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Proposal of a new metaheuristic for the picker's route designation in warehouse management

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Abstract

The order picking is the most time- and work-consuming component of total warehouse operations. As travelling takes up the most of the order picking time, reduction of the picker's route length can help decreasing it. The aim of the research is to develop a new routing *metaheuristic* with the use of R language for designing the picker's route in warehouse management that will provide better results than other, widely used routing heuristics. We apply the proposed *metaheuristic* in the classical, *picker-to-parts*, one-block rectangular warehouse with random storage assignment. We compare the results with the results obtained by its means with the most widely used routing heuristics: *s-shape*, *return* and *midpoint*. We assume the shared storage and various take-out strategies. Locations to be visited were obtained by using the COPRAS (COmplex PRoportial ASsessment) method. The criterion for assessment of applied *metaheuristic* is the length of the picking route for every take-out strategy. Obtained results indicate that the proposed *metaheuristic* provided shorter routes as compared with other routing heuristics.

Keywords: *warehouse management; order picking; shared storage; multi-criteria decision-making; routing metaheuristic; simulation methods*

1. Introduction

Warehouse management plays a very important role in running the whole company. The total warehouse activities constitute about 39% of total logistic costs in Europe and 23% in the U.S.A. [10]. At the beginning of the 21$^{\text{st}}$ century about 80% companies still utilised the classical, manual *picker-to-parts* systems [4]. More recent research indicated that this share had dropped to 74%[17]. The latest research suggests the existence of this type of warehouses in 60% of companies [16]. In such systems about 55% of all warehouse operating costs are generated by order picking [1]. Time of order picking consists of four main activities (Table 1).

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Table 1. Division of order-picking time (*Source*: [1])

Activity	Percentage of order-picking time
Travelling	55%
Searching	15%
Extracting	10%
Other activities	20%

Because travelling constitutes over half of total order picking time, it is the biggest area for improvement. This can be done by applying the appropriate storage assignment, warehouse layout and routing technique. When we consider the storage assignment, the following are used [13]:

- random,
- closest-open-location,
- dedicated,
- class-based,
- family-grouping.

Random storage assignment means that when a company replenishes its items, they are assigned randomly in the warehouse. As a result, the same items become scattered across the warehouse – they can be stored in various, sometimes very distant locations. It is worth nothing that if such items arrive to the warehouse in different replenishment orders, they are assigned to various locations. Even if they have the same identification codes, they can be described by different other identifier, like arrival date, which can help in distinguishing them with respect to the storage time. Although this type of storage assignment is rarely used in practice, it is the theoretical benchmark for comparison with more organised ones.

The closest-open-location storage assignment is characterised by assigning incoming items to the closest to the I/O (depot) point available location in the warehouse. This method is very simple and is often used when the pickers select storage locations themselves. In long turn, this storage assignment converges to the random one.

Dedicated storage means that each item has its own location or several locations (if the stored amount of this item exceeds the capacity of a single location). The virtue of this storage assignment is that it is relatively easy to remember for the pickers and does not require a specialised warehouse management system. The main drawback of such approach is poor space utilisation. This system is rarely used in practice and only for special items that, due to their size, need to have dedicated space in the warehouse. However, this storage assignment should be used for as small number of items as possible [11].

Class-based storage assignment is one of the most widely used ones. The items stored in a warehouse are divided with accordance to appropriate class membership. The most natural division criterion is their turnover. The most popular division method is based on Pareto's approach (80-20 rule). It states that 20% of the fastest-moving items account for 80% of the company's total turnover – these products constitute class A. Class B consists of 30% of medium-moving items that make up 15% of the company's total turnover and class C – 50% of the slowest-moving items that constitute the remaining 5% of the company's total turnover. Of course, the 80-20 rule is the most typical one, but there are possible other rules, like 85-15, or 50-30 [11, 13]. Items belonging to the class A are usually stored closest to the I/O point or in locations that are the most convenient for the picker to visit. They are followed by the class B items. Class C items should be placed in locations that are most distant from the I/O point. Research shows that the application of the ABC-class assignment can save up to between 32% and 45% of the picker's travel distance in comparison to the random storage assignment [13].

The family grouping storage assessment groups products that often appear in orders together. Such products are then placed close to each other in order to be picked during the same tour. In order to group products this way, we need to be able to estimate the statistical correlation between the products [14, 15].

Of course, the storage assignments can be mixed. For example we can utilise the ABC-class storage and within each class we use the random or dedicated storage.

Apart from storage assignment, we also must consider the storage type. We can talk about two storage types: dedicated (described earlier) and shared one [1]. Shared storage means that any item can be stored in many, sometimes very distant locations and, at the same time, many different items can be stored in any single location. Such system provides much better storage space utilisation in comparison with the dedicated storage. On the other hand, as locations of items change constantly, it is impossible for the pickers to memorise them. Therefore, we need to utilise a warehouse management system. Also, shared storage requires high level of discipline amongst the pickers, i.e. they need to obey the indications given by the system even, if they seem illogical at the first glance.

When utilising the shared storage, the problem of selection of locations, from which needed items need to be picked, becomes an issue, which is non-existent in case of dedicated storage. Generally, the problem of selecting locations in the shared storage systems is addressed scarcely in the existing literature. Gudehus and Kotzab [11] described four take-out strategies (FIFO, quantity adjustment, priority of partial units and taking the access unit). They will be presented and described (along with three more strategies) further in the article. Bartholdi and Hackman [1] mentioned about the necessity of certain trade-offs. The selection of least-filled locations can help emptying and replenishing them, but increases labour and travel time. On the other hand, selection of the most convenient location (the closest to the I/O point or fully satisfying the demand) saves time and labour, but result in small quantities of items remaining in the locations. We can also propose several other strategies of selection of locations. Firstly, we can prefer location located closest ti the I/O point or locations, where stored items on the pick list, are close to each other (for example they are located at the same picking aisle).

When we wish to select locations from which items being on the pick list need to be picked, we must somehow differentiate between them in order to apply any of proposed selection strategies. We can solve this problem by describing locations, where needed items are located, by means of decision criteria. Next, we can apply the appropriate multi-criteria decision-making method in order to select the locations, from which the needed items are to be picked. Realisation of specific strategy of selection of locations can be guaranteed by applying the appropriate combination of criteria's weights.

Having selected locations that are to be visited by the picker, the final issue is to designate his/her route. There are many methods of designation of the picker's route. Designation of the optimal (shortest) route seems to be the most obvious choice. For rectangular, one-block warehouse with narrow picking aisles, the optimal route can be designated by means of a special case of the Travelling Salesman Problem

(TSP). This approach was first proposed by Ratliff and Rosenthal [20]. Wildt et al. [32] considered the extensions of the TSP for the single-picker routing problem in scattered storage systems. Although in many cases it is possible to obtain the optimal routes, the results (despite having the shortest route) do not necessary are the best for functioning of the warehouse. The main reason for this is that the obtained routes often seem illogical for the pickers (they often need to switch the direction of movement), so they tend to deviate from them. Thirdly, optimal routes do not consider the usual movement direction in a warehouse [13]. Therefore, companies usually use routing heuristics that do not aim at finding the optimal routes (and never guarantee that), but are easy to obtain and implement. On some occasions, route obtained by a routing heuristic can be also optimal, but it is just a coincidence.

It is worth mentioning that it could be possible to optimise the order picking by analysing selection of locations and designation of the picker's route simultaneously [2]. However, in case of our research it would be a difficult task, as we must select locations that satisfy the take-out strategies. Therefore, both tasks – selection of locations and designation of the picker's route – are done separately.

The aim of the research is to develop a new *metaheuristic* for the warehouse management that will provide better solution for the routing problems (shorter route lengths) than the most widely used routing heuristics: *s-shape*, *return* and *midpoint*. We use the R language [19] to develop the *metaheuristic*. We apply the proposed metaheuristic in the classical, *picker-to-parts*, one-block rectangular warehouse with random storage order. We assume the shared storage and various take-out strategies. We use the COmplex PRoportial ASsessment (COPRAS) method to select locations to be visited by the picker. We compare the results with the results obtained for the most widely used routing heuristic. We generate the orders (scenarios) by means of the simulation methods.

The remaining part of the manuscript is organised as follows: section 2 presents the research methodology (presentation of the criteria describing the locations, the COPRAS method and the new *metaheuristic*). Section 3 presents the experimental results. The article ends with the concluding remarks.

2. Research methodology

2.1. Assumptions of the simulation experiment

- We assume a simple, rectangular, one-block warehouse with two main aisles (front and rear) and 20 picking aisles. Every picking aisle contains 50 locations (25 at each side of the aisle). The total number of locations is 1,000.
- The I/O (depot) point is located at the far left-hand side of the front main aisle.
- We assume the random storage assignment.
- We assume shared storage.
- Every scenario assumed an independently generated order consisting of 10 items.
- Every item was stored in variable number of locations (1–10, generated from the uniform discrete distribution).
- The available quantities of each item in each location ranged from a single unit to a quantity satisfying the demand twice and were generated from a discrete uniform distribution.

- Every location, where items on the pick list were stored, was described using five criteria:
  - storage time (x_1),
  - distance from the I/O point (x_2),
  - degree of demand satisfaction (x_3),
  - degree of demand satisfaction in full units (boxes) of stored item (x_4),
  - number of other items on the pick list stored in the proximity of the analysed location (in the same picking aisle) (x_5).
- We considered the following take-out strategies:
  - benchmark,
  - FIFO,
  - preference of locations located the closest to the I/O point (MDI/O),
  - quantity adjustment (QA),
  - taking the access unit (TAU),
  - minimisation of number of visited picking aisles (MNPA),
  - priority of partial units (PPU).
- We select the locations by means of the COPRAS method.
- We generate 100 orders (scenarios).
- For each scenario after selecting locations, we designate the picker's route by means of the the following heuristics:
  - *s-shape*,
  - *return*,
  - *midpoint*,
  - proposed *metaheuristic*.

The stages of the experiment are as follows:

1. We generate every of the 100 orders (scenarios) independently.
2. For every order We select locations to be visited by the picker by means of the COPRAS method. We apply appropriate weights to the criteria in order to ensure realisation of analysed take-out strategies. It means that for every scenario we obtain seven sent of selected locations (because we have seven take-out strategies).
3. We designate the picker's routes for locations selected for every take-out strategy in every scenario.
4. We analyse the descriptive statistics of the picker's routes obtained for every routing heuristic in every routing strategy.

5. We compare the average route lengths obtained for the *s-shape*, *return* and *midpoint* with the route lengths obtained for the proposed *metaheuristic*.

The presented research adopts some elements and assumptions (some of the criteria – distance from the I/O point, degree of demand satisfaction and number of other items on the pick list stored in the proximity of the analysed location, take-out strategies, warehouse layout, methods of generation of: orders, locations and values of some decision criteria, and the philosophy of selection of locations) from previous researches [5–7].

The extension of previous analyses lies in adding more criteria to the set (thus considering more take-out strategies) and proposal of a new routing heuristic. The assumptions (regarding the number of items on the pick list, number of locations in which any item can be stored, normalisation of demand, existence of full units, the assumption about the neighbourhood of locations, or independent replications of scenarios) are adopted in order to make analysed scenarios comparable.

Certainly, analysis of functioning of warehouse in a long term would give better insight into its performance. In such analysis we need to consider the facts that demand in orders decreases the stock levels, empties locations, thus requires more locations to be visited to pick orders, etc. However, in the present research we focus solely on the performance of routing heuristics in applied take-out strategies.

2.2. Description of the decision criteria and take-out strategies

The first criterion – storage time – is the profit-type one. It is measured on the ratio scale in days. We assume that storage time ranges between 1 and 30 days (and has discrete uniform distribution). Locations with longer storage time are more preferable than those with shorter storage time.

The second criterion – distance from the I/O point – is measured on the ratio scale. It is the loss-type criterion, measured in a contractual unit, which is the shelf width. The distance itself is calculated by means of the taxicab geometry as follows:

$$x_2 = d_{01} + d_{12} \tag{1}$$

where d_{01} – distance from the I/O point to the entrance of the picking aisle, at which the analysed location is located on the front main aisle and d_{12} – distance of the location from the front main aisle on the picking aisle.

The third criterion – the degree of demand satisfaction – is calculated by means of the following formula:

$$x_3 = \begin{cases} \frac{l}{z} & \text{if } z > l \\ 1 & \text{if } l \geqslant z \end{cases} \tag{2}$$

where l – number of units of the item on the pick list in the analysed location and z – demand for this item.

It is measured on the ratio scale and generally is the profit-type one (only for the *priority of partial units* strategy it is the loss-type criterion). The demand for each item is normalised at 100 units. For this normalised demand, we assume that the available amount of every item on the pick list in every location it is stored, follows the discrete uniform distribution with the possible values: $l \in \{1, 2, \ldots, 200\}$. The probability of any single value from this set is then equal $\frac{1}{200} = 0.005$. Therefore, probability that the demand for given item on the pick list is fully satisfied in a single location is: $P(l \geqslant 100) = \frac{101}{200} = 0.505$. On the other hand, probability that the demand is not satisfied in a single location is: $P(l < 100) = 1 - P(l \geqslant 100) = 0.495$.

The fourth criterion – degree of demand satisfaction in full units (boxes) of stored item – is the profit-type one, also measured on the ratio scale. The existence of full boxes was only taken into account for those locations with a demand satisfaction rate of 1. The probability of existence of full boxes was assumed to be 0.5. Full boxes were assumed to contain 20 units of the item. The number of full units of the item was generated from a discrete uniform distribution and takes values from 1 to the maximum possible number of full boxes resulting from the available quantity of the item at the location. The final value of the criterion is then calculated as a value of 1 if the number of units of the item in full packs is greater than or equal to the demand for the item, or the number of full boxes is divided by 5 in the opposite situation. Algorithm 1 presents the pseudocode for calculation of the value of the criterion x_4.

Notions used the algorithm are as follows:
$P(fb = 1 \mid l \geqslant 100)$ – probability of existence of full boxes,
fb – binary variable describing the existence of full boxes,
a_{fb} – number of units in full box of an item,
n_{fb} – number of full boxes.

Require: values of: $l \in \{1, 2, \ldots, 200\}$, $P(fb = 1 \mid l \geqslant 100) = 0.5$, $fb \in \{0, 1\}$, $a_{fb} = 20$, $n_{fb} \in \{1, \ldots, \lfloor \frac{l}{20} \rfloor\}$
Ensure: The value of criterion x_4

Check if $l \geqslant 100$
if $l \geqslant 100$ **then**
    Check if $fb = 1$
    if $fb = 1$ **then**
        Generate n_{fb} from uniform discrete distribution and calculate $x_4 = \begin{cases} \frac{n_{fb}}{5} & \text{if } n_{fb} < 5 \\ 1 & \text{if } n_{fb} \geqslant 5 \end{cases}$
    end if
    $x_4 = 0$
end if
$x_4 = 0$
return x_4

Algorithm 1. Pseudocode for calculation of the value of criterion x_4 (*Source: own elaboration*)

The fifth criterion – number of other items on the pick list stored in the proximity of the analysed location (in the same picking aisle) – is the profit-type one and measured on the ratio scale. The proximity of the analysed location consists of all locations placed on the shelves within the same picking aisle. Proximity can be understood very widely. It can be assumed that there are the shelves in the same rack. In such case the proximity would be very narrow, thus the probability that no other items on the pick list are stored in the same rack would be very high. On the other hand, having very large neighbourhood (proximity) of, for example, a whole sector of a warehouse would cause a large number of other items on the pick list being stored in the "neighbourhood" of an analysed location. Therefore, assuming that the proximity consists of locations located at the same picking aisle seems to be a reasonable approach. Moreover, it can serve as the strategy for selection of locations in order picking – minimisation of visited picking aisles [25].

We calculate the value of the criterion x_5 by means of the following formula:

$$x_5 = \sum_{p=1}^{10} y_p - 1 \tag{3}$$

where:
$p = 1, \ldots, 10$ – subsequent item numbers,
y_p – binary variable depicting the fact of storing the p-th item in the location located at the same picking aisle.

We subtract the value "1" because we exclude the analysed item in the analysed location from the sum.

Having calculated the values of the criteria, we must assign weights to them in order to apply a multi-criteria decision method. There are various methods of assigning weights. We can apply the naïve method meaning that all criteria have equal weights. If we, however, need to assign different weights to the decision criteria, we can divide the weighting methods into two main groups:

- expert methods,
- methods based on statistical properties of criteria.

Expert methods include: application of the Analytic Hierarchy Process (AHP) [22], rank ordering [3], or by assigning points to the criteria [12]. Methods based on statistical properties include: Shannon's entropy measure [21], correlation coefficients [8, 9], coefficients of variation [12], or method based on taking into account the normalised values of the criteria [34].

Another method of assigning weights to the criteria is application of the simulation methods – we can analyse various combinations of weights of the criteria and select this one, which would for example ensure obtaining the shortest route length [6].

In our research the appropriate weights of the criteria are applied to ensure realisation of take-out strategies (Table 2).

Table 2. Weights assigned to the criteria (*Source: own elaboration*)

Strategies	Criteria				
	x_1	x_2	x_3	x_4	x_5
benchmark	0.2	0.2	0.2	0.2	0.2
FIFO	0.8	0.05	0.05	0.05	0.05
MDI/O	0.05	0.8	0.05	0.05	0.05
QA	0.05	0.05	0.8	0.05	0.05
TAU	0.05	0.05	0.05	0.8	0.05
MNPA	0.05	0.05	0.05	0.05	0.8
PPU	0.05	0.05	0.8	0.05	0.05

The benchmark strategy uses the naïve method of assigning weights. Although this method does not represent any strategy, we use it as the basis for comparisons to other strategies. This strategy does not prefer any criterion when selecting locations. The FIFO strategy assumes that the first criterion – storage time – dominates the remaining ones. We assume that when one criterion dominates the other ones, the weight assigned to such criterion equals 0.8 and the other criteria have weights equal 0.05. Assigning the highest weight to the storage time ensures that items, which have arrived to the warehouse first, will also be picked first.

Realisation of the strategy preferring locations located the closest to the I/O point assigns the highest weight to the second criterion – distance from the I/O point. This take-out strategy should provide that the selected locations to be visited by the picker are clustered close to the I/O point. Realisation of the strategy ”taking the access unit” assigns the highest weight to the fourth criterion – degree of demand satisfaction in full units (boxes) of stored item. It aims at picking units that are already in full packs. The strategy that minimises the number of visited picking aisles is realised by assigning the highest weight to the firth criterion – number of other items on the pick list stored in the proximity of the analysed location. Adoption of this take-out strategy should allow decreasing the number of picking aisles to be visited by the picker.

The highest weight assigned to the third criterion – degree of demand satisfaction – ensures that two strategies are realised: quantity adjustment and priority of partial units. The difference lies in the fact that in the former strategy this criterion is the profit-type and in the latter – the loss-type. The aim of application of the ”quantity adjustment” strategy is to decrease the number of visited locations (by selecting the most filled, possibly fully satisfying the demand ones). The aim of application of the ”priority of partial units” strategy is visiting the least-filled locations (in relation to demand in analysed orders) in order to clear as many locations as possible from small amounts of items.

2.3. The COPRAS method

Selection of locations described by multiple criteria can be done by means of one of many multi-criteria decision-making methods. General recommendation for selection the appropriate one is that such method should be able to be used without the active participation of the decision-maker, only on the basis of the values of the criteria and their weights. It is for example possible to use the modified Hellwig's Composite Measure of Development, named the Taxonomic Measure of Location's Attractiveness (Polish abbreviation TMAL) [6], the TOPSIS method [6, 7], or the Synthetic Measure constructed on the basis of the Generalised Distance Measure (GDM) [5, 6].

In our research, we use the COPRAS method. It was developed by Zavadskas *et al.* [33]. It does not use the reference points (i.e. the best and worst alternatives), but is based on weighed sums of the profit-type (where the highest values are desirable) and loss-type (where the lowest values are desirable) criteria.

The starting point of the COPRAS method is the decision matrix $\mathbf{X}$:

$$\mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{4}$$

where: x_{ij} – value of j-th criterion in i-th alternative ($i = 1, \ldots, n$, $j = 1, \ldots, m$), m – number of criteria, n – number of alternatives.

In our case the alternatives (decision variants) are the locations, where analysed item on the pick list is stored. There are five, described earlier, decision criteria (storage time, distance from the I/O point, degree of demand satisfaction, degree of demand satisfaction in full units of stored item, and the number of other items on the pick list stored in the proximity of the analysed location).

Because all criteria are measured on the ratio scale, we can normalise them by means one of the quotient inversions (such normalisation method preserves the scale strength and enables normalisation even in the case, when for given item all values of the analysed criterion are the same):

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{5}$$

where: z_{ij} – normalised value of j-th criterion in i-th alternative ($i = 1, \ldots, n$, $j = 1, \ldots, m$).

We multiply normalised values of criteria by their weights, thus creating the weighed, normalised decision matrix:

$$t_{ij} = w_j z_{ij}, \quad i = 1, \ldots, n, j = 1, \ldots, m \tag{6}$$

In the next step we calculate the weighted sums of the profit-type (S_i^+) and loss-type (S_i^-) criteria:

$$S_i^+ = \sum_{j \in J^+} t_{ij}, \quad i = 1, \ldots, n \tag{7}$$

$$S_i^- = \sum_{j \in J^-} t_{ij}, \quad i = 1, \ldots, n \tag{8}$$

where: J^+ – profit-type criteria, J^- – loss-type criteria.

In the final step of the COPRAS method we calculate the value of the composite measure:

$$q_i = S_i^+ + \frac{\sum_{i=1}^{n} S_i^-}{S_i^- \sum_{i=1}^{n} \frac{1}{S_i^-}}, \quad i = 1, \ldots, n \tag{9}$$

$\max_i \{q_i\}$ – the best alternative (location), $\min_i \{q_i\}$ – the worst alternative (location).

We apply the COPRAS method for every item on the pick list separately. We select the highest-ranking locations, where given item is stored. If the demand for selected item in the highest-ranking location is fully satisfied, we select only this one. If the demand in the highest-ranking location is not satisfied, we select the second one in the ranking, and so on.

Although multi-criteria decision analysis (MCDA) can be used on various stages of warehouse management, in our research we use it to select locations with accordance to applied take-out strategies. Other example of using the MCDA could be the evaluation of presented method of selection of locations with respect to the values of presented criteria in selected locations. It is not, however, the aim of our research.

2.4. *Metaheuristic*

Having selected locations, we need to designate the picker's route. As mentioned earlier, the optimal one is very rarely designated. Therefore, we focus on the widely-used routing heuristics. There are five heuristics of route designation [13, 24]:

- *s-shape* or *traversal*,
- *return*,
- *midpoint*,
- *largest gap*,
- *composite/combined*.

The most frequently used heuristics in warehouse management practice are the first two (*s-shape* and *return*) [18, 26]. The easy one to designate is also the *midpoint* and it also yields good results (relatively short picker's routes) [26]. Therefore, we compare the results obtained by these routes with the results of proposed *metaheuristic*. The *metaheuristic* has the following assumptions:

- It is based on the loss function.
- It is the combination of the *s-shape* and the *midpoint* heuristics.
- In order to shorten the picker's route, we analyse replacement of crossing the whole picking aisle (like in the *s-shape* heuristic) by picking items from this aisle like in the *midpoint* heuristic.
- We calculate the values of the loss function for all combinations of replaced and not replaced visited picking aisles.
- We select the combination that minimises the total loss function.
- The basic assumption is that the number of subsequent picking aisles crossed in accordance with the *s-shape* heuristic was even. The *metaheuristic* tries to visit all aisles where entering from the bottom and returning is shorter than traversing the entire aisle on the way to the end of the warehouse, and all aisles where entering from the top and returning is shorter than traversing the entire aisle on the way back. If the number of picking aisles crossed according to the *s-shape* heuristic is even, the *metaheuristic* can generate a return route that visits all picking points; otherwise, the already visited paths should be included in the route, which in most cases breaks the optimisation.
- We assume that for one-block, rectangular warehouse the results obtained by the *metaheuristic* should yield not worse results than the remaining heuristics.

Stages of the *metaheuristic* designation are as follows:

- We assume that we need to pick items from locations being at the m picking aisles (where m is the number of picking aisles to be visited by the picker. These are the picking aisles in which all visited locations are located).
- We generate all possible combinations of replacements of crossing the picking aisles. For m picking aisles we have 2^m combinations.
- We analyse every combination:

  - Reject combination, for which the parity constraint connected with subsequent full crossings is not satisfied.
  - Replace crossings according to the current combination.
  - Calculate the loss function for the new crossing.

- Store the combinations with the lowest loss function and update it if a new combination with its smaller value is found.
- After analysing all combinations select the one with the lowest loss function.
- When picking the items from the last picking aisle while returning on the rear main aisle, the route goes back to the front main aisle and returns to the I/O point (as in the *s-shape* heuristic).

The loss function is calculated by means of the following formula:

$$\mathcal{L}_j = d_j - \min_{i \in \{1,\ldots,n_j-1\}} \{2\left[d_{ij} + (d_j - d_{i+1,j})\right] - d_{i,i+1,j}\} \tag{10}$$

where:

- n_j is total number of visited locations in j-th aisle,
- $d_{i,i+1,j}$ is the distance between the i-th and $i+1$ in j-th aisle,
- d_j – length of the j-th aisle,
- d_{ij}, $d_{i+1,j}$ – distance of the i-th and $i+1$-th location in the j-th aisle from the front main aisle,
- $\mathcal{L}_j$ is total loss for the j-th aisle.

The method is outlined in the pseudocode below:

The example comparison of routes obtained for the *s-shape*, *return*, *midpoint* heuristics and the new *metaheuristic* is presented on the Figure 1.

In the presented example the *metaheuristic* works similarly to the *midpoint* heuristic. The only difference is that the sixth picking aisle from the left is visited not from the front main aisle, but from the rear one. However, it does not have any impact on the route length, as the visited location in this picking aisle is exactly the middle rack. Bold edges on the graphs indicate that these parts of the route are traversed more than once.

3. Experimental results

We applied the following computational software:

- We generated scenarios (orders) and selected locations by means of the COPRAS method in Microsoft™ Excel®.
- All heuristics and proposed *metaheuristic* were obtained by means of the own software written in the R language [19] with the use of packages: `clusterSim` [27], `openxlsx` [23], `tidyverse` [29], `tidyverse` [29], `dplyr` [30], `tidyr` [31], `stringr` [28].

```
Calculate loss function for every aisle
Remove empty aisles from right
for all combinations of full aisles and aisles visited to and from midpoint do
    binary_vector_raw = binary representation of j
    bits = bits of binary_vector_raw
    # For combinations with subsequent number of even full aisles
    if if parity_full_s(count_by_sequence(TRUE, bits, TRUE)) is TRUE then
        current_loss = sum(loss where bits are FALSE)
        if current_loss < min_change then
            find the combination that minimises the overall loss
            min_change_bits = bits
            min_change = current_loss
        end if
    end if
end for
Create route due to combination minimising loss function
Remove empty aisles from optimal combination
```

Algorithm 2. Pseudocode for the *metaheuristic* (*Source: own elaboration*)

Elaborated own new functions will be included and shared in a new R package, which is currently under construction.

We present the results in the form of the basic descriptive statistics for every take-out strategy separately. We use the following notations:

$\bar{n}_{loc}$ – average number of visited locations,
$\bar{x}$ – arithmetic mean,
$S(x)$ – standard deviation,
V_s – coefficient of variation,
M_e – median,
Q_1 – first quartile,
Q_3 – third quartile,
A – Pearson's moment skewness coefficient,
S–W – p-value of the Shapiro-Wilk normality test,
95% C.I. – 95-percentage confidence interval for the arithmetic mean.

We present the results for the benchmark take-out strategy in Table 3.

All measures of central tendency indicate that the results obtained by the new *metaheuristic* yielded better results than other heuristics. The average route length for this strategy for the proposed *metaheuristic* was just over 258 units, followed by the results obtained by the *midpoint* heuristic (almost 267.3 units). Much longer route lengths were obtained on the average for the *s-shape* heuristic (325.6 units) and the longest (334) – for the *return* heuristic. Median values were similar to the averages meaning that the distribution of the route lengths for all heuristics were symmetric, with quite low variability (coefficients of variation were just over a dozen) thus not significantly different from normal (p-values for the Shapiro-Wilk test were for all heuristics much higher than the threshold value of 0.05). The *s-shape* and *return* heuristics yielded much worse results. Confidence intervals for the *s-shape* and *return*

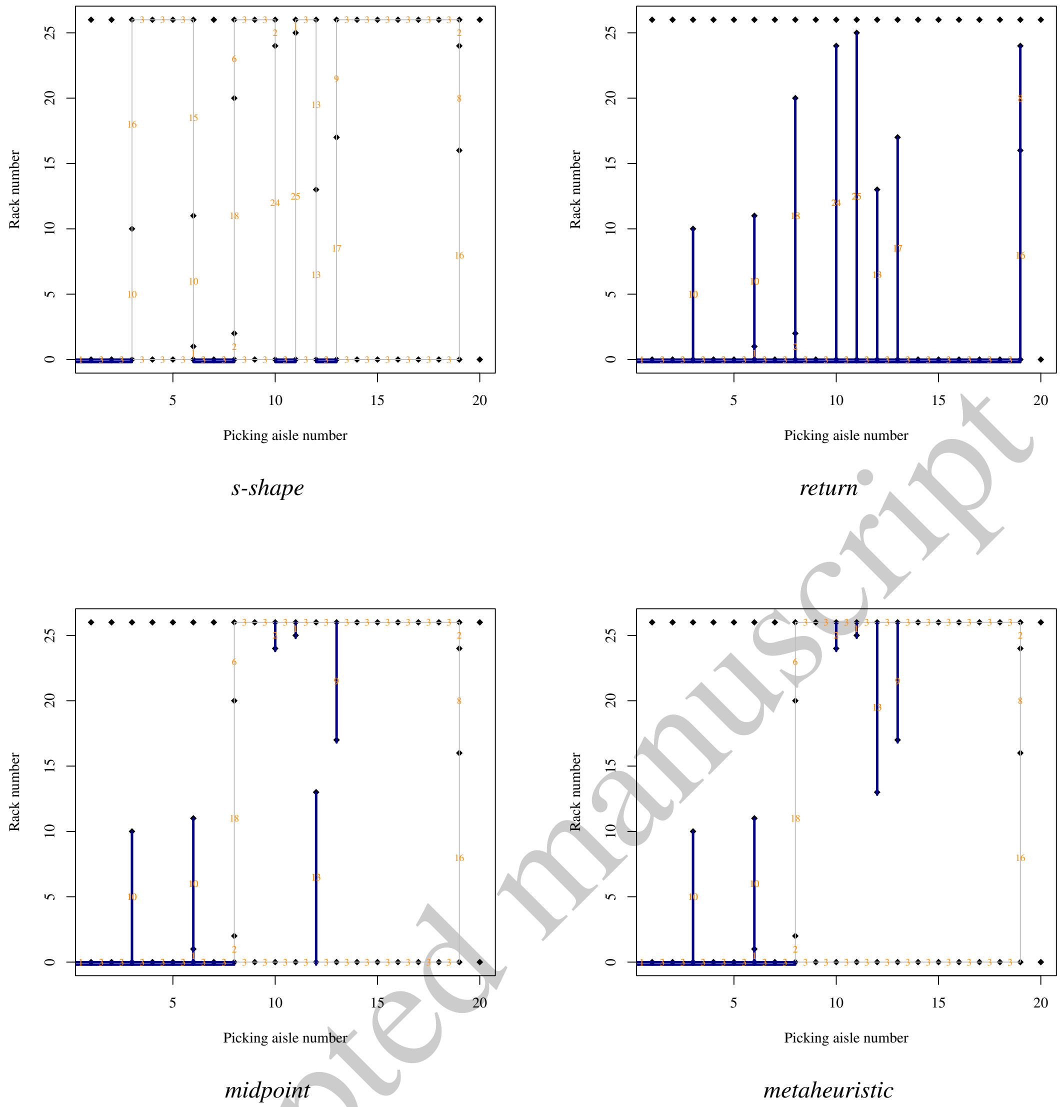

Figure 1. Routes obtained for the routing heuristics. *Source: own elaboration*.

heuristics overlapped. The same held for the *midpoint* and the new *metaheuristic*. The average number of location to pick an order when using this strategy was on the average equal 12.79.

We present the results for the FIFO take-out strategy in Table 4.

Route lengths obtained for the FIFO strategy were longer than for the benchmark one and ranged from just over 296 units for the best *metaheuristic* to just over 404 for the worst – the *return* heuristic. The second best results were obtained for the *midpoint* heuristic (with average route length equal 306.74 units) and the second worst – for the *s-shape* heuristic (381.7 units). Similarly as in the case of the benchmark strategy, median values were similar to the averages, so the distribution of the route lengths for all heuristics were symmetric, with quite low variability (coefficients of variation were just over a dozen) and mostly not significantly different from normal. Only for the *s-shape* heuristic the distribution of route length deviated from normal at the significance level 0.1. In case of this strategy, all measures of central tendency indicate that the new *metaheuristic* yielded better results than the remaining heuristics. The confidence intervals for the *s-shape* and *return* did not overlap, while for the *midpoint* and the new

Table 3. Results for the benchmark strategy (*Source: own elaboration*)

Descriptive statistics	Heuristics			
	s-shape	*return*	*midpoint*	*metaheuristic*
$\bar{n}_{loc}$	12.79			
$\bar{x}$	325.60	334.00	267.32	258.32
$S(x)$	46.99	56.02	33.08	32.62
V_s	14.43%	16.77%	12.38%	12.63%
M_e	324.00	332.00	266.00	258.00
Q_1	295.50	300.00	244.00	239.50
Q_3	358.00	366.00	287.50	276.50
A	-0.211	0.224	0.322	0.137
S–W	0.574	0.622	0.379	0.584
95% C.I.	[316.28, 334.92]	[322.88, 345.12]	[260.76, 273.88]	[251.85, 264.79]

Table 4. Results for the FIFO strategy (*Source: own elaboration*)

Descriptive statistics	Heuristics			
	s-shape	*return*	*midpoint*	*metaheuristic*
$\bar{n}_{loc}$	14.75			
$\bar{x}$	381.70	404.18	306.74	296.22
$S(x)$	49.15	64.30	38.05	35.69
V_s	12.88%	15.91%	12.40%	12.05%
M_e	376.00	407.00	305.00	292.00
Q_1	352.00	367.00	278.00	274.00
Q_3	422.00	436.00	336.00	324.00
A	-0.147	0.100	0.138	-0.062
S–W	0.074	0.800	0.786	0.502
95% C.I.	[371.95, 391.45]	[391.42, 416.94]	[299.19, 314.29]	[289.14, 303.30]

metaheuristic they did. When using this strategy, the average number of locations to pick an order was much higher than for the benchmark take-out strategy and equal 14.75.

We present the results for the quantity adjustment take-out strategy in Table 5.

Table 5. Results for the quantity adjustment strategy (*Source: own elaboration*)

Descriptive statistics	Heuristics			
	s-shape	*return*	*midpoint*	*metaheuristic*
$\bar{n}_{loc}$	10.98			
$\bar{x}$	313.98	328.06	258.26	251.00
$S(x)$	35.91	53.54	31.39	31.74
V_s	11.44%	16.32%	12.15%	12.65%
M_e	318.00	333.00	256.00	250.00
Q_1	303.50	295.50	238.00	232.00
Q_3	332.00	359.00	280.00	270.50
A	-0.370	-0.289	0.210	-0.071
S–W	**0.001**	0.734	0.556	0.620
95% C.I.	[306.85, 321.11]	[317.44, 338.68]	[252.03, 264.49]	[244.70, 257.30]

The quantity adjustment strategy yielded much better results (shorter route lengths). They ranged from average 251 units for the *metaheuristic* to 328 units for the *return* heuristic. Again, the *metaheuristic* provided the best results (but to quite small degree with the comparison to the *midpoint* heuristic). As previously, the variability of obtained distributions was small (with coefficients of variation not exceeding 16.32% for the *return* heuristic). Distributions of route lengths obtained by the *s-shape* and *return* were moderately negatively skewed. In case of the *midpoint* heuristic it was moderately positively skewed. The distribution of route lengths obtained for the new *metaheuristic* was virtually symmetric (with skewness coefficient equal -0,071). The distribution of route lengths for the *s-shape* deviated from normal significantly, which was also visible by difference between the average (almost 314) and median (318) route length. As expected, the average number of locations that need to be visited to pick an order was the lowest (less than 11) – this take-out strategy prefers locations that satisfy demand for items to the highest degree (possibly fully).

We present the results for taking the access unit take-out strategy in Table 6.

Table 6. Results for taking the access unit strategy (*Source: own elaboration*)

Descriptive statistics	Heuristics			
	s-shape	*return*	*midpoint*	*metaheuristic*
$\bar{n}_{loc}$	12.78			
$\bar{x}$	347.80	371.18	280.90	272.10
$S(x)$	40.93	54.90	30.01	27.85
V_s	11.77%	14.79%	10.68%	10.24%
M_e	347.00	373.00	277.00	271.00
Q_1	323.50	328.00	262.00	254.00
Q_3	376.00	410.50	302.50	290.00
A	0.403	0.377	0.729	0.578
S–W	**0.015**	0.068	**0.010**	**0.021**
95% C.I.	[339.68, 355.92]	[360.29, 382.07]	[274.95, 286.85]	[266.57, 277.63]

The "taking the access unit" take-out strategy prefers locations with the highest degree of demand satisfaction in full units (boxes). Therefore, the picker needed to visit more locations (on the average 12.78) in order to pick the order than in the "quantity adjustment" strategy. The need to visit more locations caused also longer mean route lengths (ranging from 272.1 for the *metaheuristic* to 371 for the *return* heuristic). Although the median route lengths were close to the average values, the skewness of obtained distributions was always positive and strong (the highest skewness was in the case of application of the *return* heuristic – the coefficient was equal 0.729). It is because we have longer right tails of the distribution (cases in which we must visit more locations, or locations located further from the I/O point). It resulted in significant deviations from the normal distribution (in case of the *s-shape*, *midpoint* and *metaheuristic* at the significance level 0.05 and for the *return* heuristic – 0.1).

We present the results for the take-out strategy preferring locations located the closest to the I/O point in Table 7.

When applying the take-out strategy, which prefers locations located the closest to the I/O point, the obtained route lengths were a bit shorter than when applying the benchmark strategy (Table 4). The average number of visited locations was 13.02. The ranking of heuristics was the same as in the case of previous strategies – the new *metaheuristic* generated the best results (with the average route length equal 255.54 units). It was followed by the *midpoint* heuristic (266.22 units), then the *s-shape* (323.4). It was closely followed by the *return* heuristic with the longest route length (on the average equal 327.7 units). The shape of the distribution of the route lengths for the *s-shape* heuristic differed from the ones obtained for other heuristics. It was strongly negatively skewed (with the coefficient of skewness equal -0.508), thus differed significantly from the normal distribution (at the 0.05 significance level). The distributions obtained for the remaining heuristics did not differ from normal and were virtually symmetrical.

Table 7. Results for the strategy preferring locations located the closest to the I/O point (*Source: own elaboration*)

Descriptive statistics	Heuristics			
	s-shape	*return*	*midpoint*	*metaheuristic*
$\bar{n}_{loc}$	13.02			
$\bar{x}$	323.40	327.70	266.22	255.54
$S(x)$	45.49	57.68	34.64	34.77
V_s	14.07%	17.60%	13.01%	13.61%
M_e	324.00	324.00	272.00	262.00
Q_1	304.50	283.00	240.00	229.50
Q_3	364.00	364.50	286.50	278.00
A	-0.508	0.088	-0.044	-0.081
S–W	**0.014**	0.721	0.675	0.483
95% C.I.	[314.37, 332.43]	[316.26, 339.14]	[259.35, 273.09]	[248.64, 262.44]

We present the results for the take-out strategy minimising the number of visited picking aisles in Table 8.

Table 8. Results for the strategy minimising the number of visited picking aisles (*Source: own elaboration*)

Descriptive statistics	Heuristics			
	s-shape	*return*	*midpoint*	*metaheuristic*
$\bar{n}_{loc}$	14.71			
$\bar{x}$	285.66	314.74	263.28	245.80
$S(x)$	46.75	55.26	39.86	36.83
V_s	16.37%	17.56%	15.14%	14.98%
M_e	294.00	317.00	267.00	245.00
Q_1	259.50	282.00	234.00	224.00
Q_3	312.00	348.50	292.00	270.00
A	-0.338	-0.386	0.064	-0.012
S–W	**0.009**	0.335	0.428	0.511
95% C.I.	[276.38, 294.94]	[303.77, 325.71]	[255.37, 271.19]	[238.49, 253.11]

The realisation of the take-out strategy that minimises the number of visited picking aisles yielded the shortest route lengths, despite relatively high number of visited locations (on the average equal 14.71). It was in accordance with previous research in this area [25]. Even if we need to visit more locations (because we do not necessarily select the most filled), but if they are clustered in smaller number of picking aisles, then the total route length can be in most cases shorter. The shortest route lengths were obtained for the new *metaheuristic* (on the average 245.8 units). The second best results were obtained for the *midpoint* heuristic (average route length equal 263.3 units). It was followed by the *s-shape* heuristic (average 285.66 units). The longest route lengths (on the average equal 314.74 units) were obtained for the *return* heuristic. The distributions of route lengths obtained for various heuristics had slightly higher level of variability (partially caused by the lowest average values). The distributions for the *midpoint* heuristic and the *metaheuristic* were symmetric, while the distributions for the *s-shape* and *return* heuristics had moderate negative skew (in case of the *s-shape* heuristic it also deviated significantly from the normal distribution). In case of this strategy the confidence intervals for route lengths of all heuristics did not overlap, so in most cases there was clear distinction between the results obtained for every heuristic.

Finally, we present the results for the priority of partial units take-out strategy in Table 9.

The priority of partial units strategy always yields the longest route lengths. It was mentioned as the trade-off by Bartholdi and Hackman [1] and proved by Dmytrów [7]. If the strategy prefers the locations

Table 9. Results for the priority of partial units take-out strategy (*Source: own elaboration*)

Descriptive statistics	Heuristics			
	s-shape	*return*	*midpoint*	*metaheuristic*
$\bar{n}_{loc}$	25.36			
$\bar{x}$	476.04	546.30	405.58	380.12
$S(x)$	45.48	73.08	46.90	38.52
V_s	9.55%	13.38%	11.56%	10.13%
M_e	480.00	538.00	405.00	380.00
Q_1	452.00	498.50	378.00	362.00
Q_3	510.50	592.00	430.50	404.00
A	-0.658	0.006	-0.316	-0.551
S–W	**0.004**	0.961	0.139	**0.009**
95% C.I.	[467.02, 485.06]	[531.80, 560.80]	[396.28, 414.88]	[372.48, 387.76]

with the smallest possible degree of demand satisfaction, the picker needs to visit much more locations (in our case on the average over 25 per order), thus travel longer distance than in case of other take-out strategies. In our case the ranking of heuristics with respect to the route lengths was the same as in previous cases. The shortest route lengths were obtained for the new *metaheuristic* (on the average just above 380). It was followed by the *midpoint* heuristic (with average route length equal 405.6 units). The second worst results were obtained for the *s-shape* heuristic (on the average 476 units). The longest route lengths (on the average equal 546.3 units) were obtained for the *return* heuristic. Variability of obtained distributions of route lengths is the lowest (mostly due to the highest mean values). Only in case of the *return* heuristic the distribution was symmetric, for all other heuristics the distributions were negatively skewed, for *s-shape* and the *metaheuristic* strongly. Also, in these two cases the obtained distributions differed significantly from normal (at the 0.01 significance level). All confidence intervals were disjoint, so similarly as in case of the previous strategy, there was clear distinction between the results obtained for all heuristics.

In order to visualise the relative differences between the average route lengths obtained for the *meta-heuristic* and the remaining routing heuristics, we present the Figure 2.

Because all the relative differences were positive, all heuristics for all take-out strategies yielded worse results (longer route lengths) than the proposed *metaheuristic*. The closest to the *metaheuristic* results were obtained for the *midpoint* heuristic. The *s-shape* and *return* heuristics yielded much worse results. The relative difference between the *midpoint* heuristic and the proposed new *metaheuristic* ranged from 2.9% for the "quantity adjustment" strategy to 7.1% for the strategy that minimises the number of visited picking aisles. In case of the "priority of partial units" take-out strategy, the *midpoint* heuristic yielded route lengths on the average by 6.7% longer than the *metaheuristic*. For the remaining take-out strategies application of the *midpoint* heuristic resulted in route lengths longer on the average by about 3.5% than in case of the new *metaheuristic*. The *s-shape* heuristic yielded worse results than the *metaheuristic* on the average by 25% (with the exception of the strategy minimising the number of visited picking aisles, for which the average route length for the *s-shape* heuristic was longer by 16.2% in comparison with the results obtained for the *metaheuristic*). The use of the *return* heuristic yielded the longest route lengths. They were on the average longer than in case of the *metaheuristic* from just above 28% (for the strategies minimising the number of visited picking aisles and preferring locations located the closest to the I/O point) to almost 44% in case of the "priority of partial units" strategy.

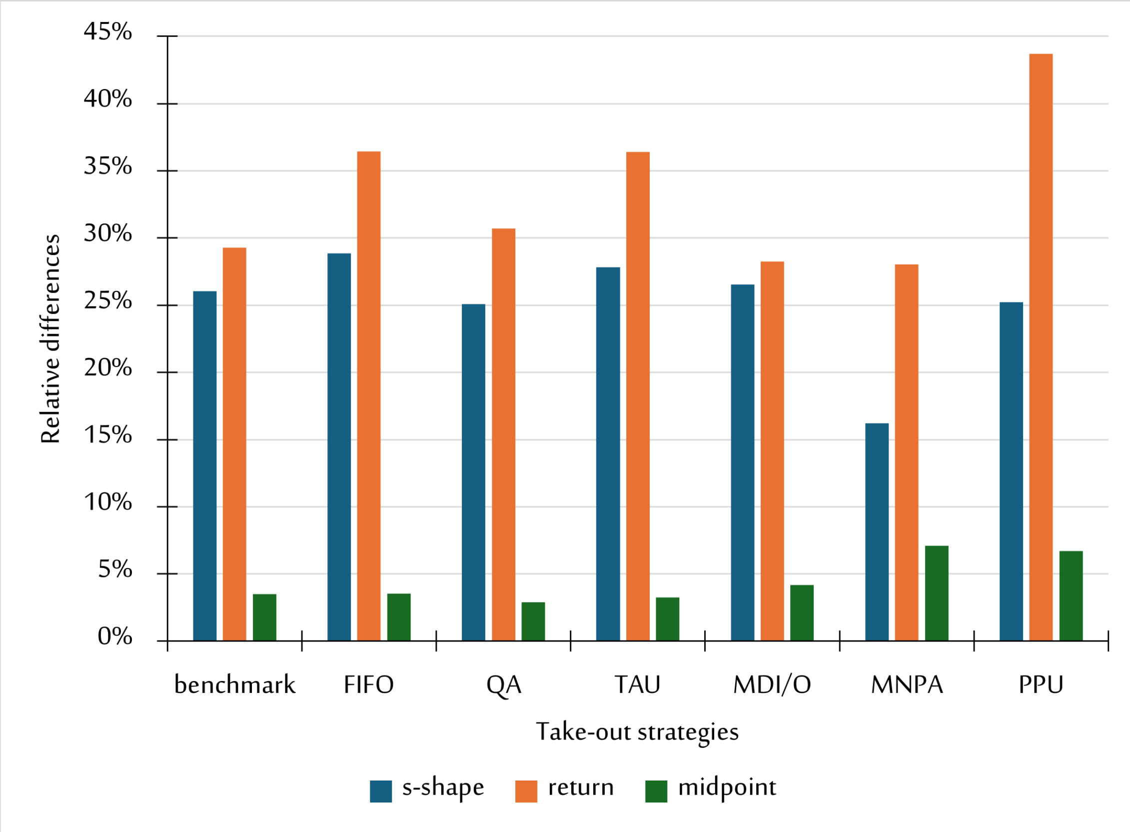

Figure 2. Comparison of average route lengths for individual heuristics with results obtained for the *metaheuristic*. *Source: own elaboration.*

The closest results to the new *metaheuristic* with respect to the route lengths were obtained for the *midpoint* heuristic. When we analysed closer the relative differences between the *midpoint* heuristic and the *metaheuristic* and compared them to the average number of visited locations for every take-out strategy, presented in tables 3– 9, they were seemingly closely related. The smallest number of visited locations was needed to pick an order when realising the "quantity adjustment" (average 10.98 locations), "taking the access unit" (average 12.78 locations) and the benchmark (average 12.79 locations) take-out strategies. For these strategies the differences in order picking route between the *metaheuristic* and the *midpoint* heuristic were the smallest. This difference was the largest for the strategies minimising the number of visited picking aisles (with the average number of visited locations equal 14.71) and the "priority of partial units" (with the average number of visited locations equal 25.36). There was, however, one exception – for the FIFO take-out strategy the average number of visited locations was 14.75 (virtually the same as for the strategy minimising the number of visited picking aisles), but the relative difference between the route lengths was less than 3.6%. Moreover, the relative differences between the new *metaheuristic* and the *midpoint* heuristic in cases of the strategies minimising the number of visited picking aisles and the "priority of partial units" seemed to stabilise. However, it needs to be confirmed in further research with larger number of items on the pick list.

4. Conclusions

The aim of the research has been successfully realised – proposed new *metaheuristic* proved to yield better results (shorter route lengths) than the three most widely used routing heuristics: *s-shape*, *return* and *midpoint*. We applied it to the simple, one-block rectangular warehouse with random storage assignment. We compared the results for various take-out strategies used in the shared storage systems. The advantage of this *metaheuristic* over the *s-shape*, *return* heuristics was very big – the former heuristic generated results on the average by 25% worse and the latter – on the average by 33% worse. The *midpoint* heuristic generated the results on the average by 4.45% worse. However, in most cases the advantage on the new *metaheuristic* increased when the number of visited locations also increased. Nevertheless, this finding needs to be confirmed in the future research. Better performance of the proposed *metaheuristic* might indicate that it can be used in practical applications.

Having the designation and experimental analysis of the proposed *metaheuristic* complete, we can consider its pros and cons. The pros of the proposed *metaheuristic* are as follows:

- It is a methodology based on two well-known routing heuristics: *s-shape* and *midpoint*.
- It contains the elements of optimisation – minimisation of the loss function.
- It was designed and proved that its application allows obtaining not worse (on the average better) results than the compared well-known routing heuristics.

We can also consider the cons of our proposal:

- It is not designed to obtain the optimal solution.
- It is not as easy to be implemented as the *s-shape*, *return* and *midpoint* heuristics.

The decision to implement any method of selection of locations and routing method is always subjective. The subjectivity can be decreased by analysing realisation of some evaluation criteria, like picking route length, order picking time, or realisation of the described criteria of selection of locations for all take-out strategies. After such evaluation, overall the best combination of multi-criteria decision-making method of selection of locations, routing heuristic and take-out strategy can be selected.

Our research has, of course, some limitations. Firstly, it was conducted for a typical, simplest type of warehouse. Secondly, for every strategy we generated only 100 replications of the simulation. The reason for this was the early stage of the algorithm, which had not yet been optimised for faster execution. And thirdly, we applied our *metaheuristic* only to the random storage assignment.

In order to address these limitations, the possible future directions of our research will include:

- Application of the *metaheuristic* to more organised storage assignments:
  - ABC within aisle,
  - ABC across aisle,
  - ABC diagonal,
  - ABC perimeter.

- Adjustment of the *metaheuristic* to the high-level warehouse.
- Adjustment of the *metaheuristic* to the multi-block warehouse.
- Conducting more detailed experiment with more (at least 1000) repetitions for each storage assignment and take-out strategy.
- Verification of the results generated by the *metaheuristic* for more items in a pick list.
- Preparation of a new R package that will include the elaborated functions.
- Simultaneous, multi-criteria evaluation of both results of selection of locations satisfying the various take-out strategies and obtained route lengths.

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