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Analytical and simulation determination of order picking time in a low storage warehouse for shared storage systems

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Abstract

The aim of the research is comparison between average order picking times obtained using the analytical model and simulation methods for shared storage systems. We also compare the results obtained with the results obtained for dedicated storage. We assume the random and ABC-class storage (with within and across aisle storage policies). We select the locations by means of the TOPSIS method for two take-out strategies: quantity adjustment (QA) and priority of partial units (PPU). We determine the route by using *s-shape* and *return* heuristics. In most cases, the simulated average order picking times are shorter than the analytical ones. It results from not considering the criteria' weights in calculation of the analytical order picking time. Also, the results for shared storage with QA strategy are in most cases better than for dedicated storage. This might imply an advantage of shared over dedicated storage, but needs further confirmation.

Keywords: warehouse management, order picking, shared storage, multi-criteria decision-making, simulation methods

1. Introduction

Each company that stores goods in warehouses must organise the order picking process. Many of them utilise automatic systems (*parts-to-picker* ones), such as automated storage and retrieval systems (AS/RS), storage and retrieval (S/R) machine, modular vertical lift modules (VLM), or carousels [31]. In general, warehouse activities constitute about 39% of total logistic costs in Europe and 23% in the U.S.A. [12]. As research at the beginning of the 21st century indicated, about 80% of companies used the classical manual *picker-to-parts* systems [5]. It was also confirmed in more recent research that in 2011, 80% of companies still utilised the manual, *picker-to-parts* systems. In 2012, this share dropped to 74% [25]. For such systems, order picking generates about 55% of all warehouse operating costs [1]. The order picking time can be divided into four activities (Table 1).

As traveling takes up over 50% of order picking time, the most visible advantages can be achieved by optimising the distance that the picker must cover. This can be done by applying the appropriate storage assignment, warehouse layout, and routing technique.

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Table 1. Division of order picking time [1]

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

There are several possible storage assignment policies that can be used in a company [22]:

- random (chaotic) storage assignment,
- closest-open-location storage assignment,
- dedicated storage assignment,
- class-based storage assignment,
- family-grouping storage assignment.

A random storage assignment means that when items arrive at the warehouse, they are assigned to available locations without any pattern, i.e. the process of assigning them is purely random (chaotic). Such a system is often used as a benchmark that shows how the utilisation of other, more organised storage assignment can improve the order picking process.

If the closest-open-location storage assignment is utilised then incoming items are allocated 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 must select storage locations by themselves. The main drawback of this assignment method, along with the chaotic system, is that in time the stored items become scattered all over the warehouse. Some research has even indicated that these two methods converge in the long term.

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). Such a storage assignment policy is relatively easy to remember for the pickers and does not require a specialised warehouse management system. The main drawback of such an approach is poor space utilisation, however it is possible to estimate optimal space requirements for each item [12, 23].

One of the most widely used storage assignment policies is the class-based one. In this approach, the items stored in a warehouse are divided according to appropriate class membership. The number of classes may vary, and there is no clear indication of how many classes the items should be divided into. According to some sources, the optimal number of classes in a low-level picker-to-parts warehouse should be between 2 and 4 [28]. On the other hand, when the automatic AS/RS are utilised, simulation studies set an optimal number of classes at 6 [37]. Other research has indicated that for various assumptions the number of classes should not exceed 6 [38]. The most frequently used approach is the division of items in a warehouse into three classes. In such a case, it is called the ABC-class assignment. Items are allocated to an appropriate class by means of their turnover frequency. Class A consists of the fastest-moving items, class B – medium and class C – the slowest-moving ones. The biggest problem in the ABC-class assignment lies in the designation of borders between classes. The most popular division method is based on the Pareto approach. It states that 20% of the fastest-moving items account for 80% of the company's total turnover – these items 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. Class A items should be placed closest to the I/O point, and they should be followed by the class B items. Class C items should be placed in the furthest places in the warehouse. Research shows that the application of the ABC-class assignment can even save between 32% and 45% of the picker's travel distance in comparison to the random storage assignment (depending on the division of the classes) [22].

The family-grouping storage assignment groups items that often appear in pick lists together. Such items are then placed close to each other to ensure that the picker will pick them during the same tour. In order to group items this way, we need to be able to estimate the statistical correlation between the items. This assignment method can be used along with other methods, for example, with the ABC-class storage to further improve the order picking process.

Apart from the storage assignment, also utilisation of an appropriate aisle design can lessen the order picking route and time. The traditional and most widely used is the rectangular layout, where the racks form parallel picking aisles and one or more orthogonal cross aisles. However, there are warehouses that differ significantly from such a layout. In specific situations, the application of such designs as the Flying-V and Fishbone can decrease the order picking routes even by 10% to 20% [16]. A detailed survey of research on warehouse design was done by Gu et al. [14]. Further areas of improvement are possible in the organisation of picking policies, such as: zone picking, wave picking, or batch picking [32].

Another issue that must be considered is how one item can be stored. It can be done by means of dedicated or shared storage systems [1]. Dedicated storage means that an analysed item is assigned to a single and always the same location (or group of neighbouring locations if its amount needed to be stored exceeds the capacity of a single location). Also, the given location is dedicated only to a single and the same item. This storing method is the same as that mentioned earlier, being a dedicated storage assignment.

On the other hand, when the shared storage system is utilised, one item can be stored in many, sometimes very distant from each other, locations and there can be many different items stored in a single location. The main advantage of utilising a shared storage system is much better space utilisation than in the case of dedicated storage. The main disadvantage of a shared storage system is that it requires a specialised warehouse management system and discipline among the pickers – if a single item can be picked from many locations, they must follow the indications of the system and should not pick items from other locations if they are not indicated by the system. Of course, shared storage system can be applied for various storage assignment policies, such as random, closest-open-location, class-based and family-grouping ones.

If a company utilises the shared storage system, then the problem of selection of a location, from which the ordered item must be picked becomes an issue. Selection of location can be connected with the necessity of certain trade-offs [1]. The selection of least-filled locations can help emptying and replenishing them, but in most cases increases 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 results in small quantities of an item remaining in the locations. In general, there are several take-out strategies that can be applied in location selection if the shared storage system is applied [15]:

- FIFO (*First-In-First-Out*) — units will be picked accordingly on their arrival to the warehouse,
- priority of partial units — locations with the lowest content of the item will be accessed first, even if it increases labour,
- quantity adjustment — the picker retrieves the item from the locations where the requested quantity is fully satisfied even if it generates additional low amounts of items in the locations,
- taking the access unit — if the amount of the item on a given location exceeds or is equal to the requested quantity, the complete unit is taken after the excess quantity is removed.

When we look at the above-mentioned strategies, we can see that various criteria are taken into consideration. For the first strategy (FIFO) when selecting location we look for this one, on which needed item arrived the earliest, therefore the storage time is considered. For the second strategy (priority of partial units) we look for the locations in which there are the smallest amounts of completed item, and thus the degree of demand satisfaction is considered. The third strategy (quantity adjustment) is opposite to the second one. We look for locations where there is the highest degree of demand satisfaction. The last strategy (taking the access unit) considers the complete units of items.

The above-mentioned strategies do not cover all possibilities. If a company utilises for example the FIFO strategy, then we can find several locations where a needed item has the same storage time. When adopting the third strategy then there can also be several locations, where the demand for an item is fully satisfied, etc. Also, the criteria that were set on the basis of these take-out strategies are not the only ones that can be used for the selection of locations, from which the picker should pick the item. Examples of other criteria are: the distance of analysed location from the I/O point, distance of location, where the ordered item is placed from locations, where other needed items are placed, level on which the location is placed (in the case of a high-level warehouse) or time to the expiration date of an item (in the case of deteriorating or perishable inventory). It is worth noting that the storage time is not the same as the time to the expiration date. The former is the profit-type criterion denoting how long the item has been stored since its arrival to the warehouse. The latter is the loss-type criterion, meaning that locations with items for which the time to the expiration date is shortest should be selected. As mentioned earlier, sometimes considering only one criterion when selecting a location that should be visited by the picker is not enough – more criteria should be considered at the same time; therefore, multi-criteria decision-making methods should be applied. This can be done by transforming the criteria into the composite measure, which value measures the so-called *location attractiveness*. This measure is calculated on the basis of the weighed distance of the analysed location from the so-called *pattern* (the perfect alternative or the perfect location) and *anti-pattern* (the worst alternative or the worst location).

Another issue that must be addressed is the designation of the picker's route. We can try to find the optimal one with respect to the route length or time. In case of the warehouse, it is the modified travelling salesman problem (TSP). Ratliff and Rosenthal [29] elaborated the method of designing the optimal (shortest) route for a rectangular one-block warehouse for narrow picking aisles (an aisle is narrow if the picker is able to pick the item from both sides of the aisle without any additional movement). De Koster et al. [6] extended the question of determining the optimal solution to the case where the I/O point is decentralised. Roodbergen and De Koster [30] proposed a procedure for determining the optimal route in a two-block warehouse (that is, the one with a cross-central aisle). Goetschalck and Ratliff [13] and Hall [17] designed the optimal route if there were wide picking aisles. If the number of cross aisles is greater than three (the number of blocks is greater than 2), then the procedure of determining the optimal route becomes more complicated and time consuming.

All the above-mentioned algorithms refer to dedicated storage. For shared storage systems, the problem of designing the pickers route was analysed by Daniels et al. [3]. They designated the three heuristics to designate the picker's route: nearest neighbour and shortest arc TSP and tabu search. Their main finding was that adopting the search heuristics outperformed the single-pass heuristics in approximation of the optimal solution.

Although optimal routes are always the shortest, they are rarely used in practice. There are several reasons for this. First, for large orders, they could be time-consuming to compute. Second, the obtained pick routes often seem illogical to pickers, who tend to deviate from them. Furthermore, they do not take into account aisle congestion or the usual movement direction. Therefore, companies more often use the heuristic methods of route designation. There are six heuristics of route designation in one-block rectangular warehouse [22, 33]:

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

The heuristics most commonly used in warehouse management practice are the first two (*s-shape* and *return*) [27, 35]. If the *s-shape* heuristic is applied, then the picker enters the first picking aisle, where the picked item is stored, travels through the whole aisle, returns through the second aisle with other needed item, etc. After going through the picking aisle with the last items to be picked, he/she returns to the I/O point (Figure 1).

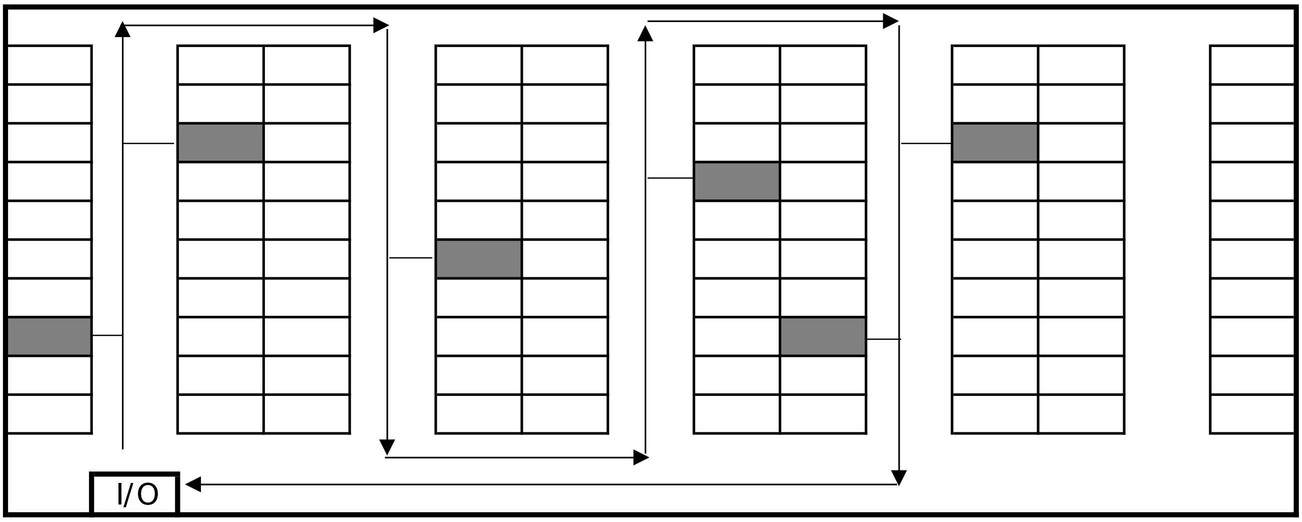

Figure 1. The *s-shape* heuristic

The *return* heuristic, on the contrary, assumes that the picker enters the first picking aisle, where the picked items are placed and goes the furthest to pick all of them from locations lying in that aisle and goes back, leaving the aisle from the same end. Then he/she goes to the second aisle, where the picked items are placed, and so on. After going to the aisle with the last items to be picked, he/she travels back to the I/O point (Figure 2).

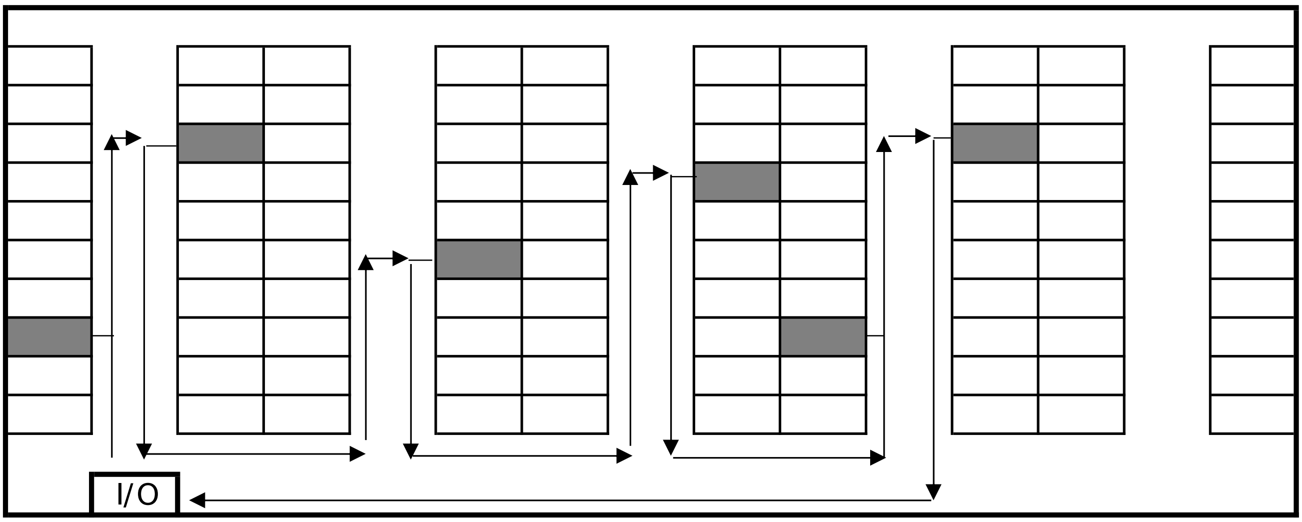

Figure 2. The *return* heuristic

All above-mentioned factors (warehouse layout, storage assignment, storage system, location selection strategy, and the picker's route designation) as well as the number of picked items influence the order picking time. However, there was no attempt to analyse the order picking time, if the needed items can be stored in various locations and their selection must be done by means of the multi-criteria decision-making methods.

The aim of the research is to compare the average order picking times obtained using the analytical model and simulation methods for shared storage systems. Although a similar analysis has already been done [34, 35], there is lack of such comparison for the selection of locations by means of the multi-criteria decision-making methods. We also add the comparison between the results obtained for shared and dedicated storage systems to check whether it is beneficial to store a given item in many locations. We conduct the research for the one-block rectangular warehouse with one I/O point, located at the beginning of the first picking aisle. We compare the results for random and ABC-class storage assignment. The latter is organised by using two policies: *within aisle* (Figure 3) and *across aisle* (Figure 4). We select the locations to be visited using the TOPSIS method.

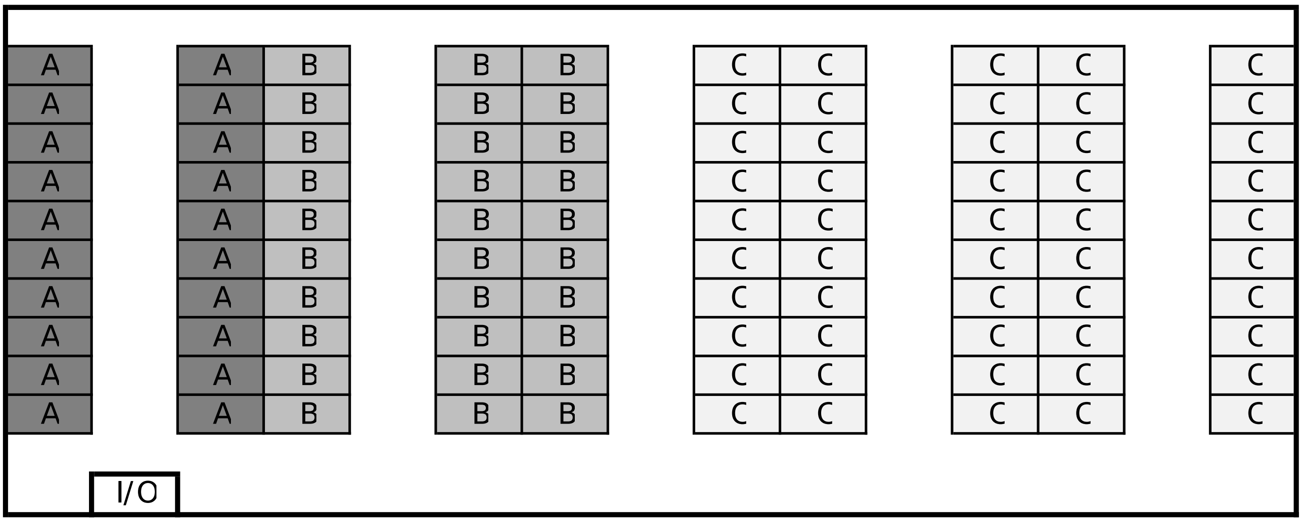

Figure 3. The *within aisle* policy

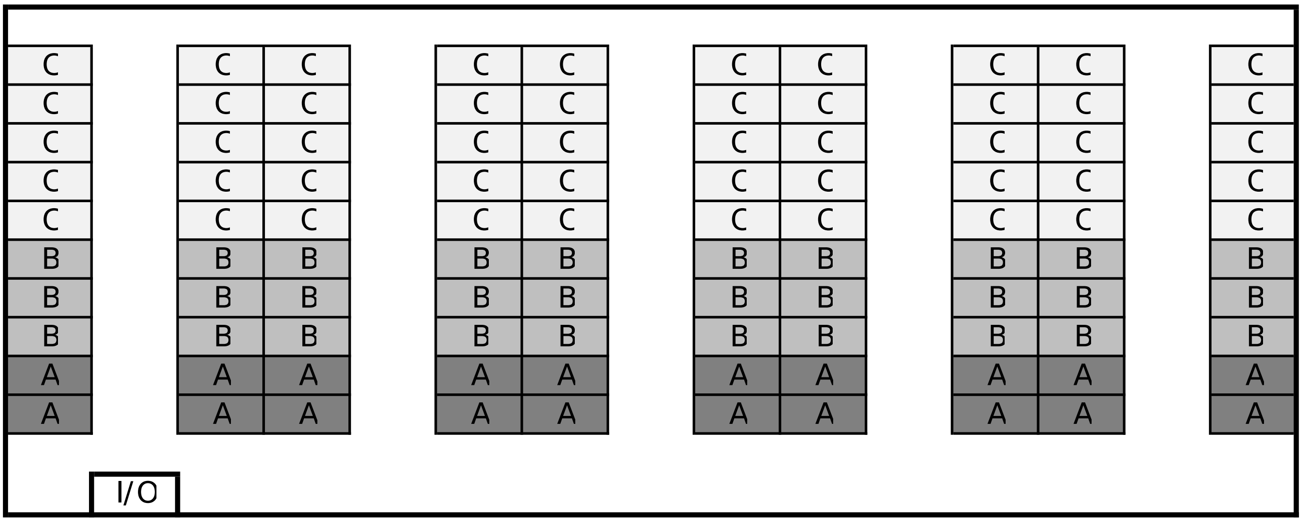

Figure 4. The *across aisle* policy

2. Research methodology

The research is primarily a simulation study. We assume a simple, one-block, rectangular warehouse with two cross 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 1000. The steps of the analysis are as follows:

1. We generate $10,000$ pick lists for every storage assignment, every storage order, every take-out strategy and every heuristic of route designation.
   (a) Every pick list consists of ten items.
   (b) Every item is stored in four locations.
   (c) Available amounts of items in each location vary from a single unit to the amount that satisfies the demand twice.
2. We select locations for every order by means of the TOPSIS method. We apply the two take-out strategies [15]:
   (a) quantity adjustment (QA),
   (b) priority of partial units (PPU).
3. For comparison purposes, we also select locations with the assumption of the dedicated storage.
4. We calculate the expected analytical order picking time for both take-out strategies and for every storage assignment, storage order and every heuristic of route designation.
5. We calculate the simulated order picking time for both take-out strategies and for every storage assignment, storage order and every heuristic of route designation.
6. We compare the results obtained for both approaches (analytical and simulation).

2.1. Generation of pick lists

The locations where all the items are stored are randomly sampled. For purely random storage assignment, for all items, every location has the same chance to be selected. For the ABC-class assignment, class A consists of items that occupy 20% of storage space, while their total share in sales is 80%. Items that constitute the class B occupy further 30% of space and have 15% in sales. The remaining 50% of storage space is destined for items belonging to class C, which constitutes the last 5% of sales. Therefore, for the ABC-class based storage, the probability of selecting locations for class A is 0.8, class B – 0.15 and class C – 0.05. Within each class we assume the random storage assignment.

2.2. Selection of locations by means of the TOPSIS method

Every location, where the needed items are placed, is described by three criteria:

- distance from the I/O point (x_1),
- degree of demand satisfaction (x_2),
- number of other needed items in the proximity of the analysed location (x_3).

The first criterion is measured on the ratio scale. It is the loss-type criterion, measured in a contractual unit, which is the shelf width. The second criterion, the degree of demand satisfaction, is calculated by means of the following formula:

$$x_2 = \begin{cases} \frac{q}{z} & \text{if } z > q \\ 1 & \text{if } q \geq z \end{cases} \tag{1}$$

where q – number of units of the item needed in the location analysed and z – demand for the item needed. 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). It is worth noting that, for example, if the demand for the item is 100 units and if we consider two locations, where the number of units in the first one is 100 and 150 in the second, both locations have the same attractiveness with respect to this criterion.

The third criterion, the number of other needed items in the proximity of the analysed location, is the profit-type one and measured on the ratio scale. The term “proximity” can be understood in various ways. It can be the same rack, the same shelf, the same aisle or even the same sector in the warehouse. Selection of the appropriate approach is very important because if we set this proximity very narrowly (as the same rack or the same shelf), it may happen that in most situations there will be no other needed items in the proximity of the analysed location, so in most situations this criterion will not differentiate locations. On the other hand, if we set the proximity too widely (as the whole sector), there might be in most cases the situation that almost every location will have all other items in the proximity, thus this criterion will also not differentiate locations. In the research, the proximity of the analysed location consists of all locations placed on the shelves within one picking aisle.

If the alternatives are described by multiple criteria, their weights must be determined. The problem of determining criteria’s weights (or variables’ weights in multivariate statistical analysis) is not an easy one. There is also no single, recognised as the best, method of determining such weights. The most common methods for determining the weights are as follows:

- naïve method – equal weights,
- rank ordering [4],
- relative information value method [20, 21, 26],
- method based on correlation coefficients [10, 11, 20],
- method based on Shannon’s entropy measure [24],
- expert methods [21],
- application of the AHP method [9, 36],
- method based on taking into account the normalised values of the criteria [39],
- simulation methods – comparing different combinations of weights and choosing the one that ensures optimisation of the adopted meta-criterion [7, 8].

We apply the expert method for the determination of weights. As we apply the two take-out strategies, for which the criterion x_2 (degree of demand satisfaction) is the most important one, we adopt the following criteria’s weights (w_j, $j = 1, \dots, m$, j – criterion number, m – number of criteria):

- $w_1 = 0.05$,
- $w_2 = 0.9$,
- $w_3 = 0.05$.

The difference between the two strategies is that for the strategy *quantity adjustment* the criterion x_2 is the profit-type one and for the strategy *priority of partial units* – loss-type. As the criterion x_2 is the most important for both the QA and PPU strategies, its high weight should ensure that locations with the highest degree of demand satisfaction will be the most attractive in the former and those with the lowest degree in the latter. Much smaller weights imposed on the remaining criteria should ensure that they allow us to differentiate the attractiveness of locations, for which the value of criterion x_2 is the same (for example, there are several locations, where the demand is fully satisfied in the QA strategy).

Such determination of weights can be recommended if we use the QA or PPU strategy. Of course, if we use another take-out strategy, the recommendations should be different. For example, let us consider the FIFO strategy. In such a case, we should add another criterion – storage time. It would be the profit-type one. This criterion should have the highest weight (to ensure that the locations containing the items with the longest storage time are the most attractive). The remaining criteria should have much smaller weights to ensure differentiation of locations’ attractiveness.

When no take-out strategy is applied, simulation methods can generally be recommended. By means of them, the decision-maker can empirically check, which one brings the optimisation of the meta-criterion (for example minimisation of order picking time).

The TOPSIS method. The TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is one of the most popular multi-criteria decision-making methods. It was created by Hwang and Yoon [18]. It is based on the weighed distance of each decision variant from the ideal alternative (i.e. one that consists of the best values of all criteria in the entire data set) and from the anti-ideal alternative (i.e. one that consists of the worst values of all criteria in the entire data set). It is desirable for the selected variant to be characterised by the smallest possible distance from the ideal alternative and the largest possible distance from the anti-ideal one. We choose the TOPSIS method for several reasons – its popularity, application of two reference points, great computational simplicity, and the fact that the participation of the decision-maker is limited to minimum (it is important when the method must be applied many times and constantly) [26].

A starting point of the TOPSIS method is the decision matrix

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

where x_{ij} – the value of the jth criterion in the ith alternative ($i = 1, \dots, n$, $j = 1, \dots, m$), m – the number of criteria, n – the number of alternatives.

As all criteria are measured on the ratio scale, we can normalise them by means one of the quotient inversions (such a normalisation method preserves the scale strength):

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}} \tag{3}$$

where: z_{ij} – normalised value of the jth criterion in ith alternative ($i = 1, \dots, n$, $j = 1, \dots, m$).

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

$$t_{ij} = w_j z_{ij}, \quad i = 1, \dots, n, j = 1, \dots, m \tag{4}$$

In the next step of the TOPSiS method we calculate the ideal (A_b) and the anti-ideal (A_w) alternative

$$A_b = \left\{ \left(\max_i t_{ij} | j \in J^+ \right), \left(\min_i t_{ij} | j \in J^- \right) | i = 1, \dots, n \right\} = t_{bj}, \quad j = 1, \dots, m \tag{5}$$

$$A_w = \left\{ \left(\min_i t_{ij} | j \in J^+ \right), \left(\max_i t_{ij} | j \in J^- \right) | i = 1, \dots, n \right\} = t_{wj}, \quad j = 1, \dots, m \tag{6}$$

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

Next we calculate the weighed distances of each alternative from the ideal (d_{i0}^+) and the anti-ideal one (d_{i0}^-) by means of the Euclidean metric:

$$d_{i0}^+ = \sqrt{\sum_{j=1}^{m} \left(t_{ij} - t_{bj}\right)^2}, \quad i = 1, \dots, n \tag{7}$$

$$d_{i0}^- = \sqrt{\sum_{j=1}^{m} \left(t_{ij} - t_{wj}\right)^2}, \quad i = 1, \dots, n \tag{8}$$

Finally, we calculate the composite measure q_i:

$$q_i = \frac{d_{i0}^-}{d_{i0}^- + d_{i0}^+}, \quad i = 1, \ldots, n \tag{9}$$

The composite measure q_i has the following properties: $q_i \in [0, 1]$, $\max_i \{q_i\}$ – the best alternative, $\min_i \{q_i\}$ – the worst alternative.

2.3. Calculation of expected analytical order picking time

The first step in estimation of order picking time is estimation of route length. It consists of two components [35]:

- distance in cross aisles,
- distance in picking aisles.

Distance in cross aisles. Expected distance travelled in cross aisles is always the same, regardless of the applied routing heuristic. It is calculated by means of the following formula [2, 35]:

$$E(D_{cross}|N) = 2d_2 \left(I - \sum_{i=1}^{I-1} \left(\sum_{l=1}^{i} p_{l.} \right)^N - 1 \right) \tag{10}$$

where:

- i, l – picking aisle number; $i, l = 1, 2, \ldots, I$,
- d_2 – distance in cross aisle between entrances to neighbouring picking aisles,
- $p_{i.}$ – the probability of being on a particular pick list position of an item stored in the i-th aisle:

$$p_{i.} = \textstyle\sum_{r=1}^{R} \left(p_{ir}^L + p_{ir}^R \right)$$

- p_{ir}^L – the probability of being on a particular pick list position of an item stored in location r on the left hand-side of the i-th picking aisle,
- p_{ir}^R – the probability of being on a particular pick list position of an item stored in location r on the right hand-side of the i-th picking aisle,
- I – number of picking aisles in the warehouse,
- N – number of items in the pick list,
- r – location in the rack number; $r = 1, 2, \ldots, R$,
- R – number of locations in the rack.

Distance in picking aisles for the *return* heuristic. The expected distance travelled in the i-th picking aisle for the *return* heuristic is calculated by means of the following formula [35]:

$$E(d_i^{return}|N) = 2 \left[d_0 \left(1 - (1 - p_{i.})^N \right) + d_1 \sum_{r=2}^{R} \left(1 - \left(1 - \sum_{s=r}^{R} \left(p_{is}^L + p_{is}^R \right) \right)^N \right) \right] \tag{11}$$

where:

- d_0 – distance from the line, on which the picker travels in the cross aisle to the first location with the item in the picking aisle,
- d_1 – distance between two neighbouring locations in the picking aisle,

- s – location in the rack number; $s = 1, 2, \ldots, R$.

The total expected distance travelled by the picker in all picking aisles is as follows [35]:

$$E(D_{pick}^{return}|N) = \sum_{i=1}^{I} E(d_i^{return}|N) \tag{12}$$

Distance in picking aisles for the *s-shape* heuristic. The expected distance travelled in the ith picking aisle for the *s-shape* heuristic does not depend on the number of items picked from this aisle (the picker travels through the entire aisle) [35]:

$$d_i^{s-shape} = (R-1)d_1 + 2d_0 \tag{13}$$

Different behaviour of the picker can occur only in the last visited picking aisle. If the number of pick aisles visited is odd, then the last one is entered from the main front aisle and the picker moves in it with accordance to the *return* heuristic.

The approximate expected route length for the *s-shape* heuristic is as follows [35]:

$$E(D_{pick}^{s-shape}|N) \approx \sum_{i=1}^{I} \left[\left(1-(1-p_{i.})^N\right)\left(P_{odd}P(R_i)E(d_i^{return}|N) + (1-P_{odd}P(R_i))\, d_i^{s-shape}\right)\right] \tag{14}$$

where:

- P_{odd} – arbitrarily assumed probability of having the odd number of picking aisles,
- $P(R_i)$ – probability that the ith picking aisle is the last one visited by the picker:

$$P(R_i) = \left(\sum_{j=1}^{i} p_{i.}\right)^N - \left(1 - \sum_{j=i}^{I} p_{i.}\right)^N$$

When we know the expected values of route distance for given heuristic ($heur$), the expected order picking time can be estimated by means of the following formula:

$$E(t^{heur}|N) = t_{mov}\left(E(D_{pick}^{heur}|N) + E(D_{cross}|N)\right) + Nt_{load} \tag{15}$$

where:

- t_{mov} – time of crossing one distance unit,
- t_{load} – time of picking the item from a single location.

3. Numerical example

The first step in calculation of the analytical approach is to estimate the expected number of locations to be visited by the picker. For the quantity adjustment strategy, we assume that locations, where items with the highest degree of demand satisfaction (criterion x_2) are placed, are most likely to be selected. For example, let us assume that for a given order, one of the items is located in four locations in which the demand is satisfied with the following degrees: 0.35, 1, 0.5, 0.95. As the quantity adjustment assumes that this criterion has weight 0.9 (versus weights 0.05 for the remaining two criteria), the second location (with full demand satisfaction) will be most likely selected. However, it might happen that if the distance of this location from the I/O point is much larger than for the fourth one, the latter might be selected. Therefore, there might be situations where two or more locations for a single item will be selected.

We assume that the demand for every picked item is 100 units. The available amounts (q) of them in every location are generated from the uniform discrete distribution. Possible amounts belong to the following sample space:

$$q \in \{1, 2, \ldots, 200\}$$

Therefore, the probability that demand is satisfied in a single location is equal to $\frac{101}{200} = 0.505$. The probability that the demand is not satisfied is then equal to $\frac{99}{200} = 0.495$. The probability that the picker visits at least one location is 1. The probability that at least two locations need to be visited in order to satisfy the demand is that in none of them it is satisfied in 100% (the amount in every location must be not more than 99 units) and equals $(0.495)^4 = 0.0600$. The probability that at least three locations are visited is that the average amount in all of them will be not more than in 49 units. Such probability equals $(0.245)^4 = 0.0036$. Subsequently, the probability that four locations need to be visited is that for all of them the average amount of items will not exceed $33.(3)$ units and equals $[0.1(6)]^4 = 0.0008$. These are the average probabilities that at least k locations are visited. Therefore, the probability that exactly three locations are visited is then $0.0036 - 0.0008 = 0.0028$. The probability that exactly two locations are visited is $0.0600 - 0.0036 = 0.0564$. The probability of visiting exactly one location is the complement of the above three to unity: $1 - 0.0600 - 0.0036 - 0.0008 = 0.9400$.

It is not as easy to calculate the average number of locations for the priority of partial units take-out strategy. It assumes that the picker picks items from the locations, where the demand is least satisfied. The probability that the picker visits only one location to pick a selected item is $(0.505)^4 = 0.0650$. Also, the probability that he/she must visit four locations is that in three of them the satisfaction of demand is lower than $0.(3)$ equals $[0.1(6)]^3 = 0.0046$. The biggest problem is to set the probability that two or three locations for a single item must be visited. We propose the simplified and approximate method to calculate it. It is the probability that for one location the degree of demand satisfaction is less than 100% (0.495) minus the probability that for remaining three of them it is fully satisfied $[(0.505)^3 = 0.1288]$. It gives the probability at the level of 0.3662. The probability of visiting three locations to pick a single item is the compliment to unity of three previously ones.

For both applied take-out strategies it is possible that the demand for certain item will not be satisfied from all four locations. Such situation occurs in the case where the average available amounts of units per location is less than 25. The probability of such phenomenon is $\left(\frac{25}{100}\right)^3 \cdot \frac{24}{100} = 0.0002$. Therefore, such a situation is very unlikely, but possible. If it happens, then we assume that the order will be realised, but demand for this specific item will be satisfied partially.

Table 2 presents the probabilities of visiting a specific number of locations to pick one item, and the expected and simulated number of locations to be visited to pick the order for the quantity adjustment (QA) and priority of partial units (PPU) strategies.

Table 2. Probabilities and number of locations to be visited for analysed take-out strategies

No of locations	QA	PPU
Probability		
1	0.9400	0.0650
2	0.0564	0.3662
3	0.0028	0.5641
4	0.0008	0.0046
Visited number of locations		
Expected number of locations per item	1.064	2.508
Expected number of locations per order	10.64	25.08
Mean simulated number of locations per order	10.91	24.07

Multiplying the probabilities by the numbers of locations, we obtain the expected number of visited locations per item. As each pick list consists of 10 items, we obtain the expected number of locations per order. The mean simulated number of locations per order is obtained by using simulations. The expected number of locations for the quantity adjustment strategy is slightly lower than the simulated one. It is because even with the small probability of taking into account other criteria for selection of locations, it might happen that more locations will be visited. The opposite situation is for the priority of partial units. It may happen that fewer locations will be visited than expected, because on rare occasions other criteria (even with very small weights) may cause that locations with higher degree of demand satisfaction will be visited. For the compared dedicated storage system, the number of visited locations will always be equal 10 (since each item is stored in one location).

In the next step of the analysis we estimate the expected order picking times for every specified storage order, warehouse layout, and take-out strategy. The number of items (N) in formulas (10)–(15) is, in fact, the number of visited locations. It equals 10.64 for the quantity adjustment strategy and 25.08 for the priority of partial units strategy (Table 2). We assume that the time of crossing one distance unit (t_{mov}) is 2 seconds and time of picking the item from a single location (t_{load}) equals 10 seconds. Table 3 presents the expected analytical order picking times, calculated by means of equation (15) and mean order picking times, obtained by means of simulation methods (denoted by $\overline{T}_{sim}^{heur}|N$).

Table 3. Expected analytical and mean simulation order picking times (in min:sec)

Take-out strategies	random		ABC across aisle		ABC within aisle	
	s-shape	*return*	*s-shape*	*return*	*s-shape*	*return*
analytical method						
QA	12:31	13:11	12:28	8:18	8:18	9:39
PPU	20:25	22:52	20:15	13:50	13:28	16:07
dedicated storage	12:03	12:40	12:00	8:00	8:01	9:16
simulation method						
QA	11:35	12:03	11:19	7:55	8:38	9:14
PPU	19:11	21:15	18:53	13:07	12:51	14:52
dedicated storage	12:35	12:43	11:55	8:03	8:26	9:22

The order picking times are always the longest for the random storage assignment. It is perfectly understandable because for the class-based storage assignment the most often ordered items are located closer to the I/O point than in case of the random storage assignment. The smallest difference between the results obtained for random storage are for ABC-class with across aisle policy and *s-shape* routing heuristic. It is because items from class A are located in all picking aisles (even the furthest ones from the I/O point – Figure 4). The *s-shape* heuristic assumes that all picking aisles are crossed and the probability that items are located in each picking aisle in ABC-class storage with across aisle layout is exactly the same as for the random storage assignment. The only difference is in case of odd number of aisles with items to be picked. In such a case, the last aisle is visited the same, as for the *return* heuristic. And because in case of the ABC storage with across aisle policy the most frequently picked items are located close to the front cross aisle, the average distance in such aisle is shorter than for the random storage assignment.

In case of the quantity adjustment (QA) take-out strategy, we obtain the best results (the shortest order picking time) for the ABC-class storage assignment with across aisle policy and using the *return* heuristic (expected analytical and average simulated order picking times are equal 8 min 18 sec and 7 min 55 sec, respectively). For the priority of partial units (PPU) strategy, application of the ABC-class based storage assignment with within aisle policy and *s-shape* heuristic yields the best results (with expected analytical and average simulated order picking times being 13 min 28 sec and 12 min 51 sec, respectively).

The research conducted so far indicates, that for the dedicated storage the *s-shape* heuristic works best with the ABC-class within aisle storage policy, while the *return* heuristic with the ABC-class across aisle storage policy [19, 35]. Our research confirms this findings also for the shared storage system.

In order to assess the improvement in the order picking time with the application of the class-based storage assignment to the random one, we present the percentage decrease in the average order picking time by applying across aisle and within aisle storage policies in Table 4.

Table 4. Percentage improvement in order picking time by application of class-based storage assignment with respect to the random one

Take-out strategies	ABC across aisle		ABC within aisle	
	s-shape	*return*	*s-shape*	*return*
analytical method				
QA	-0.41%	-37.01%	-33.64%	-26.79%
PPU	-0.80%	-39.50%	-34.04%	-29.54%
dedicated storage	-0.39%	-36.64%	-33.54%	-26.71%
simulation method				
QA	-2.29%	-34.22%	-25.48%	-23.33%
PPU	-1.57%	-38.22%	-33.04%	-30.00%
dedicated storage	-2.71%	-36.62%	-31.19%	-26.31%

For every routing heuristic, the average analytical and simulated order picking times are smaller for the class-based storage assignment. The smallest differences are for the ABC across aisle policy and the *s-shape* heuristic (as explained earlier). The largest relative differences are for the best heuristics for every storage policy (*return* heuristic for the across aisle policy and *s-shape* heuristic for the within aisle policy). In such cases, application of class-based storage brings reduction in the order picking time on the average by over 30% in comparison with the random storage. It holds for both take-out strategies and also for dedicated storage.

There is no point to compare the order picking times for the QA and PPU take-out strategies, as their aims are completely different – the QA strategy aims at the quickest order picking time, while the aim of the PPU strategy is cleaning the locations from small quantities of items. As expected, for both analytical and simulation methods, the worst results for the QA strategy always yield shorter order picking times even for the best results for the PPU strategy.

It is interesting to analyse the benefit (if any exists) of storing the same item in many locations (shared storage) with respect to storing every unit in only one location (dedicated storage). As the application of the PPU strategy does not aim at reducing order picking time, it is only sensible to compare the results for the QA take-out strategy with the dedicated storage. If there is high probability of satisfying the demand for a given item in many locations, the application of shared storage order should decrease the average order picking time with respect to the dedicated one. In our case (every item is stored in four locations and the probability that the demand is satisfied in a single one), the expected analytical order picking times are always higher for the QA strategy than for dedicated storage (Table 3). It is because of two reasons. The first one is that the calculation of analytical order picking time does not take into account the probability of selection of location (for a given product) that is closer to the I/O point. The second reason is that in equations (10) – (15) the number of locations for dedicated storage is always equal to the number of items (N), while with the application of the QA strategy, the average number of visited locations is larger by 0.64 (Table 2). Therefore, we should compare the average simulated picking times, not the analytical ones. With the exception of the ABC within aisle policy with the *s-shape* heuristic, for our assumptions, the application of the shared storage with the QA take-out strategy brings improvement in the average order picking time. The biggest relative difference (over 5%) is for the random storage assignment. For the ABC across aisle policy the application of the shared storage with the QA strategy allows one to reduce the order picking time on average by 5.09% for the *s-shape* heuristic and 1.74% for the *return* heuristic. The use of shared storage with the QA take-out strategy for ABC within aisle policy and the *s-shape* heuristic increases the order picking time on the average by 2.35%, while the application of the *return* strategy decreases the order picking time on the average by 1.5% compared to dedicated storage. Therefore, if we use the shared storage system with more locations, where items can be stored and the probability that the demand for items in the pick list is satisfied in a single location is high, we probably might expect further improvement in the order picking time with respect to the dedicated storage.

In order to compare the order picking times for the analytical and simulation approach, we calculate the relative differences for every storage order, warehouse layout and take-out strategy by means of the formula:

$$Diff_{time}^{heur}|N = \frac{E(t^{heur}|N) - \overline{T}_{sim}^{heur}|N}{\overline{T}_{sim}^{heur}|N} \cdot 100\% \tag{16}$$

We present the relative differences between analytical and simulated order picking times for each storage assignment and take-out strategy in Figure 5.

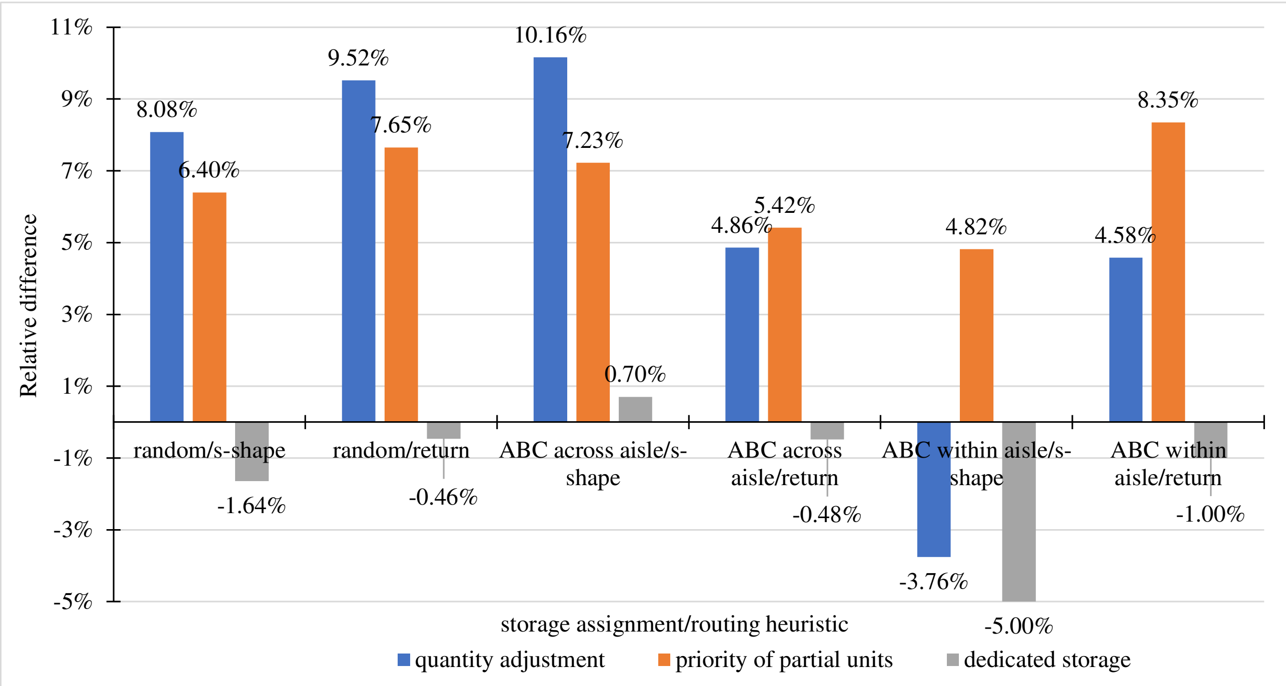

Figure 5. Relative difference of order picking time for analytical and simulation approach

For shared storage in most cases (with the exception of ABC within aisle storage, the *s-shape* heuristic and quantity adjustment strategy), simulated order-picking times are smaller than the analytical ones. The absolute differences are always higher for the priority of partial units (PPU) strategy than for the quantity adjustment (QA). It is due to the higher number of locations to visit to pick an order and because of higher difference in the expected number of locations. The expected number of locations in the analytical approach is 25.08 vs. 24.07 for the simulation approach. For the quantity adjustment approach, the difference is 10.64 vs. 10.91, respectively. These differences result from the fact that the other criteria than the degree of demand satisfaction might (to a very small extent, because their weights are much smaller) cause visiting more locations than expected for the QA strategy. For the PPU strategy, the situation is opposite – the least-filled locations should be selected. However, sometimes the distance of the location from the I/O point and the number of other picked items in its proximity may cause that the number of visited locations will be smaller (locations with higher degree of demand satisfaction will be visited). For dedicated storage, the situation is opposite (in most cases the expected analytical order picking times are shorter than the simulated ones)

When we, however, compare the relative differences, for random storage assignment and ABC across aisle storage policy with the *s-shape* heuristic they are higher for the QA strategy (Figure 5). For the remaining cases, the situation is opposite. The largest relative difference is for the ABC across aisle with *s-shape* routing heuristic and QA take-out strategy – expected analytical order picking time is by over 10% longer than the average simulated one. The smallest relative difference is for the ABC within aisle with *s-shape* routing heuristic and QA take-out strategy – expected analytical order picking time is by 3.76% shorter than the average simulated one. The relative differences are much lower in case of dedicated storage. The maximal is in the case of the ABC within aisle with *s-shape* routing heuristic (expected analytical order picking times are by 5% lower than the average simulated ones). The minimal difference is in case of the random storage with *return* heuristic – expected analytical order picking times are by 0.46% lower than the average simulated ones.

Considering the shared storage, the biggest absolute difference between expected analytical and simulated average order picking time is in case of the PPU strategy for random storage assignment and *return* heuristic – 1 min 37 seconds. The smallest difference is in case of the QA strategy for ABC within aisle storage policy and *s-shape* heuristic – 20 seconds. For dedicated storage, the biggest absolute difference (25 seconds) is in the case of the ABC within aisle storage policy and *s-shape* heuristic and the smallest – 3 seconds – for the ABC across aisle with *return* routing heuristic.

Tarczyński [35] presents a detailed comparison of route length for various routing heuristics, storage assignment methods, and warehouse layouts. Although our research focuses on order picking time, not route length, the main determinant of order picking time is time of picker's travelling. His results indicate that the relative difference between analytical and simulation route lengths do not exceed 2%. Our research mainly confirms his results in case of the dedicated storage (the exception of the ABC within aisle storage assignment and *s-shape* heuristic results from the use of approximate formula for calculation of expected analytical order picking time). The differences for the shared storage are much larger (Figure 5). There are several explanations for this. First, in the Tarczyński's research the warehouse utilises the dedicated storage (given item is stored in one location). In our research we assume the shared storage and each item is stored in four locations. Second, in his research, the number of items equals the number of locations to be visited. In our research, the number of locations is usually larger in case of shared storage. Third, in our research, the probability that a given item will be located closer to the I/O point is greater (because it is stored in four locations). It is particularly visible for the QA take-out strategy, because the probability that we need to visit only a single location to pick a given item is very high (0.94 – see Table 2) and the situation that we have more than one location, where the demand is fully satisfied is very likely. Therefore, the probability that this item is closer to the I/O point is higher than for the dedicated storage. It is also the reason why the simulated average times are generally shorter than the expected analytical ones.

The main conclusion resulting from Figure 5 is that, despite using the same parameters, the relative differences between the average analytical and simulated order picking times are much higher for shared storage than for dedicated one. It does not mean that the simulation analysis is better than the analytical approach. It means that we should consider the criteria's weights in formulas for calculation of expected analytical order picking times. This would allow us to consider the probability of decreasing the expected distance in the cross aisles and, for the *return* heuristic, the distance in the picking aisles.

4. Conclusions

The aim of our research is to compare order picking time for analytical and simulation approaches. We assume that items are stored in shared storage assignment in traditional one-block rectangular warehouse. For comparison purposes, we also provide the calculations for the dedicated storage. We assume random and ABC-class storage assignment with across aisle and within aisle policies. In case of shared storage, we conduct the analysis for two take-out strategies: quantity adjustment (QA) and priority of partial units (PPU). Every item is stored in four locations, which are described by three criteria: distance of the location from the I/O point, degree of demand satisfaction, and number of other picked items in the proximity of the analysed location. We select the locations to be visited by the picker by means of the TOPSIS method. After selecting the locations, the route is designated by means of two of the most widely used heuristics: *s-shape* and *return*.

The results obtained show that the average simulated order picking time is in most cases shorter than the expected analytical one (with the exception of ABC within aisle storage, the *s-shape* heuristic, and quantity adjustment strategy). The main reason for this is that during selection of locations (by means of the TOPSIS method), it is very probable that the average distance of selected locations from the I/O point is shorter than the expected, analytical one (the analytical calculation of order picking route does not take into consideration this probability). For the QA strategy, we obtain the shortest order picking time in case of the ABC-class storage assignment with across aisle layout and using the *return* heuristic. For the PPU strategy, application of the ABC-class based storage assignment with within aisle layout and *s-shape* heuristic yields the best results. The relative differences range from 3.76% (ABC within aisle storage, the *s-shape* heuristic and QA strategy – the only case, when the analytical estimation of the order picking time was shorter than the average simulated one) to 10.16% (ABC within aisle storage, the *s-shape* heuristic and QA strategy). The absolute differences range from 20 seconds (ABC within aisle storage, the *s-shape* heuristic and QA strategy) to 1 min 37 seconds (the PPU strategy for random storage assignment and the *return* heuristic). We also compare the results of the order picking times obtained for shared storage with the application of the QA take-out strategy with the results obtained for the dedicated storage. Simulation analysis proves that with our assumptions in most cases we can expect a shortening of the order picking time, if we apply the shared storage system and the QA strategy. The relative differences are up to 5%.

The results obtained prove that the expected analytical order picking times are calculated accurately. However, it is possible to calculate them more accurately if we include weights imposed to the criteria. In our case, one criterion – the degree of demand satisfaction has much greater weight than the remaining two (0.9 vs. 0.05). Although such small weights do not influence the order picking times to a high degree, higher weights imposed on other criteria would certainly create higher differences. Therefore, the direction of future research will be taking into consideration weights imposed on the decision criteria in calculation of expected, analytical order picking time. Also, the comparison between dedicated and shared storage will be further examined. The different assumptions (different number of locations, where the items from the pick list are stored, and different degrees of demand satisfaction in each location) will be analysed.

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