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Abstract

An application of an adapted Harmony Search (HS) algorithm is proposed in this study in order to minimize manual warehouses' pickers travel distance. Firstly, the distance matrix has been determined through a hybrid algorithm, and then HS is used to compute the pickers' travel distance, developing a MATLAB® simulation model. This model performance is tested on twenty-five scenarios, resulting from variable length of the order pick lists and different manual storage configurations. Thirty picklists are evaluated for each scenario, for a total of 750 simulations. The results provided by the algorithm, compared with those returned by a metaheuristic algorithm and two heuristic routing policies, suggest that HS provides better outputs results than the remaining algorithms. The algorithm is also very efficient from a computational perspective, which allows marking out the pickers route in real-time.

Keywords: picking; manual warehouse; routing; travel distance; Floyd-Warshall; Harmony Search.

1 Introduction

Warehouses are typically used for storing or buffering (de Koster, Le-Duc & Roodbergen, 2007) raw materials, WIP, products, consisting of different areas (Roodbergen, Sharp & Vis, 2008; Cao, Jiang, Liu & Jiang, 2018). Supply chain costs are influenced by essential warehouse management activities (Pan, Shih & Wu, 2015). Logistic areas such as shipping, warehousing, receiving, and order picking are crucial to each supply chain (van Gils, Ramaekers, Caris & de Koster, 2018). Among warehouses processes, order picking is the most decisive, as a matter of fact, engraves the total operating costs for 50-70% (Isler, Righetto & Morabito, 2016; Henn & Schmid, 2013; Accorsi, Manzini & Bortolini, 2012; Petersen & Aase, 2004; Hsieh & Tsai, 2006). Typically, a customer's order is converted into a pick list, where the items' location, number, and the picking sequence are detailed. In a manual process, a picker moves into the warehouse, picking and transporting the items from stock, till the central location for packaging and distribution (Hall, 1993; Marchet, Melacini & Perotti, 2015). Among the activities of this process, traveling is the dominant component. Furthermore, travel time has no value for the picking process and is only a cost in terms of a labor hour. Hence, minimizing it is a suitable way for improving the order picking performance (Lu, McFarlane, Giannikas & Zhang, 2016). Routing policies sequence the picklist items to minimize travel times (Roodbergen, Sharp & Vis, 2008). In particular, the pickers' routing through a warehouse is a particular NP-hard traveling salesman problem (TSP) case in which travel is restricted to following aisles (Hall, 1993). In single block storage, different heuristic procedures exist for routing order pickers. In particular, six different strategies – Traversal (also known as S-shape), Return, Midpoint, Largest gap, Combined and Optimal – occur and vary from basic to structured (Petersen, 1997; Dukić & Oluić, 2014). However, although the procedures are very flexibles and simple, optimization algorithms are always the core research (Lu, McFarlane, Giannikas & Zhang, 2016; Petersen, 1999). Optimization problems come up with Heuristic algorithms to find problems better solutions, even if it is not sure to get the optimum (Raouf & Metwally, 2013). Heuristic algorithms are overcome from metaheuristic one, literally intended to find solutions using higher-level techniques (Yang, 2009).

For the TSP, few precise algorithms can identify the optimal solution, and, in any case, these algorithms only apply under specific conditions (De Santis, Montanari, Vignali & Bottani, 2018). Nonetheless, (Bouzidi & Riffi, 2014) presented a metaheuristic HS adapted to solve the TSP efficiently. Indeed, the study stated the adaptation efficacy of the HS algorithm related to other methods for solution quality, research time, and results in improvement (i.e., reduction in the percentage of errors). Downstream of these studies, this work proposes an adaptation of the HS metaheuristic algorithm in a manual warehouse to show the adaptability of this Metaheuristic algorithm to pickers' time problem. By comparing the output elaborated by the adapted HS algorithm through the results of the WWO algorithm developed by Bottani, Rinaldi, Montanari, Murino & Centobelli (2016) and with two heuristic algorithms, the paper will also establish that the proposed identify the best pickers path and is computational efficiently.

In the remainder of this paper, a deep literature analysis has been conducted about the optimization of the routing manual warehouses, contextualizing the picking process application based on the HS algorithm implementation discussing the most critical aspects in the literature. Then the traditional HS metaheuristic algorithm is described. Hence the designed framework is presented and a numerical example is also proposed to detail the computational procedure in a simple scenario fully. Subsequently the approach is applied to various more complex warehouse configurations to evaluate its capability to get better solutions to the defined problem, and the results returned are discussed. Finally, the study's key findings, discussing the implications, limitations, and suggestions for future research studies are summerized.

2 Literature analysis

Routing policies state the order sequence used by the picker to take the requested items off (Grosse & Glock, 2015). Routing order pickers can easily be interpreted as an alternative to the NP-hard TSP, and indeed, general TSP model formulations are used for the picking problem (Scholz, Henn, Stuhlmann & Wäscher, 2016). In simple warehouse layout, fast and exact algorithms for optimal route subsist whilst for complex storage configurations, no exact algorithm is achievable (Scholz & Wäscher, 2017; Theys et al. 2010). The first exact approach was proposed by Ratliff & Rosenthal (1983) using dynamic programming and is valid for a single block warehouse. A 50-aisle problem can be solved in about 1 minute, and the picking list size does not influence much on the solution time using this procedure. Nowadays, optimal routes can be designated in less than 1 second (Tarczynski, 2013). In order to minimize the pickers travel distance in a warehouse, heuristic algorithms are mostly used, e.g., the so-called S-shape (Bahrami, Aghezzaf & Limere, 2017; Roodbergen & de Koster, 2001a). Moving from this consideration, de Koster & Der Poor (1998) have compared the performance of heuristic algorithms and the optimal one. They found that the algorithm of Ratliff & Rosenthal (1983) can be modified in such a way that shortest order picking routes can be found both in centralized and decentralized warehouses. The extended algorithm optimizes in average 25% per travel time route. Roodbergen & de Koster (2001b) have constructed an algorithm, where aisle is variable for the front, the rear, and in the middle, thanks to a cross-aisle.

For difficult layout warehouse configurations, don't exist exact algorithms because the dynamic programming problem is not easy to be generalized for two or more cross-aisles. As a result, heuristic algorithms with added cross-aisle have been found (De Santis et al. 2018, Hall 1993). Theys et al. (2010) have studied the order pickers' route in warehouses with multi parallel aisle. The authors have reformed the TSP applying the Lin-Kernighan-Helsgaun algorithm and reported a 47% lower distance route compared to traditional TSP heuristics.

As mentioned above, metaheuristics are intended to find solutions using higher-level modern techniques. Some metaheuristic algorithms have been adapted and applied in the picking problem. To be more precise, Bottani, Cecconi, Vignali & Montanari (2012) have focused on items reallocation to minimize the pickers' path. In particular, the authors formulated a Genetic Algorithm for a new items' allocatio. Batch picking and picker routing problem have been jointly solved by Cheng, Chen, Chen & Yoo (2015) through an innovative hybrid-algorithm consisting of the PSO and the ACO algorithms. The PSO found the best batch picking strategy by minimizing the sum of travel distances, while the ACO searched for the most effective path for each batch. Wisittipanich & Kasemset (2015) elaborated two innovative metaheuristic algorithms – Differential Evolution (DE) and Global Local and Near-Neighbor Particle Swarm Optimization (GLNPSO) – to address warehouse cell optimization in order to minimize the entire travel distances to fill the given picking list. Bottani, Rinaldi, Montanari, Murino & Centobelli (2016) have proposed the more recent WWO algorithm (Zheng, 2015) for identifying the optimal picker routing in a rectangular warehouse. A MATLAB® model was used to optimize the adapted WWO algorithm. The authors demonstrated that this study identifies efficiently the shortest pickers' route. Cortés et. al. (2017) have formulated, solving the picking routing problems in medium and large distribution centres. Two TS-hybrid added to a general TS have implemented. The statistical analysis showed that the two-hybrid algorithms presented better results than TS and SA. De Santis et al. (2018)

introduced an algorithm to optimize the pickers' routing in warehouses. The FW-ACO algorithm combined the ACO metaheuristic and the Floyd-Warshall (FW) algorithm. The authors concluded that this study added excellent results related to other studies.

Öztürkoğlu & Hoşer (2017; 2019) have proposed the HS algorithm in the picking field; however, these studies did not focus on the routing problem. Instead, the authors have presented a layout design problem for composite warehouses. The HS algorithm finds out the tunnel position minimizing the average picker travel time in a randomized storage policy case. The authors have used the Harmony Search algorithm since more adaptable for design best solutions (Saka et al.2011).

Because metaheuristic algorithms provide better results than traditional techniques and HS algorithm in picking context is poorly discussed, this research focuses on implementing this metaheuristic algorithm for the routing problem and to optimize the travel distance and the computational time.

3 The HS algorithm

The HS algorithm (Geem, Kim & Loganathan 2001) is a metaheuristic population-based method able to solve hard and combinatorial or discrete optimization problems (Mansor, Abas, Shibghatullah & Rahman, 2017). HS follows the musical process of a musician who is searching for a perfect harmony (Lee & Geem, 2005). Musical harmony reflects the solution vector, while the musician's improvisations reflect the local/global search schemes followed by the algorithm during the optimization. When improvising, a musician can: 1) repeat a famous tune exactly from his/her memory; 2) play something similar to that tune, again on the basis of its memory; or 3) compose a new set of notes randomly. These three processes can be translated into as many options in a quantitative optimization process, namely: 1) the usage of harmony memory (HM); 2) the process of pitch adjusting; and 3) randomization (Yang, 2009; Geem, Kim & Loganathan, 2001).

The steps for the application of the HS algorithm are as follows:

- Step 1. Initialization of the problem and parameters setting: harmony memory size (HMS), harmony memory considering rate (HMCR), pitch adjusting rate (PAR) and number of improvisations (NI);
- Step 2. Initialization of the HM;
- Step 3. Improvisation of a new harmony from HM on the basis of memory considerations, pitch adjustments, and random selection;
- Step 4. Inclusion of the newly generated harmony in HM if it performs better than the worst harmony;
- Step 5. If termination criteria are not satisfied, return to Step 3.

The overall scheme of the HS algorithm is shown in Figure 1.

Insert Figure 1

HS algorithm was very appropriate to optimize problems like job shop scheduling (Wanga, Pan & Tasgetiren, 2011), university programs formulation (Al-Betar, Khader & Zaman, 2012; Shahrakia & Ebrahimib, 2015) and network design (Liu, Yu & Li, 2012; Baskan, 2014; Geem, Tseng & Williams, 2009).

3.1 Problem initialization and parameter setting

For a minimization problem, the problem is formulated as follows:

$$\begin{aligned} &Minimize\ f(x) \\ &subject\ to\ x_i \in X_i,\ \ i = 1,2,\dots,N \end{aligned} \tag{1}$$

where:

$f(x)$ is the objective function;

x is a possible solution which typically consists in N decision variables (x_i);

X_i denotes the possible range of values for each variable, i.e.

$X_i = \{x_i(1), x_i(2), \dots, x_i(k)\}$ for discrete decision variables $\left(x_i(1) < x_i(2) < \dots < x_i(K)\right)$; or

${}_Lx_i \le X_i \le {}_Ux_i$ for continuous decision variables. In this case, ${}_Lx_i$ and ${}_Ux_i$ are the lower and upper bounds for each decision variable, respectively;

K is the number of possible values for a discrete variable.

As far as the remaining HS parameters are concerned, HMS is the number of solution vectors (i.e. the total number of members in the population) in the HM. HMCR is instead a parameter of the improvisation process, used to determine whether the value of a decision variable is to be selected for the solution stored in the HM or randomly chosen from the available range of possible values. PAR is used to determine whether the decision variables are to be adjusted to a neighbor value; finally, NI corresponds to the number of iterations allowed to reach convergence (Al-Betar, Khader & Zaman, 2012; Das, Mukhopadhyay, Roy, Abraham & Panigrahi, 2011).

3.2 HM initialization

For initialization purpose, the HM matrix is to be filled with as many randomly generated solution vectors as the HMS.

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \dots & x_{N-1}^2 & x_N^2 \\ \dots & \dots & \dots & \dots & \dots \\ x_1^{HMS-1} & x_2^{HMS-1} & \dots & x_{N-1}^{HMS-1} & x_N^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \dots & x_{N-1}^{HMS} & x_N^{HMS} \end{bmatrix} \tag{2}$$

The number of rows, in particular, equals the HMS, while the number of columns equals the number of variables of each possible solution.

3.3 Harmony improvisation from HM

During improvisation, a new harmony vector, $x' = (x'_1, x'_2, \dots, x'_N)$, is to be generated from HM based on memory considerations, pitch adjustments, and random selection. In the memory consideration, the value of the first decision variable (x'_1) for the new vector can be chosen from any of the values in the specified HM range $\left(x_1'^{1} \sim x_1'^{HMS}\right)$. Values of the remaining decision variables (x'_i) can be chosen in the same manner, or, alternatively, new values can be determined using the HMCR parameter, as follows:

$$x'_i = \begin{cases} x'_i \in \left\{x_i'^{1}, x_i'^{2}, \dots, x_i'^{HMS}\right\} & with\ probability\ HMCR \\ x'_i \in X_i & with\ probability\ (1 - HMCR) \end{cases} \quad (3)$$

Every element of the new harmony vector, $x' = (x'_1, x'_2, \dots, x'_N)$, is therefore evaluated to check whether it should be pitch-adjusted. This procedure makes use of the PAR, that sets the rate of adjustment for the pitch chosen from the HM as follows:

$$pitch\ adjusting\ decision\ for\ x'_i = \begin{cases} Yes & with\ probability\ \ PAR \\ No & with\ probability\ \ (1 - PAR) \end{cases} \quad (4)$$

The value of $(1 - PAR)$ sets the rate of doing nothing. If the pitch adjustment decision for $x_i$is Yes and x'_i is assumed to be $x_i(k)$, i.e., the k^{th} element in X_i, the pitch-adjusted value of $x_i(k)$ will be:

$$x'_i = x_i(k + m) \quad for\ discrete\ variables$$

$$x'_i = x'_i + \alpha \qquad for\ continuous\ variables \quad (5)$$

where:

$m \in \{\dots, -2, -1, 1, 2, \dots\}$ is the neighboring index;

α is the product $bw * u$;

bw is an arbitrary distance bandwidth for the continuous design variable; and

$u \in [-1; 1]$ is a uniform probability distribution.

HMCR and PAR help the algorithm find globally and locally improved solutions, respectively (Afkousi-Paqaleh, Rashidinejad & Pourakbari-Kasmaei, 2010).

3.4 HM updating

Whenever the new harmony vector $x' = (x'_1, x'_2, \dots, x'_N)$ fits the objective function better than the worst harmony vector in the HM, the new harmony will replace the existing worst harmony in the HM.

3.5 Termination criterion

If the termination criterion (maximum *NI*) is satisfied, the computation stops. Otherwise, step 3 and step 4 are repeated.

4 The proposed approach: adaptation of HS algorithm for picking

The framework of the approach proposed in this study is shown in Figure 2. In Table 1 the relating notation is presented.

Insert Table 1

From figure 2 it can be seen that the adapted approach includes additional steps compared to the traditional HS metaheuristic, such as some preliminary steps and the implementation of the FW algorithm (cf. (De Santis, et al., 2018)). In particular, this latter algorithm is required to implement and develop the HS algorithm for searching the shortest distance in different warehouses configurations. For clarity, a description of the main steps of the approach is provided in the section that follows; for further details about graphical storage depiction the reader is referred to (De Santis, et al., 2018).

Insert Figure 2

4.1 Warehouse layout structure

The layout structure consists of several picking aisles that have storage locations on both sides. Order pickers can change pick aisle using the cross-aisles positioned perpendicular to the aisles themselves (Roodbergen, Sharp & Vis, 2008). Every time cross-aisles are present, the number of cross aisles equals the number of blocks plus one (Roodbergen & de Koster, 2001a). The main advantage of having extra cross-aisles in a warehouse is the increased number of routing options, resulting in lower travel distance (Vaughan & Petersen, 1999). Three blocks with five aisles with 6 storage locations per aisle side is represented in Figure 3. Solid black squares in the figure indicate the exemplary positions in the rack – picking location – from which items have to be picked (Roodbergen & Vis, 2006).

Insert Figure 3

4.2 Model hypothesis

The proposed model is explained through the following hypotheses:

- Multi-block rectangular warehouse;
- No vertical movements to pick up items (i.e., low-level picking);
- During the picker tour, the direction can be changed;
- Aisles can be traveled in both directions;
- The picking aisle is narrow enough to pick items from both sides without covering additional distance;

- The picker starts from the bottom left corner of the depot and returns back once the picklist is completed (i.e., one picker per picking list);
- The amount of items picked in each picklist never saturates the capacity of the picker; hence, capacity constraints are not considered in modeling the problem.

4.3 The FW and HS algorithm

Calculating the shortest path between all vertices in an edge-weighted directed graph through the FW algorithm implementation (Hougardy, 2010). The FW algorithm, determining the shortest path using the graph theory, makes use of the "distance matrix", built as follows:

Step 1. Initialization. The solution matrix same as the input graph is initialized. At the start point process (*h=0*), the distance matrix structure is initialized as follows:

$$D^{(0)} = \left(D_{ij}^{0}\right) \, where \; D_{ij}^{0} = \begin{cases} d_{ij}, if \; a \; direct \; route \; connects \; node \; i \; and \; j \\ 0, \;\; if \; i = j \\ \infty, if \; no \; direct \; routes \; connect \; node \; i \; and \; j \end{cases} \tag{6}$$

Step 2. Matrix update. The solution matrix is updated by considering all vertices as an intermediate vertex. A new node is then added for the computation of the shortest path between nodes *i* and *j*. Therefore, the distance matrix is updated to D_{ij}^{h} applying the following formula:

$$D_{ij}^{h} = min\left\{D_{ij}^{h-1}, D_{ih}^{h-1} + D_{hj}^{h-1}\right\} \, if \; i \neq j \tag{7}$$

D_{ij}^{h} is the nodes i to j updated distance considering h intermediate nodes $\{1, \dots, h\}$.

Step 3. Checking the termination condition. If $h = NT$, the algorithm ends. The D_{ij}^{NT} element of the distance matrix is the length of the shortest path from nodes *i* to *j*.

The FW algorithm is an input in the proposed model. It is the set of the total number of nodes (*NT)* indicating the picking positions where to pick up the item requested by the customer. The algorithm generates a *NT*NT* distance matrix. The FW algorithm was implemented in MATLAB®, to automatically determine the distance matrices in the different warehouse configurations analyzed.

Starting from the FW algorithm's distance matrix, the next step is to determine the shortest path for a given picklist through the HS algorithm.

Step 1. The first step is the same of that of the original algorithm described above. In particular, the optimization problem is defined as follows:

$$Minimize \; \sum_{j=1}^{np-1} D_{j,j+1}, \quad \forall j = 1,2, \dots, np \tag{8}$$

Moreover, as mentioned before, the HS algorithm parameters required to solve the optimization problem are specified. A static method has been chosen for setting the parameters' value.

Step 2. This is the same as the second step (HM initialization) of the traditional HS procedure.

Step 3. This is almost the same as the third step (Harmony improvisation from HM) of the traditional HS procedure. The new harmony vector, $x^{new} = \{x_1^{new}, \dots x_j^{new}, x_{np}^{new}\}, j = 1, \dots, np$, will be generated using memory considerations, pitch adjustments, and random selection. The choice of the values for the decision variables follows the same rules of the harmony improvisation, and in particular any value can be chosen from the specified HM range $\left(x_1^{new1} \sim x_1^{newHMS}\right)$ or, alternatively, new values can be determined using the HMCR parameter:

$$x_j^{new} = \begin{cases} x_{i,j}^{HM} \; with\, probability\, HMCR\; (i = rand[1, HMS]\; and\; j\; fixed) \\ x_{i,J}^{HM}\, with\, probability\; 1 - HMCR\; (i = rand\; [1, HMS]\; and\; j = rand[1, np] \end{cases} \quad (9)$$

Then, the components of the new harmony vector, $x^{new} = (x_1^{new}, x_2^{new}, \dots, x_N^{new})$, should be analysed to determine whether they should be pitch-adjusted; the procedure for pitch-adjustment is described in eq.10:

$$x_j^{new} = \begin{cases} x_{i,j}^{HM} & with\, probability \quad PAR \\ x_j^{new} & with\, probability \quad (1 - PAR) \end{cases} \quad (10)$$

Step 4. As per the traditional HS approach, in case the new harmony vector, x^{new}, fits the objective function better than the worst harmony vector in the HM, the new harmony is kept in the HM, while the worst harmony is removed.

Step 5. If the termination condition (i.e. maximum *NI*) has been reached, the computation stops. Otherwise, the algorithm is repeated stating from steps 3.

4.4 Numerical example

For the sake of clarity, the application of the proposed approach is shown in a numerical example in this section. For testing purpose, a simple scenario (small warehouse and short picklist) is taken, to allow the computational procedure to be almost entirely reproduced. The chosen warehouse layout consists of 2 blocks, with 3 aisles per block and 3 storage locations per aisle side; k_x=5 [m] and k_y=1 [m] are set for this warehouse. A picklist composed of *np*=7 elements (nodes: 2, 7, 11, 14, 16, 19, 23) is considered.

Insert Figure 4

As Figure 4 shows, the graph of this representative warehouse consists of 27 total nodes (*NT*). The cells highlighted to represent the storage locations of items (7) in the picklist. The distance matrix (27*27) generated by the FW algorithm is shown in Table 2.

Insert Table 2

Once the distance matrix has been obtained, the minimum path is calculated by implementing the HS algorithm.

As mentioned above, HMCR and PAR help the HS algorithm find globally and locally improved solutions (Dell'orco, Baskan & Marinelli, 2013). To ensure good performance of the algorithm, Geem, 2006; Bouzidi & Riffi, (2014) have recommended that HMCR values range from 0.70 to 0.95, 0.20, PAR values from 0.2 to 0.50, and HMS values from 10 to 50. In line with these considerations, and after performing a preliminary series of hand-tuning experiments on the adapted HS algorithm, the parameters were set as follows: HMS=np; HMCR=0.95; PAR=0.45; *NI*=500.

The modified HS algorithm was implemented under the commercial software MATLAB®. The simulation procedure was run on an AMD Athlon, 3GHz with 4GB RAM desktop computer equipped with Windows 7 Professional. Once the last iteration has been completed, the HS algorithm returns the following picking sequence, whose path is shown in Figure 5.

0 – 11 – 19 – 23 – 14 – 16 – 7 – 2 – 0

Insert Figure 5

The specific results of the performance evaluation for the HS algorithm, shown for distance, computational time, and convergence, are highlighted in Figure 6 and Table 3.

Insert Figure 6

Insert Table 3

The results in Table 3 show that the shortest path, for this configuration, is 42 meters, obtained after 241 iterations (see also Figure 6), i.e., less than 5% of the whole set of solutions (7! = 5040) for the problem under examination. Moreover, the computational time required to run the algorithm amounts to 2.51 seconds.

5 Application and discussion

5.1 Warehouse layouts

An exhaustive test of performance of the proposed approach was made on five warehouse configurations, obtained by varying the number of blocks (1-5, step 1); length of the order picklist was varied as well (10-50 items, step 10). Twenty-five scenarios (5 sizes of pick lists x 5 warehouse configurations) were examined overall, and 30 different pick lists were tested for each scenario to ensure significance of the results obtained; the total number of simulations was 750.

The experiments were carried out considering a representative warehouse layout, with longitudinal aisles, where shelves are placed on both sides, and with 32 picking positions for each aisle side. In the multi-block layouts, the picking positions (*ppa* and *ppb*) in the sub-aisles of the two- and four-block warehouses are equally distributed and accounts for 16 and 8, respectively. In the three- and five-block configurations, instead, the picking positions are divided differently. In the first case (three blocks), in the sub-aisles of two blocks farthest from the depot, there are ten picking positions, while in the remaining block, there are 12 picking positions. In the five-block layout, there are 6 picking positions in the sub-aisles of the four blocks furthest from the depot, while there are 8 picking positions in the remaining block.

In general, while the total number of picking positions remains the same (i.e., 640) in each warehouse layout, the number of *NT* changes (and in particular increases) as a function of the number of blocks, consistently with the increase in the number of cross-aisles and, therefore, of service nodes.

A rectangular warehouse, with a base of 55 meters and a depth that ranges from 40 to 52 meters depending on the number of blocks, is assumed. The aisle width is 3 meters.

5.2 Experimental results

As mentioned before, the validation of the HS algorithm results was made by comparing the travel distance obtained with that resulting from the application of one metaheuristic algorithm (i.e., WWO algorithm) and two traditional routing policies (i.e., S-shape and largest gap). The WWO was chosen as a suitable algorithm for benchmarking the results of the proposed approach as WWO proved to be always able to identify the global optimal solution in the tests carried out by Bottani, Rinaldi, Montanari, Murino & Centobelli (2016). Table 4 reports the results of the proposed approach in terms of distance travelled and computational time, depending on the warehouse configuration and problem complexity; these outcomes were obtained with the parameters settings detailed in Section 4. In Table 4, the percentage of the standard deviation of the outcomes is also reported. Data in bold highlight the best result(s) obtained for each scenario, as well as the algorithm(s) that returned the most effective solution(s).

Insert Table 4

5.3 Discussion

From the results in Table 4, the following primary considerations emerge. In terms of the picking distance, it is evident that the HS and WWO algorithms provide almost identical results. In particular, the HS algorithm generates better solutions in 18 configurations out of 25, compared to 7 for the WWO algorithm. To be more precise, as can be seen from Table 4, with ten order lines the HS algorithm provided slightly worse results than the WWO (i.e., 200.60 vs. 200.00 meters) in one configuration only, i.e., the three-block warehouses; the same consideration holds true for order lines of 30 and 50 items. With order lines of 20 or 40 items, instead, the WWO algorithm turned out to be better than the HS in two configurations (i.e., the three- and four-block warehouses). Nonetheless, the travel distance returned by the HS is better than that of the WWO algorithm by approximately 0.37% on average. In four- and five-block configurations, the improvement is more significant, reaching 0.55% and 0.59%, respectively. Moreover, in five-block warehouses, the HS approach generates solutions that are always better than those of the WWO algorithms.

These outcomes do not contradict the results reported in Bottani, Rinaldi, Montanari, Murino & Centobelli (2016). Indeed, although these authors found that WWO was always able to find the optimal solution in their testing scenarios, the configurations tested referred to one-block warehouses only, while no tests were proposed for multiple-blocks warehouses. Therefore, the outcomes of the present study rather complement the findings previously available and allow us to argue that the HS approach overcomes the WWO algorithm for complex warehouse configurations.

Outcomes also show that the performance of the two metaheuristics varies as a function of the picklist size. In general terms, the HS overcomes the WWO algorithm, with a peak of 1.05% reduction in the length of the picking tour for pick lists of 30 items. A greater size of the picking list involves a lower difference in the performance of the two algorithms (0.23% and 0.05% respectively for 40 and 50 items in the picking list). The standard deviation of the calculated distances decreases as well: this is probably due to the fact that with more items in the picklist, the positions of items become closer in the warehouse, so that the tour is almost defined and the heuristic algorithms have less room for shortening the total travel distance. On the contrary, for small pick lists, items to be picked are sparse in the warehouse, so that their specific picking position and the way it is reached can make the difference in terms of the total distance travelled.

Compared to the remaining heuristic routing policies, it is immediate to see that the travel distance returned by the modified HS algorithm is always shorter; this result was expected (and obviously desirable); in fact, to prove its effectiveness, it is almost essential that a newly proposed metaheuristic algorithm overcomes at least the performance of the heuristic routing policies. The results obtained show that the modified HS approach generates a travel distance, which, on average, is 26.90% and 11.46% shorter than that obtained by applying the S-shape and largest gap policies, respectively.

With respect to the computational time, results show once again that the performance of the HS algorithm is much better than that of the WWO algorithm. In particular, HS shows an average computational time approximately 24% lower than that of WWO. This effective performance can be attributed to the quite simple structure of the HS algorithm as well as to its combination with the FW approach, which in previous studies (e.g. De Santis, Montanari, Vignali & Bottani, 2018) was demonstrated to enhance the performance of metaheuristic algorithms.

6 Conclusions

This study has proposed an adapted approach to reduce the picking distance in manual warehouses. To be more precise, this paper has: 1) suggested the combination of the HS metaheuristic algorithm with the FW one; 2) shown its application to the picking problem in a manual warehouse; and 3) tested its performance in terms of travel distance and computational time.

The adapted approach includes some preliminary steps, which basically refer to the implementation of the FW algorithm; this latter was applied as a useful approach to mathematically reproduce the different warehouse configurations and to preliminarily derive the shortest distance between each pair of nodes in the warehouse. Then, the proposed framework includes 5 steps that reflect the logic of the traditional HS algorithm; this latter is used to determine the shortest distance for each picking tour in the various warehouse configurations. All steps were coded in MATLAB® to be run automatically.

The implementation of the proposed approach was first shown with respect to a typical warehouse layout, simple enough to allow the detailed description of all the steps of the procedure. The algorithm performance was then tested on five different warehouse configurations, with variable number of blocks and picking list size. Twenty-five scenarios were considered overall, with 30 random picking lists for each of them, for a total of 750 simulations.

From a theoretical perspective, the outcomes obtained highlights how the proposed approach outperforms both the heuristic routing policies and the WWO algorithm in determining the shortest route of pickers. Moreover, by analysing the computational time, it is easy to deduce that the HS algorithm adds quality compared to some well-known heuristic policies and to the WWO algorithm. In summary this study has proposed a metaheuristic hybrid algorithm whose results encourage its application in practice. Besides, the approach proposed in this paper contains a set of additional steps compared to the traditional HS algorithm, which enhance its effectiveness in minimising the travel distances of pickers in warehouses. From a practical perspective, this paper focuses on manual warehouses and has been tested in some selected configurations. Nonetheless, this study can be implemented in additional layouts or configurations, to test its performance in further scenarios. As the proposed approach was effective in improving the order picking performance in the scenarios tested, it is expected to provide interesting outcomes in different configurations too.

Although the outcomes of this paper can be seen as of general validity, this paper has some limitations that should be mentioned. As an example, in this study, random storage of items in the warehouse was assumed; however, for picking lists of small sizes it would probably be preferable to use a class-based storage policy, to further decrease the travel distance. For picking lists of greater size, instead, a random storage policy is likely to provide results similar to the class-based one, which suggests that testing this latter policy would not be essential. Moreover, in this study, the picker starts from the receiving area and returns to the same place once he has picked the full set of items in the picking list; however, for order pick lists of 40 or 50 items, it would be appropriate to include the capacity of the picker as a constraint of the problem. To this end, it could be interesting to apply a multi-objective optimization procedure to reduce the travel distance and maximize the saturation of the picker's capacity, to evaluate whether (and to what extent) the capacity of the picker could affect the travel distance. Moreover, further research might take into consideration a different type of layouts, with a particular attention to non-conventional warehouses (Fishbone, U-Shaped, and Flying-V). Indeed, changing the warehouse layout would certainly involve variations in the distance travelled and in the time taken to complete a picking tour, which could lead to additional insights. Further research may also concern on the presence of different width of aisles (wide aisle o ultra-narrow aisle), which would lead to congestion in the aisles.

References

[1] R. de Koster, T. Le-Duc e K. Roodbergen, «Design and control of warehouse order picking: a literature review,» *European Journal of Operational Research,* vol. 182, n. 2, pp. 481-501, 2007.

[2] K. Roodbergen, G. Sharp e I. Vis, «Designing the layout structure of manual order picking areas in warehouses,» *IIE Transactions (Institute of Industrial Engineers),* vol. 40, n. 11, pp. 1032-1045, 2008.

[3] W. Cao, P. Jiang, B. Liu e K. Jiang, «Real-time order scheduling and execution monitoring in public warehouses based on radio frequency identification,» *International Journal of Advanced Manufacturing Technology,* vol. 95, n. 5-8, pp. 2473-2494, 2018.

[4] J.-H. Pan, P.-H. Shih e M.-H. Wu, «Order batching in a pick-and-pass warehousing system with group genetic algorithm,» *Omega,* vol. 57, pp. 238-248, 2015.

[5] T. van Gils, K. Ramaekers, A. Caris e R. 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, pp. 1-15, 2018.

[6] C. Isler, G. Righetto e R. Morabito, «Optimizing the order picking of a scholar and office supplies warehouse,» *International Journal of Advanced Manufacturing Technology,* vol. 87, n. 5-8, pp. 2327-2336, 2016.

[7] S. Henn e V. Schmid, «Metaheuristics for order batching and sequencing in manual order picking systems,» *Computers & Industrial Engineering,* vol. 66, pp. 338-351, 2013.

[8] R. Accorsi, R. Manzini e M. Bortolini, «A hierarchical procedure for storage allocation and assignment within an order-picking system. A case study,» *International Journal of Logistics Research and Applications,* vol. 15, n. 6, pp. 351-364, 2012.

[9] C. Petersen e G. Aase, «A comparison of picking, storage, and routing policies in manual order picking,» *International Journal of Production Economics,* vol. 92, n. 1, pp. 11-19, 2004.

[10] L.-F. Hsieh e L. Tsai, «The optimum design of a warehouse system on order picking efficiency,» *The International Journal of Advanced Manufacturing Technology,* vol. 28, n. 5-6, pp. 626-637, 2006.

[11] R. Hall, «Distance approximations for routing manual pickers in a warehouse,» *IIE Transactions (Institute of Industrial Engineers),* vol. 25, n. 4, pp. 76-87, 1993.

[12] G. Marchet, M. Melacini e S. Perotti, «Investigating order picking system adoption: a case-study-based approach,» *International Journal of Logistics Research and Applications,* vol. 18, n. 1, pp. 82-98, 2015.

[13] W. Lu, D. McFarlane, V. Giannikas e Q. Zhang, «An algorithm for dynamic order-picking in warehouse operations,» *European Journal of Operational Research,* vol. 248, pp. 107-122, 2016.

[14] C. Petersen, «An evaluation of order picking routeing policies,» *International Journal of Operations & Production Management,* vol. 117, n. 11, pp. 1098-1111, 1997.

[15] G. Dukić e Č. Oluić, «Order-picking routing policies: simple heuristics, advanced heuristics or optimal algorithm,» *Journal of Mechanical Engineering,* vol. 50, n. 11, pp. 530-535, 2014.

[16] C. Petersen, «The impact of routing and storage policies on warehouse efficiency,» *International Journal of Operations & Production Management,* vol. 19, n. 10, pp. 1053-1064, 1999.

[17] O. Raouf e M.-B. Metwally, «A survey of harmony search algorithm,» *International Journal of Computer Applications,* vol. 70, n. 28, pp. 17-26, 2013.

[18] X.-S. Yang, «Harmony search as a metaheuristic algorithm,» *Studies in Computational Intelligence,* vol. 191, pp. 1-14, 2009.

[19] R. De Santis, R. Montanari, G. Vignali e E. Bottani, «An adapted ant colony optimization algorithm for the minimization of the travel distance of pickers in manual warehouses,» *European Journal of Operational Research,* vol. 267, pp. 120-137, 2018.

[20] M. Bouzidi e M. Riffi, «Adaptation of the harmony search algorithm to solve the travelling salesman problem,» *Journal of Theoretical and Applied Information Technology,* vol. 62, n. 1, pp. 154-160, 2014.

[21] E. Bottani, M. Rinaldi, R. Montanari, T. Murino e P. Centobelli, «An adapted water wave optimization algorithm for routing order pickers in manual warehouses,» in *Proceedings of the Summer School Francesco Turco,* 2016.

[22] H. Grosse e C. Glock, «The effect of worker learning on manual order picking processes,» *International Journal of Production Economics,* vol. 170, pp. 882-890, 2015.

[23] A. Scholz, S. Henn, M. Stuhlmann e G. Wäscher, «A new mathematical programming formulation for the single-picker routing problem,» *European Journal of Operational Research,* vol. 253, pp. 68-84, 2016.

[24] A. Scholz e G. Wäscher, «Order batching and picker routing in manual order picking systems: the benefits of integrated routing,» *Central European Journal of Operations Research,* vol. 25, n. 2, pp. 491-520, 2017.

[25] C. Theys, O. Bräysy, W. Dullaert e B. Raa, «Using a TSP heuristic for routing order pickers in warehouses,» *European Journal of Operational Research,* vol. 200, n. 3, pp. 755-763, 2010.

[26] H. Ratliff e A. Rosenthal, «Order-Picking in a rectangular warehouse: a solvable case of the traveling,» *Operations Research,* vol. 31, n. 3, pp. 507-521, 1983.

[27] G. Tarczynski, «Warehouse real-time simulator – how to optimize order picking time,» *SSRN Electronic Journal,* 2013.

[28] B. Bahrami, E.-H. Aghezzaf e V. Limere, «Using simulation to analyze picker blocking in manual order picking systems,» *Procedia Manufacturing,* vol. 11, pp. 1798-1808, 2017.

[29] K. Roodbergen e R. De Koster, «Routing methods for warehouses with multiple cross aisles,» *International Journal of Production Research,* vol. 39, n. 9, pp. 1865-1883, 2001.

[30] R. de Koster e E. Der Poor, «Routing orderpickers in a warehouse: a comparison between optimal and heuristic solutions,» *IIE Transactions,* vol. 30, pp. 469-480, 1998.

[31] E. Bottani, M. Cecconi, G. Vignali e R. Montanari, «Optimisation of storage allocation in order picking operations through a genetic algorithm,» *International Journal of Logistics: Research and Applications,* vol. 15, n. 2, p. 127–146, 2012.

[32] C.-Y. Cheng, Y.-Y. Chen, T.-L. Chen e J.-W. Yoo, «Using a hybrid approach based on the particle swarm optimization and ant colony optimization to solve a joint order batching and picker routing problem,» *Internation Journal of Production Economics,* vol. 170, pp. 805-814, 2015.

[33] W. Wisittipanich e C. Kasemset, «Metaheuristics for warehouse storage location assignment,» *Chiang Mai University Journal of Natural Sciences,* vol. 14, n. 4, pp. 361-377, 2015.

[34] Y.-J. Zheng, «Water wave optimization: A new nature-inspired metaheuristic,» *Computers and Operations Research,* vol. 55, pp. 1-11, 2015.

[35] P. Cortés, R. Gómez-Montoya, J. Muñuzuri e A. Correa-Espinal, «A tabu search approach to solving the picking routing problem forlarge- and medium-size distribution centres considering theavailability of inventory and K heterogeneous material handlingequipment,» *Applied Soft Computing Journal,* vol. 53, pp. 61-73, 2017.

[36] Ö. Öztürkoğlu e D. Hoşer, «A polynomial time tour algorithm for order picking operations in warehouses and new aisle designs,» in *Proceedings of the International Conference on Industrial Engineering and Operations Management*, Rabat, Marocco, 2017.

[37] Ö. Öztürkoğlu e D. Hoser, «A discrete cross aisle design model for order-picking warehouses,» *European Journal of Operational Research,* vol. 275, n. 2, pp. 411-430, 2019.

[38] M. Saka, I. Aydogdu, O. Hasancebi e Z. Geem, «Harmony search algorithms in structural engineering,» *Studies in Computational Intelligence,* vol. 359, pp. 145-182, 2011.

[39] Z. Geem, J. Kim e G. Loganathan, «A new heuristic optimization algorithm: harmony search,» *Simulation,* vol. 76, pp. 60-68, 2001.

[40] N. Mansor, Z. Abas, A. Shibghatullah e A. Rahman, «Modified parameters of harmony search algorithm for better searching,» in *IOP Conference Series: Materials Science and Engineering,* Melaka (Malaysia), 2017.

[41] K. Lee e Z. Geem, «A new meta-heuristic algorithm for continuous engineering optimization: harmony search theory and practice,» *Computer Methods in Applied Mechanics and Engineering,* vol. 194, n. 36-38, pp. 3902-3933, 2005.

[42] L. Wanga, Q.-K. Pan e M. Tasgetiren, «A hybrid harmony search algorithm for the blocking permutation flow shop scheduling problem,» *Computers & Industrial Engineering,* vol. 61, n. 1, pp. 76-83, 2011.

[43] M. Al-Betar, A. Khader e M. Zaman, «University course timetabling using a hybrid harmony search metaheuristic algorithm,» *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews,* vol. 42, n. 5, pp. 664-681, 2012.

[44] A. Shahrakia e S. Ebrahimib, «A new approach for forecasting enrollments using harmony search algorithm,» *Journal of Intelligent & Fuzzy Systems,* vol. 28, n. 1, pp. 279-290, 2015.

[45] L. Liu, H. Yu e L. Li, «Distribution network reconfiguration based on harmony search/genetic hybrid algorithm,» in *China International Conference on Electricity Distribution, CICED*, Shanghai (China), 2012.

[46] O. Baskan, «Harmony search algorithm for continuous network design problem with link capacity expansions,» *KSCE Journal of Civil Engineering*, vol. 18, n. 1, pp. 273-283, 2014.

[47] Z. Geem, C.-L. Tseng e J. Williams, «Harmony search algorithms for water and environmental systems,» *Studies in Computational Intelligence*, vol. 191, pp. 113-127, 2009.

[48] S. Das, A. Mukhopadhyay, A. Roy, A. Abraham e B. Panigrahi, «Exploratory power of the harmony search algorithm: Analysis and improvements for global numerical optimization,» *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics,* vol. 41, n. 1, pp. 89-106, 2011.

[49] M. Afkousi-Paqaleh, M. Rashidinejad e M. Pourakbari-Kasmaei, «An implementation of harmony search algorithm to unit commitment problem,» *Electrical Engineering*, vol. 92, n. 6, pp. 215-225, 2010.

[50] K. Roodbergen e R. de Koster, «Routing order pickers in a warehouse with a middle aisle,» *European Journal of Operational Research*, vol. 133, n. 1, pp. 32-43, 2001.

[51] T. Vaughan e C. Petersen, «The effect of warehouse cross aisles on order picking efficiency,» *International Journal of Production Research*, vol. 37, n. 4, pp. 881-897, 1999.

[52] K. Roodbergen e I. Vis, «A model for warehouse layout,» *IIE Transactions (Institute of Industrial Engineers)*, vol. 38, n. 10, pp. 799-811, 2006.

[53] S. Hougardy, «The Floyd–Warshall algorithm on graphs with negative cycles,» *Information Processing Letters,* vol. 110, p. 279–281, 2010.

[54] M. Dell'orco, O. Baskan e M. Marinelli, «A harmony search algorithm approach for optimizing traffic signal timings,» *Promet - Traffic - Traffico,* vol. 25, n. 4, pp. 349-358, 2013.

[55] Z. Geem, «Optimal cost design of water distribution networks using harmony search,» *Engineering Optimization*, vol. 38, n. 3, pp. 259-277, 2006.