depend on the number of picks per aisle. Petersen [21] established that according to the pick list size, some routing policies perform better than others do and concluded that managers must analyse the trade-off between the efficiency of optimal solutions and the ease of implementation of heuristics procedures. Other studies analysed the performance of routing policies under different factors and levels [12], [20], [38]–[40], in order to determine which policy yields the minimum travelled distance. In these studies, it is not possible to establish a policy that achieves superior performance in all scenarios, whereby a simple procedure is presented called Minimum Heuristic (MinH) routing policy that integrates several routing policies, resulting in the minimum distance between the evaluated policies. The MinH pretends to find a fast, efficient, and good quality solution for every warehouse configuration and pick list size. Figure 2, presents the flowchart of the MinH heuristic.

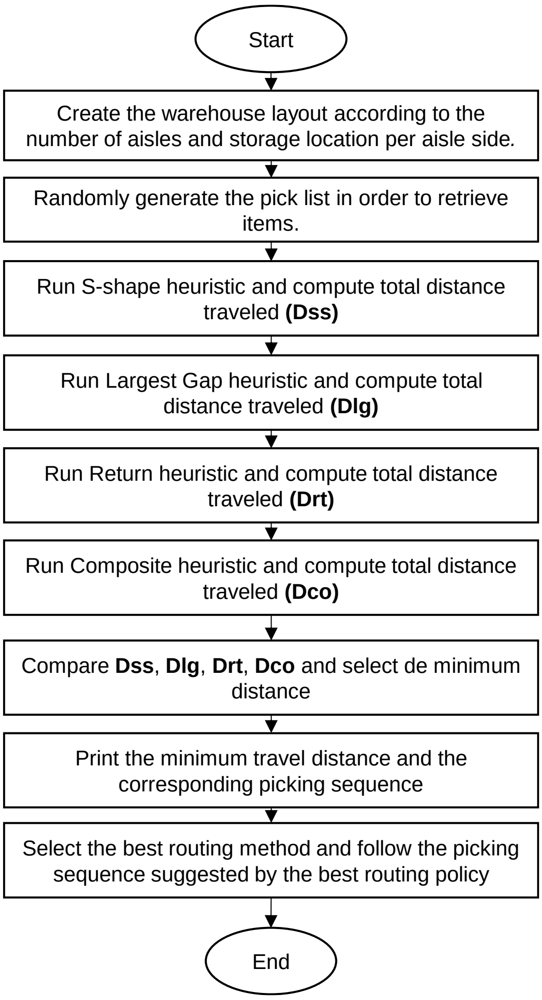


**Figure 2**. Flowchart for the MinH heuristic

Therefore, the MinH heuristic provides in each scenario, a tour based on the routing policy with the best performance among the s-shape, largest gap, return or composite routing policy.

## 3.2 **Model assumptions**

Within the assumptions considered in this article to test the different picking routing policies, including the MinH heuristic, conventional warehouse configurations are proposed with measures such as those shown in Figure 3, where the warehouse layout has several picking aisles with one front cross-aisle, one back cross-aisle, and one Depot located in the lower left corner of the warehouse. A low-level manual picking environment is assumed where picking can be done from both sides of an aisle (within an aisle two-sided picking is assumed), and the horizontal distance within picking aisles is not considered. It is assumed that each item is assigned to one storage location and every location has the same size. Single order picking and random storage policy are applied, pick lists are generated using random numbers to determine the items for the pick list, and when picking an article, the order picker is positioned in the middle of the cell.

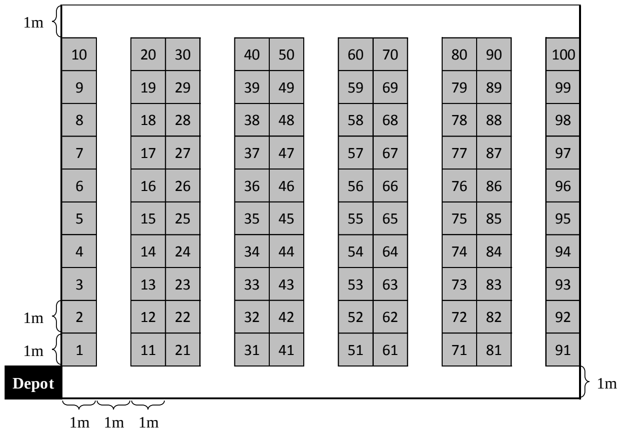


**Figure 3**. Warehouse layout measures

## 4. PROPOSED MODEL

In this section, an experimental design is planned to evaluate the performance of the MinH heuristic against s-shape, largest gap, return and composite heuristics, which are used as benchmark methods. Other picking routing factors such as the number of aisles, number of storage positions per aisle side, and pick list size (order size) are assessed in the experimental study. To perform the experimental study, total travelled distance is considered as the response variable.

A full factorial design 6x5x8x5 is chosen to conduct extensive experiments since the experimental runs are randomly performed. Therefore, this factorial design is used to analyse which combination factor levels produce the minimum total travelled distance as well as the performance of MinH heuristic. Therefore, the simulation experiment consists of 1.200 treatments, and 25 replicates per treatment are performed to reduce the stochastic effect, resulting in 30.000 experimental runs. Additionally, experimental factors are independent of each other, which contribute to the feasibility of the general full factorial design. Factors, factor levels, and response variable, about full factorial design 6x5x8x5 is summarized in Table 1.

**Table 1**. Experimental parameters

| Factor | Factor levels (number of levels) | Response Variable |
|---|---|---|
| Number of Aisles (NA) | 2; 5; 7; 10; 15; 25 (6) | Travelled distance |
| Locations per aisle side (LPA) | 10; 20; 30; 40; 50 (5) | |
| Pick list size (PLS) | 5; 10; 15; 20; 25; 30; 35; 40 (8) | |
| Routing policy (RP) | s-shape; largest gap; return; composite; MinH(5) | |

Routing strategy heuristics and other factors for the experimental runs are encoded in VBA (Visual Basic for Applications) for Microsoft Excel® 2017. The savings of MinH heuristic over the routing policies (benchmarks) under the planned scenarios are measured using Eq. (7), where the performance of the routing policies represents the average travelled distance.

$$\text{Savings} = \frac{\text{Benchark perf.} - \text{MinH heuristic perf.}}{\text{Benchark perf.}} \qquad (7)$$

## 5. RESULTS AND DISCUSSION

Table 2, summarizes the results of the experiment analysed by full factorial model ANOVA, using Minitab Statistical Software® 17. It is detected that all experimental factors (NA, LPA, PLS and RP) and their interaction effects are significant at an α of 0.001 (p-value<0.001) on total average distance. In these experiments, multiple interactions effects are significant statistically; therefore, two-way interaction effects are analysed to study the difference among picking routing factors.

**Table 2**. 6 × 5 × 8 × 5 full factorial mixed-model ANOVA on average travelled distance

| Source | df | Sum of squares (SS) | Mean square (MS) | F-Value | p-value |
|---|---|---|---|---|---|
| *Main Effects* | | | | | |
| NA | 5 | 610.794.429 | 122.158.886 | 108.383 | 0,000* |
| LPA | 4 | 338.093.359 | 84.523.340 | 74.992 | 0,000* |
| PLS | 7 | 156.482.699 | 22.354.671 | 19.838 | 0,000* |
| RP | 4 | 58.768.468 | 14.692.117 | 13.035 | 0,000* |
| *Two way interaction* | | | | | |
| NA*LPA | 20 | 63.206.340 | 3.160.317 | 2.804 | 0,000* |
| NA*PLS | 35 | 80.572.810 | 2.302.080 | 2.042 | 0,000* |
| NA*RP | 20 | 15.745.578 | 787.279 | 698 | 0,000* |
| LPA*PLS | 28 | 30.975.150 | 1.106.255 | 981 | 0,000* |
| LPA*RP | 16 | 12.910.431 | 806.902 | 716 | 0,000* |
| PLS*RP | 28 | 8.087.233 | 288.830 | 256 | 0,000* |

*Significant at α < 0.001

Due to the focus of this research, we are interested in two-way interaction effects that include the RP factor, in order to identify if NA, LPA and PLS factors directly influence the variation of the total travel distance of each routing policy. In this sense, it is observed in Table 2 that the two-way interaction effects NA*RP, LPS*RP and PLS*RP are significant at an α of 0.001 (p-value<0.001), and according to MS values, it is detected that the average travel distance of the routing policies is affected mainly by the number of aisles (NA), locations per aisle (LPA) and pick list size (PLS).

Thus, a linear model can be expressed in Eq. (7) to explain the phenomenon of the experimental design, where $y$ represents the total travel distance, $\beta_0$ is the independent coefficient, $\beta_i$ and $X_i$ represents the coefficient and value of factor $i$ respectively, $\beta_{ij}$ and $X_{ij}$ represent the coefficient and the interaction of the factors $i$ y $j$ respectively, and $\varepsilon$ is the model error.

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_{12} X_{12} + \beta_{13} X_{13} + \beta_{14} X_{14} + \beta_{23} X_{23} + \beta_{24} X_{24} + \beta_{34} X_{34} + \varepsilon \qquad (7)$$

Based on the adjusted R-square value, this linear model explains the 97,65% of the behaviour of the travelled distance in the warehouses, which is a good quality linear model. Therefore, the RP factor and its interaction effects with other factors must be taken into account in the design or improvement of picking operations in order to get the shortest travel distance. Because of this, the main effect of routing policies (RP) factor is analysed to determine which routing policies performs better and worst. The performance is measured based on average travel distance and savings of the MinH heuristic over the routing policies. Based on Figure 4, it is detected that MinH and largest gap generate the shortest average distance in all the instances with of 254 and 260 meters per picking route, respectively.

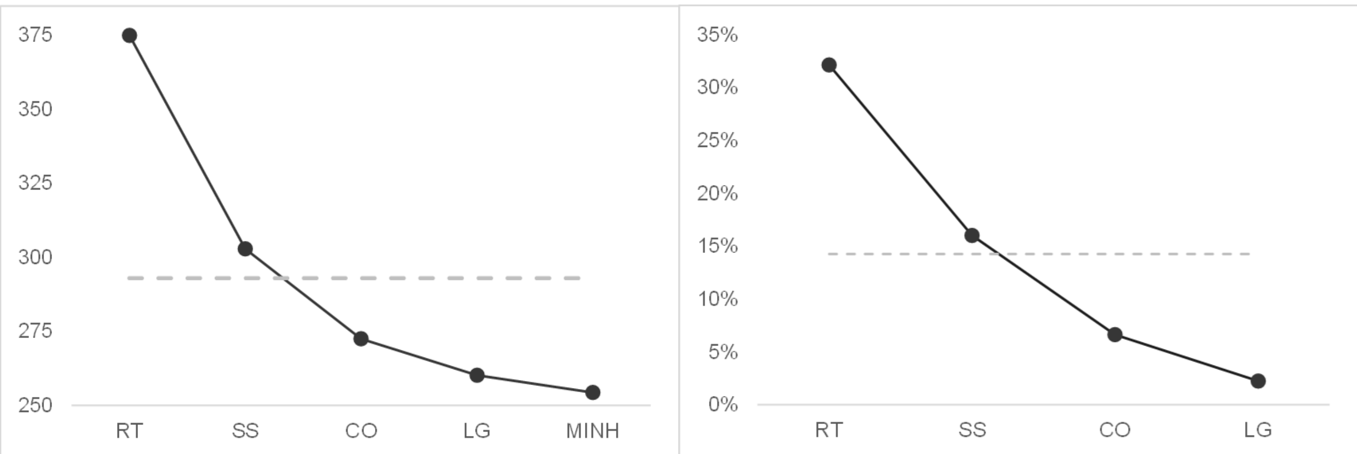


**Figure 4**. Routing policies average travel distance and savings of MinH over routing policies

Therefore, MinH produces a reduction of 6 meters per picking route (2,3%) against LG policy, which is considered a slight difference between them. Moreover, the worst solution is produced by Return (RT) policy with an average travel distance of 375 meters per picking route. Hence, MinH reduces the average travel distance by 121 meters per picking route (32,2%) compared to Return (RT) policy. Comparing the average travel distance of MinH, average savings of 14,3% are obtained relative to traditional routing policies, proving that MinH produces the best solution for picking routing problem considering factors such as the number of aisles, locations per aisle side and pick list size.

Figure 5, shows the interaction between routing policies and the number of aisles. As the number of aisles increases the average travel distances increases, and the performance among routing policies differs more. In the case of two corridors, an identical performance is found for SS, LG, CO and MinH policies because these heuristics traverse both corridors when there are items to be retrieved in each aisle.

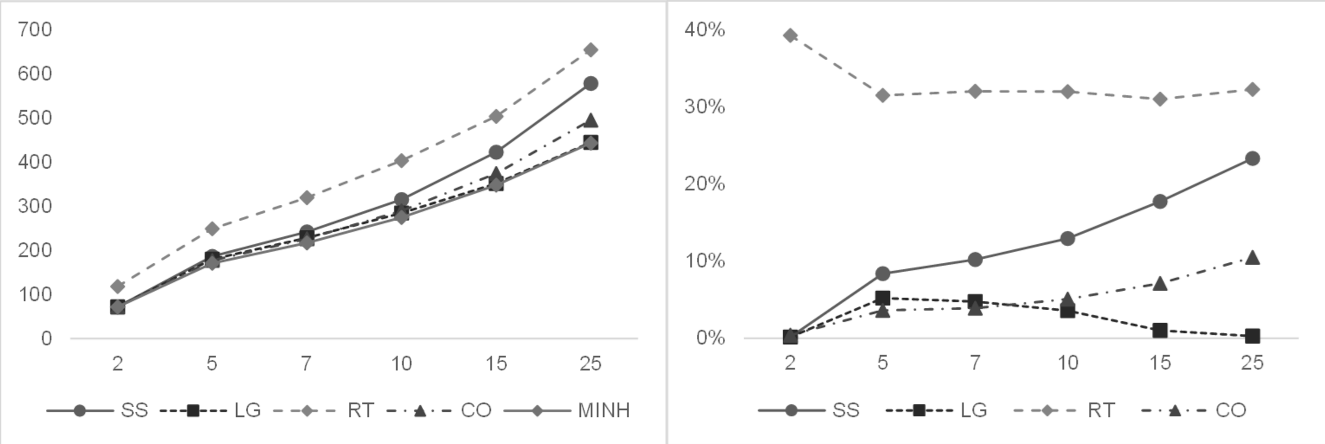


**Figure 5**. Routing policies average travel distance by number of aisles and savings of MinH over routing policies

From Figure 5, is clear that the performance of the composite and largest gap strategies is much better than the performance offered by s-shape and return policies. Particularly, composite policy performs better than the largest gap in narrower layouts with 5 or 7 aisles, while largest gap gives shorter travelled distances in wider layouts with 10, 15 or 25 aisles. Therefore, as the number of aisles increases, the largest gap improves performance. As the number of aisles is smaller, the policy composite improves performance and tends to have a similar performance with respect to MinH heuristic. MinH generates savings over the largest gap between 3,6% (NA=10) and 5,2% (NA=5). On the other hand, MinH is more efficient over s-shape policy as the number of aisles increases, saving up to 23% the average travel distances for the case of 25 aisles. In addition, MinH is more efficient on average over the routing policies as the number of corridors increases.

Figure 6, visualizes the effect of the locations per aisle. It can be observed for each routing policy that the higher the locations per aisle side, the higher the average travel distance. This is because deeper layouts require more travel distance in order to complete a pick list.

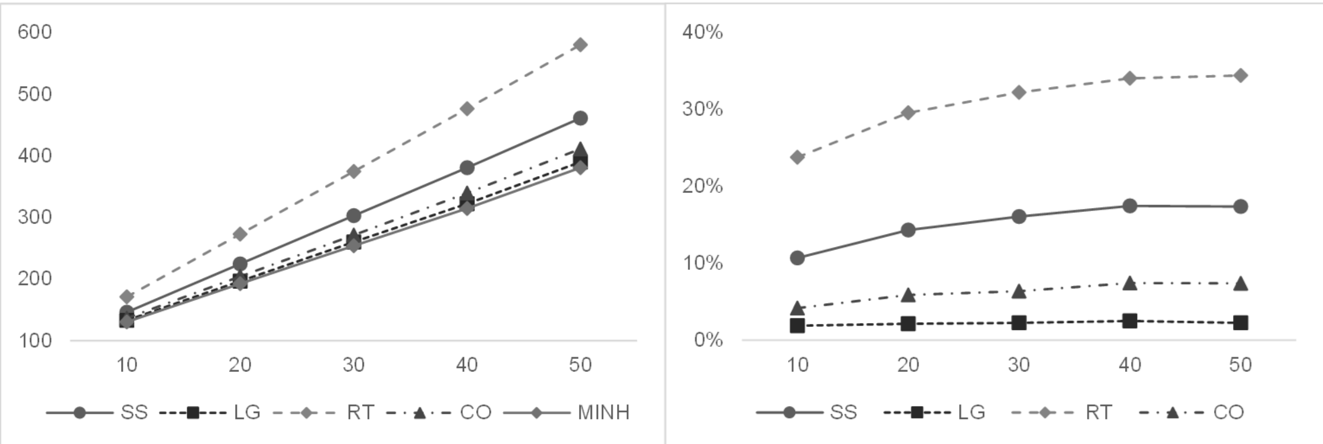


**Figure 6.** Routing policies average travel distance by LPA and savings of MinH over routing policies

Again, the return routing policy was outperformed by all other routing policies in all simulated treatments, and the composite performs better than S-shape policy in every level of the LPA factor. Unlike the analysis of the number of aisles, largest gap policy performs better than all other routing policies as the depth of aisles increases, indicating that it is the best policy to minimize the travel distance within an aisle. Due to this, the MinH heuristic generates small differences in traveled distance compared to the largest gap policy, with savings of around 2%. On the other hand, MinH is more efficient than s-shape policy, saving from 10,7% (LPA=10) to 17,4% (LPA=50) the average traveled distance. Furthermore, as the aisle depth increases, the savings of MinH over routing policies increases. Regarding pick list size, Figure 7, shows that as the order size becomes larger average travel distance tends to increase on every routing policy because it means to visit more storage locations throughout the warehouse.

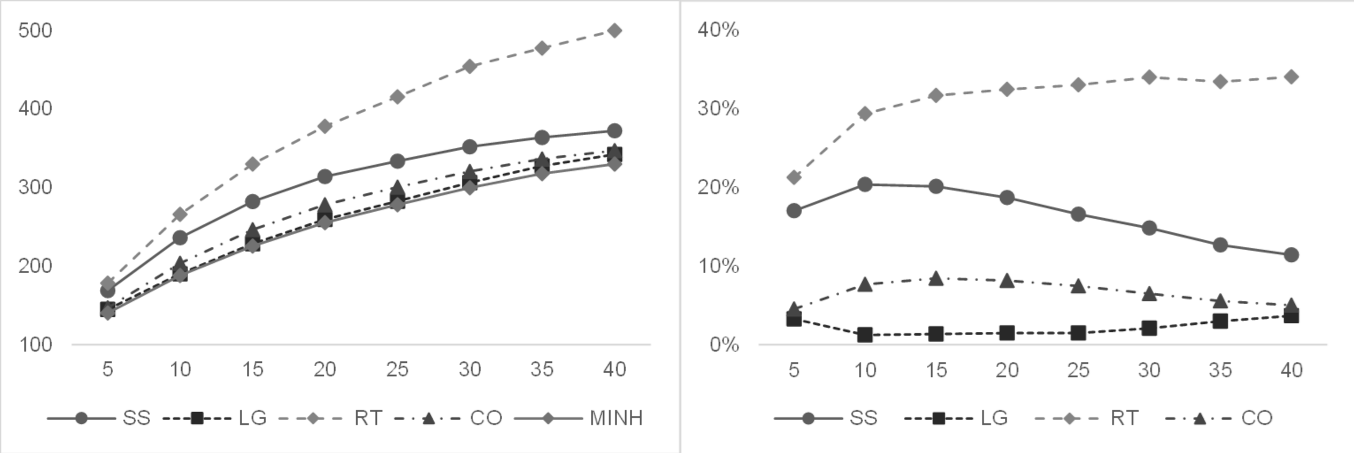


**Figure 7.** Routing policies average travel distance by PLS and savings of MinH over routing policies

Similar to previous analyzes, return and s-shape policies generate for all pick list sizes larger average travel distances compared to composite and largest gap policies. For small pick list sizes (5 items), composite and largest gap policy work similar due to the operation of both policies becomes practically the same when the number of locations per aisle to be visited tends to be one. However, as the pick list increases from 10 to 25 items per pick list, MinH generates small differences in traveled distance compared to the largest gap policy, with savings of 1%, and savings of 3,3% (PLS=5) and 3,7% (PLS=40).
From pick list sizes of 30, 35 and 40 items, composite and largest gap policies work similarly again, because these picking list sizes involve visiting all aisles of the warehouse, both in the lower and in the upper section, resulting in a similar routing pattern.
The s-shape policy improves its efficiency compared to MinH as the pick list size increases, as this increases the number of aisles and locations per aisle to visit; however, MinH offers savings from 11,4% (PLS = 40) to 20,4% (PLS = 10) over s-shape policy. Moreover, MinH presents higher average savings over routing policies for medium pick list sizes (PLS = 15, 20, 25). Moreover, MinH presents higher average savings over routing policies for medium pick list sizes (PLS = 15, 20, 25).
Regarding the results, it is found that in all cases the return policy generates the worst performance, with average travel distances considerably above the other routing policies, to the point where MinH offers on average a savings of 32,2% for the evaluated instances. Regarding the s-shape policy, the MinH heuristic offers significant savings of 16% in traveled distance, and these savings become more noticeable when the number of aisles increases, the number of locations per aisle side increases, and the pick list size decreases.
Except for the warehouse configuration with two aisles, in all cases evaluated the use of the largest gap and composite are preferred rather than s-shape, suggesting that largest gap and composite policies should be implemented in routing picking instead of s-shape.
Likewise, the heuristic MinH is preferred in all the evaluated instances because this routing heuristic chooses the minimum distance generated by the routing policies analyzed (s-shape, largest gap, return, composite). This suggests implementing the MinH heuristic in different models of picking optimization that usually uses simple routing policies, such as order batching and/or picking sequencing models. Thus, solutions of better quality can be offered for these models at a low computational cost.

### 5.1 **Managerial implications**

This research provides managers with greater insight into the design of efficient warehouse and picking routing policies. The results of the simulation experiments provide insights into routing decisions in order to manage picking routing activities efficiently. Compared to the benchmark (i.e. s-shape, largest gap, return, composite policies), MinH heuristic performs better in all proposed scenarios. Over the 25 replications, MinH presented average savings of 14,3% over the average travel distance of the benchmark. The picking routing process can be performed from 2,3% to 32,2% more efficiently by applying the MinH heuristic into different layout configurations and pick list sizes.
As the simulation experiments focus on several layout configurations and pick list sizes for a random storage policy, the proposed MinH heuristic is rather easy to implement and result in large performance benefits. Furthermore, all main effects, as well as all interaction effects, have proven to be statistically significant. This implicates that warehouse managers should consider decisions layout configuration, pick list size and routing simultaneously in order to minimize the distance travelled and optimize the overall warehouse performance.
Hence, MinH heuristics avoids practitioners to weigh the advantages and disadvantages of the various routing policies in their operating environment (number of aisles, locations per aisle, pick list size) before settling a picking tour and avoids the conditional efficiency of routing policies that depends on warehouse configuration and pick list size.

## 6. CONCLUSIONS

This paper compared the performances of four routing policies such as s-shape, largest gap, return and composite policy in several warehouse configurations and pick list sizes. We have introduced the MinH heuristic, which computes de travel distance of each of the abovementioned policies and select the policy with the minimum distance to retrieve the items of a pick list. Then through an experimental design, the average travel distance of the routing policies and MinH heuristic was illustrated, varying the number of aisles, locations per aisle side, and pick list size. This research verifies that under different warehouse configurations and pick list sizes, composite and largest gap outperform the most used routing policy in the literature, the s-shape policy.

In addition, the results of the study clearly indicate that MinH heuristic achieves the best average travel distance over all the test problems due to its ability to form routes from the routing policy with the best performance. The evaluation of an extensive range of routing instances indicates that the largest savings obtained with MinH over the routing policies are in the case where the number of aisles increases, the number of locations per aisle side increases, and pick list sizes is medium. Therefore, MinH becomes an efficient and effective solution for the picker routing problems for any warehouse configuration and pick list size, offering significant savings over traditional routing policies.

Finally, the MinH heuristic can be easily implemented and immediately helps warehouse managers to obtain significant performance benefits reducing the total travel distance. Future research should focus on analysing the MinH heuristic performance under different storage policies such as class-based storage or popularity-based storage, volume-based ABC curves. In addition, it is recommended to integrate the MinH heuristic in order batching and/or sequencing models for the order picking problem, especially in those models that only apply the S-shape policy, in order to improve the quality of the solutions obtained.

## 7. REFERENCES


[1] Ballestín, F. Pérez, Á. Lino, P. Quintanilla, S. and Valls, V. (2013), "*Static and dynamic policies with RFID for the scheduling of retrieval and storage warehouse operations*", Computers and Industrial Engineering, Vol. 66, No. 4, pp. 696–709.

[2] Roodbergen, K.J. Vis, I.F.A. and Taylor, G.D. (2015), "*Simultaneous determination of warehouse layout and control policies*", International Journal of Production Research, Vol. 53, No. 11, pp. 3306–3326.

[3] Menéndez, B. Pardo, E. G. Sánchez-Oro, J. and Duarte, A. (2017), "*Parallel variable neighborhood search for the min-max order batching problem*", International Transactions in Operational Research, Vol. 24, No. 3, pp. 635–662.

[4] Chen, M.-C. Huang, C.-L. Chen, K.-Y. and Wu, H.-P. (2005), "*Aggregation of orders in distribution centers using data mining*", Expert Systems with Applications, Vol. 28, No. 3, pp. 453–460.

[5] Manzini, R. Bozer, Y. and Heragu, S. (2015), "*Decision models for the design, optimization and management of warehousing and material handling systems*", International Journal of Production Economics, Vol. 170, No. 1, pp. 711–716.

[6] Hsu, C.-M. Chen, K.-Y. and Chen, M.-C. (2005), "*Batching orders in warehouses by minimizing travel distance with genetic algorithms*", Computers in Industry, Vol. 56, No. 2, pp. 169–178.

[7] Chen, T. L. Cheng, C. Y. Chen, Y. Y. and Chan, L. K. (2015), "*An efficient hybrid algorithm for integrated order batching, sequencing and routing problem*", International Journal of Production Economics, Vol. 159, No. 1, pp. 158–167.

[8] Rubrico, J.I.U. Ota, J. Higashi, T. and Tamura, H. (2008), "*Metaheuristic Scheduling of Multiple Picking Agents for Warehouse Management*", Industrial Robot: An International Journal, Vol. 35, No. 1, pp. 58–68.

[9] Gu, J. Goetschalckx, M. and McGinnis, L. F. (2007), "*Research on warehouse operation: A comprehensive review*", European Journal of Operational Research, Vol. 177, No. 1, pp. 1–21.

[10] Tompkins, J.A. White, J.A. Bozer, Y.A. and Tanchoco, J.M.A. (2010), *Facilities Planning (4th ed.)*, New Jersey, USA, Wiley.

[11] Gong, Y. and Koster, R. B. M. (2011), "*A review on stochastic models and analysis of warehouse operations*", Logistics Research, Vol. 3, No. 4, pp. 191–205.

[12] Petersen, C. G. and Aase, G. (2004), "*A comparison of picking, storage, and routing policies in manual order picking*", International Journal of Production Economics, Vol. 92, No. 1, pp. 11–19.

[13] Goetschalckx, M. and Ashayeri, J. (1989), "*Classification and design of order picking*", Logistics World, Vol. 2, No. 2, pp. 99–106.

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

[15] Zhang, J. Wang, X. Chan, F. T. S. and Ruan, J. (2017), "*On-line order batching and sequencing problem with multiple pickers: A hybrid rule-based algorithm*", Applied Mathematical Modelling, Vol. 45, No. 1, pp. 271–284.

[16] Hsieh, L. F. and Tsai, L. H. (2006), "*The optimum design of a warehouse system on order picking efficiency*", International Journal of Advanced Manufacturing Technology, Vol. 28, No. 5–6, pp. 626–637.

[17] Centeno, M. A. and Sundaram, R. (2004), "*Considering due time in manual order picking operations*" in IIE Annual Conference and Exhibition 2004, Houston, TX, United States, pp. 1215–1220.

[18] Henn, S. Scholz, A. Stuhlmann, M. and Wäscher, G. (2015), "*A New Mathematical Programming Formulation for the Single-Picker Routing Problem in a Single-Block Layout*", Working paper No. 5, Magdeburg, Germany, Otto-von-Guericke-Universität Magdeburg.

[19] Hsieh, L.-F. and Huang, Y.-C. (2011), "*New batch construction heuristics to optimise the performance of order picking systems*", International Journal of Production Economics, Vol. 131, No. 2, pp. 618–630.

[20] Dukic, G. and Oluic, C. (2007), "*Order-picking methods: Improving order-picking efficiency*", International Journal of Logistics Systems and Management, Vol. 3, No. 4, pp. 451–460.

[21] Petersen, C.G. (1999), "*The impact of routing and storage policies on warehouse efficiency*", International Journal of Operations and Production Management, Vol. 19, No. 10, pp. 1053–1064.

[22] Theys, C. Bräysy, O. Dullaert, W. and Raa, B. (2010), "*Using a TSP heuristic for routing order pickers in warehouses*", European Journal of Operational Research, Vol. 200, No. 3, pp. 755–763.

[23] Rao, S.S. and Adil, G.K. (2013), "*Class-based storage with exact S-shaped traversal routeing in low-level picker-to-part systems*", International Journal of Production Research, Vol. 51, No. 16, pp. 4979–4996.

[24] Won, J. and Olafsson, S. (2005), "*Joint order batching and order picking in warehouse operations*", International Journal of Production Research, Vol. 43, No. 7, pp. 1427–1442.

[25] Ho, Y.-C. Su, T.-S. and Shi, Z.-B. (2008), "*Order-batching methods for an order-picking warehouse with two cross aisles*", Computers and Industrial Engineering, Vol. 55, No. 2, pp. 321–347.

[26] Kulak, O. Sahin, Y. and Taner, M. E. (2012), "*Joint order batching and picker routing in single and multiple-cross-aisle warehouses using cluster-based tabu search algorithms*", Flexible Services and Manufacturing Journal, Vol. 24, No. 1, pp. 52–80.

[27] Choy, K.L. Sheng, N. Lam, H.Y. Lai, I.K.W. Chow, K.H. and Ho, G.T.S. (2014), "*Assess the effects of different operations policies on warehousing reliability*", International Journal of Production Research, Vol. 52, No. 3, pp. 662–678.

[28] Azadnia, A.H. Taheri, S. Ghadimi, P. Mat Saman, M.Z. and Wong, K. Y. (2013), "*Order batching in warehouses by minimizing total tardiness: A hybrid approach of weighted association rule mining and genetic algorithms*". The Scientific World Journal, Vol. 2013, No. 1, pp. 1-13.

[29] Li, J. Huang, R. and Dai, J. B. (2017), "*Joint optimisation of order batching and picker routing in the online retailer's warehouse in China*", International Journal of Production Research, Vol. 55, No. 2, pp. 447–461.

[30] Gómez-Montoya, R.A. Correa-Espinal, A.A. and Hernández-Vahos, J.D. (2016), "*Picking Routing Problem with K homogenous*

*material handling equipment for a refrigerated warehouse*", Revista Facultad de Ingenieria, Vol. 2016, No. 80, pp. 9–20.

[31] Cortés, P. Gómez-Montoya, R.A. Muñuzuri, J. and Correa-Espinal, A. (2017), "*A tabu search approach to solving the picking routing problem for large- and medium-size distribution centres considering the availability of inventory and K heterogeneous material handling equipment*", Applied Soft Computing Journal, Vol. 53, pp. 61–73.

[32] Ratliff, H.D. and Rosenthal, A.S. (1983), "*Order-Picking in a Rectangular Warehouse: A Solvable Case of the Traveling Salesman Problem*", Operations Research, Vol. 31, No. 3, pp. 507–521.

[33] Petersen, C.G. (1997), "*An evaluation of order picking routeing policies*", International Journal of Operations and Production Management, Vol. 17, No. 11, pp. 1098–1111.

[34] Zuniga, C. A. Olivares-Benitez, E. Tenahua, A. M. and Mujica, M. A. (2015), "*A methodology to solve the Order Batching Problem*", in IFAC Proceedings, Vol. 48, pp. 1380–1386.

[35] Scholz, A. Henn, S. Stuhlmann, M. and Wäscher, G. (2016), "*A new mathematical programming formulation for the Single-Picker Routing Problem*", European Journal of Operational Research, Vol. 253, No. 1, pp. 68–84.

[36] Valle, C.A. Beasley, J.E. and Salles da Cunha, A. (2016), "*Modelling and Solving the Joint Order Batching and Picker Routing Problem in Inventories*", in Combinatorial Optimization (Vol. 9849, pp. 81–97), "Springer International Publishing.

[37] Hall, R. W. (1993), "*Distance approximations for routing manual pickers in a warehouse*", IIE Transactions, Vol. 25, No. 4, pp. 76–87.

[38] Hwang, H. Oh, Y.H. and Lee, Y.K. (2004), "*An evaluation of routing policies for order-picking operations in low-level picker-to-part system*", International Journal of Production Research, Vol. 42, No. 18, pp. 3873–3889.

[39] van Gils, T. Braekers, K. Ramaekers, K. Depaire, B. and Caris, A. (2016), "*Improving order picking efficiency by analyzing combinations of storage, batching, zoning, and routing policies*", in 7th International Conference on Computational Logistics, Hasselt University, Diepenbeek, Belgium, Springer Verlag, pp. 427-442.

[40] Petersen, C.G. and Schmenner, R. W. (1999), "*An evaluation of routing and volume-based storage policies in an order picking operation*", Decision Sciences, Vol. 30, No. 2, pp. 481–501.

[41] Henn, S. (2015), "*Order batching and sequencing for the minimization of the total tardiness in picker-to-part warehouses*", Flexible Services and Manufacturing Journal, Vol. 27, No. 1, pp. 86–114.

[42] Grosse, E.H. Glock, C.H. and Ballester-Ripoll, R. (2014), "*A simulated annealing approach for the joint order batching and order picker routing problem with weight restrictions*", International Journal of Operations and Quantitative Management, Vol. 20, No. 2, pp. 65–83.

[43] Mutingi, M. and Mbohwa, C. (2017), "*Optimizing order batching in order picking systems: Hybrid grouping genetic algorithm*", Studies in Computational Intelligence, Vol. 666, No. 1, pp. 121–140.

[44] Liu, J. Limère, V. and Van Landeghem, H. (2012), "*An improved largest gap routing heuristic for order picking*", in 10th International Industrial Simulation Conference 2012, Transportation Management College, Dalian Maritime University, Dalian City, China, EUROSIS, pp. 179–184.

[45] Goetschalckx, M. and Ratliff, D. H. (1988), "*Order Picking In An Aisle*", IIE Transactions, Vol. 20, No. 1, pp. 53–62.

[46] Dunke, F. and Nickel, S. (2016), "*Evaluating the quality of online optimization algorithms by discrete event simulation*", Central European Journal of Operations Research, pp. 1–28.

[47] Matusiak, M. de Koster, R. Kroon, L. and Saarinen, J. (2014), "*A fast simulated annealing method for batching precedence-constrained customer orders in a warehouse*", European Journal of Operational Research, Vol. 236, No. 3, pp. 968–977.

[48] Dukić, G. and Oluić, Č. (2004), "*Order-picking routing policies: Simple heuristics, advanced heuristics or optimal algorithm*", Strojniski Vestnik/Journal of Mechanical Engineering, Vol. 50, No. 11, pp. 530–535.

[49] Petersen, C. G. (1995), "*Routeing and storage policy interaction in order picking operations*", Decision Sciences Institute Proceedings, Vol. 3, pp. 1614-1616.

[50] Cano, J.A. Gómez-Montoya, R.A. and Salazar, F. (2017), "*Routing policies in multi-parallel warehouses: an analysis of computing times*", Espacios, Vol. 38, No. 51, p. 23.

[51] Koch, S. and Wäscher, G. (2016), "*A Grouping Genetic Algorithm for the Order Batching Problem in Distribution Warehouses*", Journal of Business Economics, Vol. 86, No. 1, pp. 131–153.

[52] Cheng, C.-Y. Chen, Y.-Y. Chen, T.-L. and Yoo, J.-W. (2015), "*Using a hybrid approach based on the particle swarm optimization and ant colony optimization to solve a joint order batching and picker routing problem*", International Journal of Production Economics, Vol. 170, No. 1, pp. 1–10.

[53] Hong, S. Johnson, A. L. and Peters, B. A. (2016), "*Order batching in a bucket brigade order picking system considering picker blocking*", Flexible Services and Manufacturing Journal, Vol. 28, No. 3, pp. 425–441.

[54] Cano, J.A. Correa-Espinal, A.A. and Gómez-Montoya, R.A. (2018), "*A review of research trends in order batching, sequencing and picker routing problems*", Espacios, Vol. 39, No. 4, p. 3.

[55] Lu, W. McFarlane, D. Giannikas, V. and Zhang, Q. (2016), "*An algorithm for dynamic order-picking in warehouse operations*", European Journal of Operational Research, Vol. 248, No. 1, pp. 107–122.

[56] Caron, F. Marchet, G. and Perego, A. (1998), "*Routing policies and COI-based storage policies in picker-to-part systems*", International Journal of Production Research, Vol. 36, No. 3, pp. 713–732.

# Evaluacija izbora usmeravajućih politika za poboljšanje efikasnosti skladišta

**Jose Alejandro Cano, Alexander Alberto Correa-Espinal, Rodrigo Andrés Gómez-Montoya**

Primljen (08.06.2017.); Recenziran (20.09.2017.); Prihvaćen (03.11.2017.)

**Abstrakt**

*U ovom radu izvršena je evaluacija različitih politika rutiranja (s-oblik, najveće praznine, povratne i kompozitne smernice) uz uvođenje nove heuristike nazvane Minimum Heuristic (MinH) za rešavanje problema izbora rutera. Performanse politika rutiranja i heurističke verzije MinH potvrđene su eksperimentalno. Prilikom dizajna eksperimenta ključni elementi su, broj brodova koji varira, lokacija po prelazu i veličina liste izbora. Rezultati eksperimenata pokazuju redukovane putne distance MinH hevirističkih pravila rutiranja, naglašavajući da je u svim slučajevima hevristička funkcija MinH za 14,3% bolja od postojećih politika rutiranja.*

**Ključne reči:** *eksperimentalni dizajn; heuristika; izbor narudžbine; rutiranje; skladištenje.*