Impact of the Method of Criteria Normalisation on the Order Picking Route and Time

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Abstract:

Purpose: The purpose of the article is the selection of the best criteria for the normalisation method in order to achieve the minimal order picking route and time.

Design/Methodology/Approach: When a company utilizes warehouse with the shared storage system, every product can be stored in many, sometimes very distant from each other, locations. Locations were selected by the multiple-criteria decision-making technique – TOPSIS. The research was conducted by means of the simulation methods. Every location was described by three criteria (distance from the I/O point, degree of demand satisfaction and the number of other picked products in the proximity of the analyzed location), for which 37 combinations of weights and 18 normalization formulas were applied. For every combination of weights and normalization method 1000 orders were generated.

Findings: The best results were obtained when high weight was assigned to the degree of demand satisfaction. It was hard to indicate unequivocally the best normalization method. However, quotient inversions generally yielded slightly worse results than standard scores and feature scaling.

Practical Implications: Obtained results indicate that the presented approach can be useful in real warehouse management. It is a quite versatile method that can be adopted to various situations.

Originality/value: Although the routing problem in order picking has already been widely discussed, the literature about the problem of selection of locations in shared storage is quite scarce. Therefore, the presented approach can serve as one method of selection of locations in the shared storage system.

Keywords: Multi-criteria decision-making, order picking, TOPSIS, normalisation, simulation methods.

JEL classification: C15, C44.

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1. Introduction

On the average, warehouse activities constitute up to 39% of total logistics costs in European companies (Fumi *et al.,* 2013). Of all warehouse activities, order picking constitutes the largest part (about 55%) of all warehouse operating costs (Bartholdi and Hackman, 2019). Order picking can be organised in many ways. Companies can utilise automated 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 (Roodbergen and Vis, 2009). However, as of the beginning of the 21st century, about 80% of companies still used the classical, manual *picker-to-parts* systems (De Koster *et al.,* 2007). Despite the fact that by 2012 this share dropped to 74% (Napolitano, 2012), these systems are still used in the largest part of companies. For the *picker-to-parts* systems the order picking can be divided into four main activities (Bartholdi and Hackman, 2019). The distribution of order picking time in such systems is presented in Table 1.

Table 1. *Distribution of order-picking time*

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

Source: *Bartholdi & Hackman, 2019.*

Travelling consists of over the half of the order picking time. The rest of activities, although sum to 45%, alone constitute much smaller parts. Therefore, when the process of order picking is to be optimised, the biggest improvements can be achieved by reducing the order picking route. The order picking route is the route that the picker must travel to pick the order. There are three main features that influence the length of order picking route: storage assignment, warehouse layout and routing technique.

The storage assignment is the first issue that must be considered when planning the warehouse. There are five main types of storage assignment (Kofler, 2014; Le-Duc, 2005):

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

For random storage assignment, when goods arrive at the warehouse, they are placed in available locations randomly, without any pattern and regardless of the properties of products' rotation, demand, etc. The advantage of random storage assignment is good space utilisation, but the main drawback of this approach is that the goods are

scattered around the warehouse and the same products can be placed in sometimes very distant from one another locations. Although purely random assignment is rarely met in real situations, it is frequently used in theory as a benchmark showing, how utilisation of other, better organised storage assignments can improve the process of order picking.

The other type of storage assignment is the closest-open-location one. When goods arrive at the warehouse, they are stored in the closest to the I/O point locations. This approach is used when the pickers select storage locations by themselves. Advantages and drawbacks of this storage assignment are the same as for the random one. In a long term, the closest-open-location storage assignment converges to the random one.

Dedicated storage assignment means that every product is assigned to a single location (or group of locations if requested amounts do not fit into the single location) and every location is dedicated to single product. The advantage of dedicated storage assignment is that every product has one and the same place in the warehouse, therefore it is easy (even for the large number of products) for the pickers to memorise the placement of products. The drawback of this approach is poor space utilisation.

Class-based storage assignment is one of the most frequently used systems in real situations. Products are placed in the warehouse with accordance to appropriate class membership. Products are assigned to appropriate class on the basis of their popularity (for example turnover or the COI index) (Kofler, 2014). There is no clear indication, into how many classes the products should be divided. Some authors suggest that for the low-level *picker-to-parts* system optimal number of classes should be between 2 and 4 (Petersen *et al.,* 2004). Van den Berg and Gademann (2000) performed the simulation analysis for the automated systems, such as AS/RS and concluded that in such case the number of classes should be 6. When various assumptions were considered, Yu, de Koster and Guo (2015) concluded that the number of classes should never exceed 6. The most frequently used number of classes is 3. In such case, we talk about the ACB-class storage assignment. It is worth noting that the division of products into appropriate classes can be different for various cases.

For example, in inventory theory products are divided into classes with respect to contribution of value of their sales in total value of sales. Such approach is not appropriate for placing products in the warehouse, where measures based on turnover should be used instead (Frazelle, 2002). The most popular division method is based on Pareto's strategy. It assumes that 20% of the fastest-moving products accounts for 80% of total turnover (class A). Next 30% of products accounts for 15% of total turnover (class B) and remaining 50% of products – for 5% of total turnover (class C). Products belonging to the class A should be placed in locations that are the closest to the I/O point and products in the class C – in the most distant from the I/O point locations. By applying the ABC-class based storage can itself decrease the order picking route and time even by 45% (Le-Duc, 2005).

The family-grouping storage assignment means that the products that are frequently ordered together, are considered. Such products should be placed in the warehouse close together in order to pick them from locations placed at the same aisle.

It is worth noting that the above-mentioned storage assignment type can be used together. For example, after dividing products into classes ABC, within each class they can be placed randomly or with the closest-open-location assignment. The dedicated storage assignment within classes ABC is also possible.

Regardless of the storage assignment type, the order picking route and time can be decreased by utilisation of appropriate aisle design. The most widely used warehouse layout is the rectangular one with parallel picking aisles and one or more orthogonal cross aisles. Its popularity also results from the fact that it is the easiest one to implement. However, there are possible other layouts. Sometimes they depend on the shape of buildings, where warehouses are located. One of the most popular, different from the rectangular one, is the L-shaped layout (De Koster *et al.,* 2007). For specific locations of the I/O point, such designs as the Flying-V and Fishbone can decrease the order-picking routes even by 10% to 20% (Gu *et al.,* 2010; 2012). Other methods of improving the order picking process are connected with its organisation. The most popular organisation of picking policies include zone picking, wave picking or batch picking (Shah and Khanzode, 2017).

The classification of storage assignment types results from the most general division of the storage types. There are two of them: dedicated and shared storage (Bartholdi and Hackman, 2019). Dedicated storage has already been described earlier. Shared storage has much more in common with random or the closest-open location assignments. When company utilises the shared storage, then every product can be stored in many locations and every location can hold any number of products.

Products can be scattered around the whole warehouse (if pure random or closest-open location strategies are used) or around all locations belonging to specific classes (if the ABC-class storage assignment is used in combination with random or closest-open location ones). The advantages and disadvantages of the random storage system are roughly the same as in the case of random and closest-open location ones. The space utilisation is good, but locations of products change constantly with time, what makes impossible to pickers to memorise them. Utilisation of such system forces to satisfy at least three requirements: application of warehouse management system, discipline amongst the pickers and a method of selection of locations to be visited during order picking.

Problem of selection of locations when a company utilises shared storage type has little coverage in literature. Bartholdi and Hackman (2019) stated that in case of shared storage selection of locations from which ordered products are to be picked is often connected with certain trade-offs. The picker can pick product from the most convenient (i.e., being located close to the I/O point or fully satisfying the demand)

locations – such approach saves time and labour but results in small quantities of products that remain in many locations. On the other hand, we can select the least-filled locations – this allows to clean them from small amounts of products, but increases the route length and order picking time (Dmytrów, 2018). When deteriorating items are stored in a warehouse, the main criterion of selection of location will be storage time – the locations in which picked products are stored the longest, will be selected first – other criteria are much less important in this case. Summing up, we can distinguish four take-out strategies (Gudehus and Kotzab, 2012):

- 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 product will be accessed first, even if it increases labour;
- quantity adjustment – the picker retrieves the product from the locations where the requested quantity is fully satisfied even if it generates additional low amounts of products in the locations;
- taking the access unit – if the amount of the product on a given location exceeds or is equal to the requested quantity, the complete unit is taken after the excess quantity is removed.

As we can see, there are three criteria that can be applied in these strategies. The first one takes into consideration storage time, remaining three strategies consider the level of demand satisfaction. The last strategy also considers complete access units of a product. Of course, taking only one criterion in every strategy does not cover all possibilities of distinguishing locations. For example, when a company uses the first strategy, it may happen that there will be at least two locations with picked product with the same storage time. Other criteria should be considered, for example demand satisfaction or distance from the I/O point.

Therefore, in order to differentiate between locations, where the same, picked products are placed, we must consider multi-criteria decision-making approach. It can be done by transforming the criteria into the composite measure. Its value can be understood as the *location's attractiveness*. It is calculated on the basis of weighed distance of the analysed location from the so-called *pattern* (the perfect alternative or, in this case, perfect location) and *anti-pattern* (the worst alternative or, in this case, worst location). In order to calculate the composite measure, values of the criteria must be normalised.

The aim of the research was to find the best criteria normalisation method in order to minimise the picker's route length and order picking time. The research was based on the simulation methods – orders were generated randomly. For every criteria's combination of weights and normalisation method 1000 orders were generated. The best combination of weights and normalisation method would be the one(s) with minimal route length and order picking time.

2. Research Methodology

In the first stage of the analysis the criteria, by which the locations were described, were defined. They were as follows:

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

The first criterion is the loss-type one. It is measured on the ratio scale in conceptual unit, which is the shelf width. It is calculated by means the taxicab geometry, by means of the following formula:

$$x_1 = n_{aisle} + n_{shelf} \tag{1}$$

where n_{aisle} – picking aisle number of an analysed location, n_{shelf} – shelf number of an analysed location. The original formula for the taxicab geometry simplifies to the one, presented by the formula (1) because with the assumed warehouse layout (the rectangular one with parallel picking aisles and two orthogonal cross aisles) the coordinates of the I/O point (aisle and shelf numbers) are assumed to be equal 0. It should be emphasised that the distance of the analysed location from the I/O point has nothing in common with the distances of the location from the pattern and anti-pattern, used to calculate the composite variable.

The second criterion is also measured on the ratio scale. It is the profit-type criterion, calculated by means of the following formula:

$$x_2 = \begin{cases} \dfrac{l}{z}, & \text{if} \quad z > l \\ 1 & \text{if} \quad l \geq z \end{cases} \tag{2}$$

where l – number of units of the picked product in the analysed location and z – demand for the picked product.

Values of the second criterion are in the interval $(0, 1\rangle$. If for example the demand for the picked product is 100 units and it is placed in two locations and if 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 (its value in both cases equals 1).

The third criterion, or the number of other picked products 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 different ways. It can be the same rack, the same shelf, the same isle 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 picked products 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 products in the proximity, thus this criterion will also not differentiate locations. In the research, the proximity of the analysed location are all locations placed on the shelves within one picking aisle.

After selection of the criteria, the next step is to weight them, because the composite variable, which is created on their basis, is based on the weighed distance from the pattern and anti-pattern. If there is no substantive reason to do so, weights should be equal. In our case, however, there is a reason to weight the criteria. This reason is minimisation of order picking time and route. There are many methods of weighing the criteria. One of them is based on the criteria's variability. Criteria with high variability should have higher weight because they differentiate analysed alternatives to much higher degree than criteria with small variability. Another method of assigning weights is based on the correlation between criteria and the meta-criterion. Higher correlation (of course in its absolute value) results in higher weight. Another method is based on the Shannon's entropy (Lotfi and Fallahnejad, 2010) or the AHP method (Saaty, 1980). In case of presented analysis, it was difficult to assume any of the above-presented method because the orders were generated, and the values of the criteria changed constantly. Therefore, it was assumed that combinations of weights were fixed and for such fixed combinations the simulations were performed. Various fixed combinations of weights were used. In order to consider wide spectrum of weights, it was assumed that weights for each criterion changed by 0.1. The distribution of weights between the criteria is presented in Table 2.

Table 2. *Distribution of weights over the criteria*

Weight type	Criterion 1	Criterion 2	Criterion 3
Equal	0.(3)	0.(3)	0.(3)
Extreme dominance	0.8	0.1	0.1
Strong dominance	0.7	0.2	0.1
Significant dominance 1	0.6	0.3	0.1
Significant dominance 2	0.6	0.2	0.2
Medium dominance 1	0.5	0.4	0.1
Medium dominance 2	0.5	0.3	0.2
Small dominance 1	0.4	0.4	0.2
Small dominance 2	0.4	0.3	0.3

Source: Own elaboration.

The first combination, with equal weights, was used as the reference. The second weight type presents the extreme dominance of one criterion over the remaining ones (one criterion is eight times more important than the remaining ones). The third type presents strong dominance, etc. The last type, small dominance 2, reflects the situation close to the first one. Application of the vectors presented in Table 2 for all criteria

(for example the second one will result in: [0.8 0.1 0.1], [0.1 0.8 0.1] [0.1 0.1 0.8]) gives a total of 37 combinations of weights. They are presented in Table A1 in the Appendix.

Having specified the criteria and the system of weights, the next step is calculation of the composite variable that measures the weighed distances of analysed location from the pattern and anti-pattern. There are many multi-criteria decision-making methods that are based on the idea of calculation of the composite measure. Among them, the following can be distinguished: COPRAS (Complex Proportional Assessment of Alternatives), SAW (Simple Additive Weighting), VIKOR, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) and many others (Saaty and Ergu, 2015). The TOPSIS method was selected in the research. The main reason for its selection was its simplicity and popularity.

Every product in the order was considered separately. For each product all locations, where it was placed, were considered. Every location, where the analysed product was placed, was described by appropriate values of all three criteria. The steps of the calculation of the synthetic measure by means of the TOPSIS method are as follows (Hwang and Yoon, 1981):

1. The values of each criterion were normalised.
2. The *pattern* (minimum values for the loss-type criteria and maximum for the profit-type criteria) and *anti-pattern* (maximum values for the loss-type criteria and minimum for the profit-type criteria) were calculated.
3. The weighed distances of each i-th alternative (location) from the pattern (d_{i0}^+) and anti-pattern (d_{i0}^-) were calculated by means of the Euclidean metrics.
4. On the basis of the distances from the pattern and anti-pattern, the synthetic measure for i-th alternative (location) was calculated:

$$q_i = \frac{d_{i0}^-}{d_{i0}^- + d_{i0}^+} \tag{3}$$

5. The q_i values were sorted in a descending order.
6. The highest-ranking locations were selected, until the demand was satisfied.

The first step of the TOPSIS method consists in normalisation of criteria. There are many normalisation methods that can be divided into three main groups: standardisation, feature scaling and quotient transformations. In general, normalisation formula can be written as follows (Walesiak, 2018):

$$z_{ij} = b_j x_{ij} + a_{ij} = \frac{1}{B_j} x_{ij} - \frac{A_j}{B_j} \ (b_j > 0) \tag{4}$$

where: x_{ij} – value of j-th criterion in i-th alternative (location), z_{ij} – normalised value

of j-th criterion in i-th alternative (location), A_j – shift parameter to arbitrary zero for j-th variable, B_j – scale parameter for j-th variable, $a_j = -\frac{A_j}{B_j}$, $b_j = \frac{1}{B_j}$. For linear transformations of variables, we can obtain 18 normalisation methods. They are presented in Table A2 in the Appendix. Formulas n1 and n2 are standard scores, based on arithmetic mean and median, respectively. Formulas n3, n3a and n4 are various variants of feature scaling. Formula n4 is also known as the min-max normalisation. Formulas n6, n6a, n7, m8, n9, n9a, n10 and n11 are the quotient transformations. Formula n11 was originally used by Hwang and Yoon in the TOPSIS method. Generally, there is arbitrariness in selection of normalisation method. The main limitation is scale, on which criteria are measured. If they are measured on the ratio scale, then all 18 formulas can be used.

For criteria measured on the interval scale, formulas n6, n6a, n7, m8, n9, n9a, n10 and n11 (e.g. quotient transformations) cannot be used. In our case all criteria are measured on the ratio scale, therefore all formulas can be used. It is worth noting that there are possible situations when some (and sometimes all) normalisation formulas cannot be used. First situation is when values of all criteria are equal 0 (such situation may happen in case of the third criterion – number of other picked products in the proximity of the analysed location). In such case we cannot apply any formula. The workaround to such situation is assuming that normalised values of the criterion are equal 0 and it does not influence the value of composite measure. Other troublesome situation is when all values of given criterion are the same (but different from 0). In such case we can apply the formulas n8, n9, n9a, n10 and n11. For all other formulas, previously described workaround must be used.

The steps 1-6 of the TOPSIS method were repeated for every product in the order. After selection of locations for all products in the order, the locations were listed, and the picker's route was designated. The problem of designation of the picker's route is widely considered in the literature. There are several methods of designating the picker's route in the *picker-to-parts* warehouse (Le-Duc, 2005):

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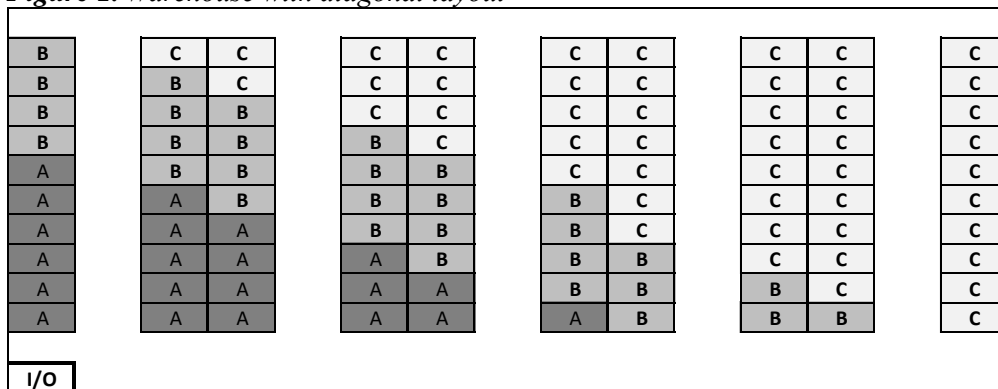- return,
- midpoint,
- largest gap,
- composite,
- combined.

The optimal method of designation the picker's route allows to obtain the route with minimal length. This method is based on the modified Travelling Salesman Problem. It was first applied for the single-block rectangular warehouse with two cross aisles by Ratliff and Rosenthal (1983). Its extension to the more number of cross aisles was

done by Roodbergen and De Koster (2001). Although it is always possible to obtain the optimal solution, thus optimal route length, optimal strategy is rarely used in practice. There are several reasons for this. Firstly, for large orders procedure of finding this solution is time-consuming. Secondly, obtained route often seems illogical to the pickers that tend to deviate from it. Thirdly, it does not consider aisle congestion and usual moving direction. Therefore, instead of using the optimal routing strategy, heuristic methods are usually used. Two most popular ones are the *s-shape* and *return* heuristics (Pan *et al.,* 2014). In-depth comparison of results obtained for various routing heuristics was done for example by Tarczyński (2012).

In the research the classical, single-block rectangular warehouse with two cross aisles was assumed. The products were stored with the ABC-class assignment. Within each class random storage was used. When the ABC-class storage assignment is used, various layouts can be applied. The most popular ones are within aisle, across aisle, diagonal and perimeter (Kofler, 2014). Initial calculations had proved that amongst all combinations of routing heuristics and warehouse layout generally good results were obtained for the diagonal layout and *return* routing heuristics, therefore this combination was used in the research. The diagonal layout of a warehouse is presented on Figure 1 and the *return* heuristics is presented on Figure 2.

Figure 1. *Warehouse with diagonal layout*

Source: *Own elaboration.*

The *return* heuristics assumes that the picker enters the first aisle, where the picked products are placed and goes the furthest to pick all products 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 products are placed and so on. After visiting locations lying in the last visited aisle, the picker travels back to the I/O point.

Having selected criteria, combinations of weights, multi-criteria decision-making technique, warehouse layout and routing heuristics the orders were generated by means of the simulation methods. The simulation experiment was based on the following pattern:

Figure 2. *The return heuristics*
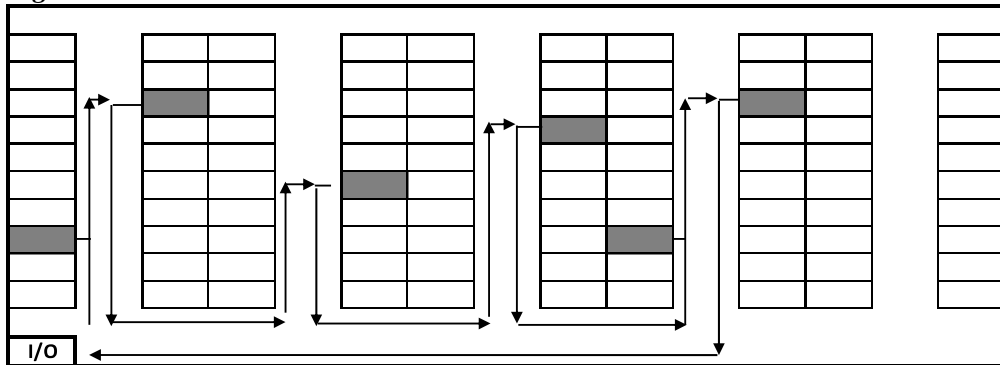
Source: *Own elaboration.*

1. A simple, rectangular warehouse with 1,000 locations, two cross aisles, 20 pick aisles was assumed. Every rack contained 25 locations.
2. The warehouse utilised the random and ABC-class storage assignment with diagonal layout.
3. Every order consisted of ten products.
4. Every product was stored in four locations.
5. Available amounts of products in each location varied from a single unit to the amount that satisfied the demand twice.
6. For all combinations of weights and normalisation method, 1,000 orders were generated and by means of the TOPSIS method, locations were selected.
7. After the selection of locations, the picker's route by means of the *return* heuristics was designated.
8. For each route, its length was measured, and the order-picking time was calculated. The order-picking time was the sum of the picker's movement and collection time. It was assumed that the time of passing the distance unit (shelf width) was 2 seconds and the product collection time from the location – 10 seconds.
9. For 37 combinations of weights and 18 normalisation methods, a total 666,000 simulations were done.

3. Empirical Results

For every normalisation method the best results (shortest route lengths) were obtained when big weight was put on the degree of demand satisfaction (sometimes also with the distance from the I/O point) and low weight on the third criterion – number of other picked products in the proximity of the analysed location. And vice versa – for every normalisation method the worst results were obtained when big weight was put on the third criterion and small – on the second one. When comparing the best results for every normalisation method, the best one turned to be the n12. For this method and the combination of weights [0.1 0.8 0.1] was 184.93 units and was by 3% shorter than for the worst one (n7). For the worst combinations of weights this difference was

equal to 3,56% and for benchmark combination – 5,17%. The best results (for n12 normalisation method and vector of weights [0.1 0.8 0.1]) were by 12.3% better than the worst results (for n4 normalisation method and vector of weights [0.4 0.1 0.5]).

Generally, when we apply the best (or the worst, but we will more likely consider only the best combinations, i.e. these, for which route lengths are the shortest) combinations of weights, the differences between particular normalisation methods are very small. Mean route lengths for the best, the worst and benchmark combinations of weights across all normalisation methods are presented in Table 3.

Table 3. *Results of the experiment – route length*

Method	Vector of weights /route length	Combination of weights		
		benchmark	the best	the worst
n1	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.5 0.1 0.4]
	route length	200.086	186.912	209.824
n2	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.5 0.1 0.4]
	route length	**202.956**	189.670	207.794
n3	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.1 0.1 0.8]
	route length	193.732	188.886	209.454
n3a	weights	[0.(3) 0.(3) 0.(3)]	[0.3 0.5 0.2]	[0.3 0.1 0.6]
	route length	197.296	186.260	206.802
n4	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.4 0.1 0.5]
	route length	197.032	185.082	**210.546**
n5	weights	[0.(3) 0.(3) 0.(3)]	[0.3 0.6 0.1]	[0.7 0.1 0.2]
	route length	196.380	187.870	208.120
n5a	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.7 0.1 0.2]
	route length	195.952	185.912	207.856
n6	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.4 0.1 0.5]
	route length	192.556	185.384	209.846
n6a	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.4 0.1 0.5]
	route length	196.426	189.694	207.734
n7	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.3 0.1 0.6]
	route length	202.240	**190.774**	210.436
n8	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.7 0.1 0.2]
	route length	196.134	185.796	207.406
n9	weights	[0.(3) 0.(3) 0.(3)]	[0.5 0.4 0.1]	[0.1 0.2 0.7]
	route length	199.902	187.484	206.844
n9a	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.8 0.1 0.1]
	route length	**<u>192.458</u>**	187.448	**<u>203.048</u>**
n10	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.2 0.2 0.6]
	route length	198.086	188.028	205.886
n11	weights	[0.(3) 0.(3) 0.(3)]	[0.5 0.4 0.1]	[0.4 0.1 0.5]
	route length	197.432	188.594	204.862
n12	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.7 0.1 0.2]
	route length	196.498	**<u>184.930</u>**	207.940
n12a	weights	[0.(3) 0.(3) 0.(3)]	[0.4 0.5 0.1]	[0.5 0.1 0.4]
	route length	194.332	187.370	207.386
n13	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.1 0.2 0.7]
	route length	194.718	185.022	208.812

Note: *The best values were bolded and underlined, the worst values were bolded.*
Source: *Own elaboration.*

Mean order picking times for the best, the worst and benchmark combinations of weights across all normalisation methods are presented in Table 4.

Table 4. *Results of the experiment – order picking time*

| Method	Vector of weights /order picking time	Combination of weights benchmark	the best	the worst
n1	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.5 0.1 0.4]
	order picking time	536.322	484.254	580.388
n2	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.5 0.1 0.4]
	order picking time	545.292	498.440	573.228
n3	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.6 0.1 0.3]
	order picking time	522.094	489.952	580.458
n3a	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.3 0.1 0.6]
	order picking time	529.522	483.444	572.844
n4	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.4 0.1 0.5]
	order picking time	528.364	483.114	**581.482**
n5	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.7 0.1 0.2]
	order picking time	528.26	488.088	576.340
n5a	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.7 0.1 0.2]
	order picking time	527.674	484.844	578.002
n6	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.4 0.1 0.5]
	order picking time	519.692	482.828	580.332
n6a	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.4 0.1 0.5]
	order picking time	530.902	**498.538**	572.828
n7	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.3 0.1 0.6]
	order picking time	**548.440**	496.278	580.472
n8	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.7 0.1 0.2]
	order picking time	522.818	481.792	572.422
n9	weights	[0.(3) 0.(3) 0.(3)]	[0.3 0.6 0.1]	[0.6 0.1 0.3]
	order picking time	531.074	491.834	568.894
n9a	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.8 0.1 0.1]
	order picking time	**515.366**	487.896	**561.926**
n10	weights	[0.(3) 0.(3) 0.(3)]	[0.2 0.7 0.1]	[0.6 0.1 0.3]
	order picking time	527.782	489.826	565.798
n11	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.6 0.1 0.3]
	order picking time	526.484	490.372	567.604
n12	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.7 0.1 0.2]
	order picking time	528.836	**479.370**	577.030
n12a	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.5 0.1 0.4]
	order picking time	524.044	488.214	574.992
n13	weights	[0.(3) 0.(3) 0.(3)]	[0.1 0.8 0.1]	[0.7 0.1 0.2]
	order picking time	525.276	481.504	576.136

Note: The best values were bolded and underlined, the worst values were bolded.
Source: *Own elaboration.*

For the order picking time, the situation is similar as for the route length. The shortest time (just less than 8 minutes) was obtained for normalisation method n12 and vector of weights [0.1 0.8 0.1]. The longest time – 9 min 42 s – was obtained for normalisation method n4 and vector of weights [0.4 0.1 0.5] (the difference was 17.56% in favour of the best situation). Amongst the best combinations of weights, the order picking time for the best normalisation method was by 3,8% shorter than for the worst method (n6a). Amongst the worst combinations of weights, the difference

between the results for best normalisation method (n9a) was by 3,36% shorter than for the worst one (n4). For the benchmark combination the difference between the best and the worst normalisation methods was about 6%. The distributions of the best results (obtained for normalisation method n12 and vector of weights [0.1 0.8 0.1]), the worst results (obtained for normalisation method n4 and vector of weights [0.4 0.1 0.5]) and the results being the benchmark (assumed as the best for the benchmark combination of weights – they were obtained for the normalisation method n9a) are presented on Figures 3 and 4.
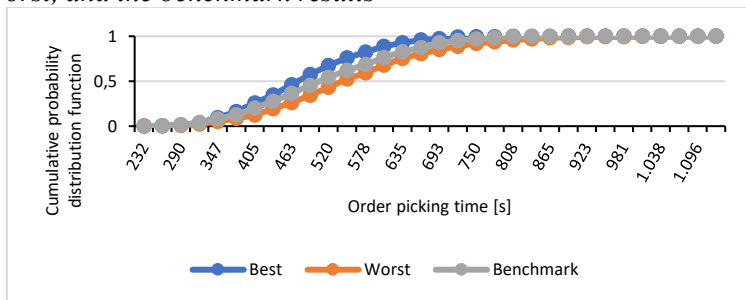
Figure 3. *Empirical cumulative distribution function of route lengths for the best, the worst and the benchmark results*
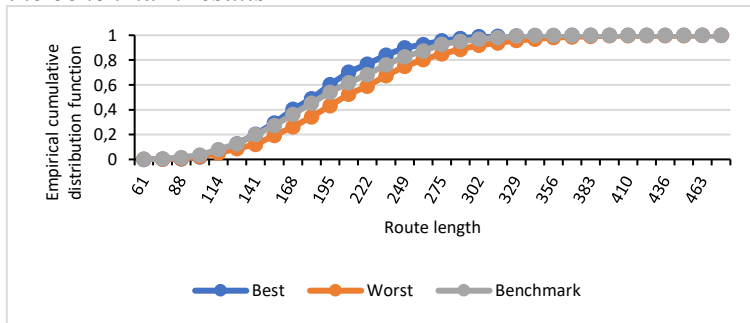
Source: *Own elaboration*

As seen from the Figure 3, the distribution of route length for analysed three situations behaved with accordance to their mean values. Empirical cumulative distribution function was the steepest for the best situation – the route lengths were the shortest. For the worst situation, the opposite occurred. Benchmark results were placed in the middle. The differences between route lengths were checked by means of Kruskal-Wallis *H* test (the Levene's test rejected the hypothesis about the equality of variances) (Aczel and Sounderpandian, 2009). At the significance level 0.01 the null hypothesis had to be rejected. A *post-hoc* pairwise comparisons Dunn's test (Aczel and Sounderpandian, 2009) indicated that order picking routes were statistically different among all three situations.

Figure 4. *Empirical cumulative distribution function of order picking times for the best, the worst, and the benchmark results*

Source: *Own elaboration.*

The courses of empirical cumulative distribution functions for analysed three situations were very similar to those for the route lengths. Again, the slope of the curve for the best situation was the highest and the opposite for the worst. As for the route length, also in case of order picking time the Kruskal-Wallis test indicated that for all three analysed situations the differences were statistically significant.

4. Conclusions

In the paper, the impact of method of criteria's normalisation on order picking route and time was analysed. Regardless of the normalisation method, the best results (the shortest order picking route and time) were obtained when high weight was put on the second criterion – degree of demand satisfaction, sometimes with the first criterion – location's distance from the I/O point. Weight put on the third criterion – number of other picked products in the proximity of the analysed location – should be low (Tables 3 and 4). Both for the route length and order picking time the best results were obtained when n12 normalisation method was applied and vector of weights [0.1 0.8 0.1] was used. It is hard to find the unequivocally the best normalisation methods. In general, quotient inversions generally yielded slightly worse results than standard scores and feature scaling. On the other hand, several normalisation methods (n8, n9, n9a, n10 and n11) can be applied in more situations – when the values of all values of a criterion are the same, different from 0. Therefore, despite the fact of slightly worse results it is wise to recommend one of these methods.

Presented approach is quite versatile – it can be easily adopted to larger number of criteria. When we consider previously discussed take-out strategies, obtained results indicate that the quantity adjustment approach was used. By means of presented in the research approach other take-out strategies can be considered. In order to apply the FIFO strategy, the storage time criterion with the highest weight should be introduced. If we wish to apply the "priority of partial units" strategy, the second criterion should be treated as the loss-type, instead of the profit-type (and, of course, it should have high weight). In order to apply the "taking the access unit" strategy, a new criterion describing the number of complete access units in locations.

Future area of the research will introduce the application of presented approach for high-storage warehouse and various take-out strategies.

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Appendix:

Table A1. *Combinations of weights*

Name	Vector of weights	Name	Vector of weights
C1	[0.(3) 0.(3) 0.(3)]	C20	[0.3 0.5 0.2]
C2	[0.1 0.1 0.8]	C21	[0.3 0.3 0.4]
C3	[0.1 0.8 0.1]	C22	[0.3 0.4 0.3]
C4	[0.1 0.2 0.7]	C23	[0.4 0.1 0.5]
C5	[0.1 0.7 0.2]	C24	[0.4 0.5 0.1]
C6	[0.1 0.3 0.6]	C25	[0.4 0.2 0.4]
C7	[0.1 0.6 0.3]	C26	[0.4 0.4 0.2]
C8	[0.1 0.4 0.5]	C27	[0.4 0.3 0.3]
C9	[0.1 0.5 0.4]	C28	[0.5 0.1 0.4]
C10	[0.2 0.1 0.7]	C29	[0.5 0.4 0.1]
C11	[0.2 0.7 0.1]	C30	[0.5 0.2 0.3]
C12	[0.2 0.2 0.6]	C31	[0.5 0.3 0.2]
C13	[0.2 0.6 0.2]	C32	[0.6 0.1 0.3]
C14	[0.2 0.3 0.5]	C33	[0.6 0.3 0.1]
C15	[0.2 0.5 0.3]	C34	[0.6 0.2 0.2]
C16	[0.2 0.4 0.4]	C35	[0.7 0.1 0.2]
C17	[0.3 0.1 0.6]	C36	[0.7 0.2 0.1]
C18	[0.3 0.6 0.1]	C37	[0.8 0.1 0.1]
C19	[0.3 0.2 0.5]		

Source: *Own elaboration.*

Table A2. *Normalization methods*

Method	Formula	Method	Formula
n1	$\dfrac{x_{ij} - \bar{x}_j}{s_j}$	n7	$\dfrac{x_{ij}}{r_j}$
n2	$\dfrac{x_{ij} - Me_j}{1{,}4826 \cdot MAD_j}$	n8	$\dfrac{x_{ij}}{\max\limits_i \{x_{ij}\}}$
n3	$\dfrac{x_{ij} - \bar{x}_j}{r_j}$	n9	$\dfrac{x_{ij}}{\bar{x}_j}$
n3a	$\dfrac{x_{ij} - Me_j}{r_j}$	n9a	$\dfrac{x_{ij}}{Me_j}$
n4	$\dfrac{x_{ij} - \min\limits_i \{x_{ij}\}}{r_j}$	n10	$\dfrac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}$
n5	$\dfrac{x_{ij} - \bar{x}_j}{\max\limits_i |x_{ij} - \bar{x}_j|}$	n11	$\dfrac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$
n5a	$\dfrac{x_{ij} - Me_j}{\max\limits_i |x_{ij} - Me_j|}$	n12	$\dfrac{x_{ij} - \bar{x}_j}{\sqrt{\sum_{i=1}^{m} (x_{ij} - \bar{x}_j)^2}}$
n6	$\dfrac{x_{ij}}{s_j}$	n12a	$\dfrac{x_{ij} - Me_j}{\sqrt{\sum_{i=1}^{m} (x_{ij} - Me_j)^2}}$
n6a	$\dfrac{x_{ij}}{MAD_j}$	n13	$\dfrac{x_{ij} - \dfrac{\max\limits_i \{x_{ij}\} + \min\limits_i \{x_{ij}\}}{2}}{\dfrac{r_j}{2}}$

Source: *(Walesiak, 2018)*
Notes:
x_{ij} – value of *j*-th criterion in *i*-th alternative (location),
$\bar{x}_j$ – arithmetic mean of *j*-th criterion,
Me_j – median of *j*-th criterion,
s_j – standard deviation of *j*-th criterion,
r_j – range of *j*-th criterion,
MAD_j – median absolute deviation of *j*-th criterion,
$\min\limits_i \{x_{ij}\}$ – minimal value of *j*-th criterion,
$\max\limits_i \{x_{ij}\}$ – maximal value of *j*-th criterion.