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Comparison of Several Linear Ordering Methods for Selection of Locations in Order-picking by Means of the Simulation Methods

Abstract: When a company uses a shared storage system, selection of locations during the order-picking process is not an obvious task. Every location where the picked product is placed, can be described by means of several variables, such as: storage time, distance from the I/O point, degree of demand satisfaction, or the number of other picked products in the order. Therefore, the "attractiveness" of each location from the point of view of a certain order can be described by means of synthetic variable, on the basis of which a ranking is created. For each product, the decision-maker selects the highest-ranking locations and designates a route for the picker. In the article, by means of the simulation methods, results obtained by several classification methods will be compared. These methods are: Taxonomic Measure of Location's Attractiveness (based on the Hellwig's Composite Measure of Development), the TOPSIS method with the Euclidean and GDM distances and the Generalised Distance Measure used as the composite measure of development.

Keywords: Taxonomic Measure of Location's Attractiveness, TOPSIS, Generalised Distance Measure, order-picking, simulation methods

JEL: C14, C15, C38

1. Introduction

Order-picking is the most cost- and labour- intensive activity in the warehouse management. Depending on the sources, it generates from about 55% (Bartholdi, Hackman, 2016: 25) to about 65% of all warehouse costs (Miłaszewicz, Rut, 2014: 12347). If we divide the order-picking time into its main components, over half of this time is dedicated to the picker's travelling to locations, where the picked products are located. The distribution of the order-picking time is presented in the Table 1.

Table 1. Division of the order-picking time

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

Source: Bartholdi, Heckman, 2016: 25

Because travelling comprises the greatest part of the order-picking, the reduction of the travelling time can bring the most visible advantages. The order-picking time can be reduced in several ways. First, the storage assignment can be optimised. It can be done with respect to the picking route (and, consequently, the order-picking time) by introducing the class-based storage. One of the most commonly applied methods is the ABC-class based storage (Gudehus, Kotzab, 2012: 479–480). By using this storage system, the products are divided into three classes – class A consists of 20% of all products that account for 80% of total turnovers, class B – next 30% of products that account for 15% of total turnovers and class C – the remaining 50% of products that account for 5% of total turnovers (Le-Duc, 2005: 40). Products belonging to class A should be placed near the I/O point, because they are ordered most frequently. Products belonging to class B should be placed behind the products that belong to class A and class C products – in the furthest part of the warehouse. Utilisation of the ABC-storage system can decrease the picker's travel distance even by over 40% with the comparison to the random (chaotic) strategy (Le-Duc, 2005: 41).

Apart from the storage assignment, a very important factor is the storage order. In general, goods in a warehouse can be stored in a fixed or free storage order (Gudehus, Kotzab, 2012: 478). The other names for these systems are: dedicated or shared storage systems (Bartholdi, Hackman, 2016: 14–18). The dedicated storage system means that every product can be stored only in one location and each location is dedicated only for a single product. The shared storage system means that any product can be stored in many, often very distant from each other,

locations and each location can store more than one product. Both methods have their advantages and disadvantages. The main advantage of the dedicated storage system is that it is relatively easy for the picker to remember where each product is stored and such system does not require specialised warehouse management system. However, such system also has disadvantages, amongst which the most important is poor storage space utilisation. If we assume the classical inventory replenishment system, the storage space utilisation will be on the average 50%. The shared storage system is free from this disadvantage. If many products are stored in a single location, then the mean storage space utilisation is much higher than for the dedicated storage system. Of course, the shared storage system also has its drawbacks. The main disadvantage of the shared storage system is that locations of every product change constantly, so it is impossible for the picker to remember them. In case of the shared storage system, the company must use a warehouse management system. The shared storage system also requires more discipline in warehouse processes.

If any product can be stored in many locations, then selection of location, from which ordered product should be picked, becomes the decision problem. If the product can be accessed in many locations, there are several possible strategies (Gudehus, Kotzab, 2012: 579):

1) FIFO – units will be picked accordingly to their arrival to the warehouse;
2) priority of partial units – locations with the lowest content of the product will be accessed first, even if it increases labour;
3) quantity adjustment – the opposite of the priority of partial units – the picker retrieves the product from the locations where requested quantity is fully satisfied even if it generates additional low numbers of products in locations;
4) 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.

On the other hand, Niemczyk (2012) states that there are three main rules of dispensing of goods from the warehouse:

1) LIFO (*Last In First Out*) – the last units that arrived to the warehouse would be picked first;
2) FIFO (*First In First Out*) – the first units that arrived to the warehouse would be picked first;
3) FEFO (*First Expired First Out*) – units that are to expire first, will be picked first.

Sometimes, one of the above-mentioned strategies is the only one that can be applied. It refers to the FIFO or FEFO ones. They are the only strategies that can be used for the quickly-expiring products, like fresh foods. Of course, there still may be more than one location with the same product, expiring equally quickly or being in the warehouse for an equally long time, so there are other criteria

needed to distinguish between these locations. That is why applying only one of the above-mentioned criteria is often not enough. For example, even if the decision-maker uses the FEFO strategy, if there are two or more locations, where the picked, equally quickly expiring product is located, one of them must be selected. In such case, other criterion, for example the quantity adjustment, must also be taken into consideration to select the location. If we add more criteria, then the location's selection becomes a multiple-criteria decision problem. Among many multiple-criteria decision-making methods, there are the discrete methods, which have much in common with the linear ordering methods that can be met in the multivariate statistical analysis. Both groups of methods change the objects/decision variants, described by multiple variables/criteria into the objects/decision variants described by means of the synthetic measure. On the basis of the decision theory, methods such as AHP, ANP, Electre, SAW, COPRAS, or TOPSIS were invented (Trzaskalik, 2015; Podvezko, 2011). On the other hand, in the field of multivariate statistical analysis such methods as the composite measure of development (Hellwig, 1968) or Generalised Distance Measure, used as the composite measure of development – GDM (Walesiak, 2016a) were created. Methods (although not all) from both groups can be used in both multivariate statistical analysis (Bąk, 2016) and multiple-criteria decision-making (Wachowicz, 2011). The goal of the article is to compare the effectiveness of several linear ordering methods used as tools to select locations in the process of order-picking. The following methods will be compared:

1) Taxonomic Measure of Location's Attractiveness (Polish abbreviation – TMAL), based on the Hellwig's Composite Measure of Development;
2) Generalised Distance Measure used as a composite measure of development (GDM);
3) TOPSIS method based on the Euclidean distances;
4) TOPSIS method based on the GDM distances.
5) The comparison will be made with use of the simulation methods.

2. Description of applied analytical methods

2.1. Specification of decision criteria and applied systems of weights

In the research, locations in which the picked products are stored, are described by means of three criteria:

x_1 – distance from the I/O point,
x_2 – degree of demand satisfaction,
x_3 – number of other picked products in the neighbourhood of the analysed location.

The first criterion, measured on the ratio scale, is the loss-type criterion. It is measured in contractual unit, which is the shelf width.

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

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

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

The third criterion – the number of other picked products in the neighbourhood of the analysed location is the profit-type criterion. It is measured on the ratio scale. The term "neighbourhood" can be understood differently with respect to the warehouse type. If the warehouse is a high storage one then it could be the rack. For the typical, low-level warehouse, it could be the racks within the aisle and this is the case in our research.

The decision criteria should be weighed. The decision-maker may apply several methods to determine their weights. Both statistical and expert methods can be used. The statistical methods can be based on the criteria's variability, although this method is very often thought to be controversial (Kukuła, 2000: 70), or Shannon entropy (Lotfi, Fallahnejad, 2010). Among the expert methods, one of the most important one is the AHP method (Trzaskalik, 2015). In this method, the experts specify preferences by pairwise comparison of the criteria and (or) sub-criteria. The weights can also be specified subjectively, when the decision-maker decides about the importance of each criterion on the basis of his/her experience. Such approach can be applied in the situation, where there is a small number of criteria. For the larger number of criteria, it is difficult to assign weights without any supporting methods. In this research, the results obtained for seven combinations of weights were compared and are presented in Table 2.

Table 2. Analysed combinations of weights

Combinations of weights	x_1	x_2	x_3
C1	0.(3)	0.(3)	0.(3)
C2	0.500	0.250	0.250
C3	0.250	0.500	0.250
C4	0.250	0.250	0.500
C5	0.400	0.400	0.200
C6	0.400	0.200	0.400
C7	0.200	0.400	0.400

Source: own elaboration

The combination C1, in which every criterion has the same weight, is the reference. The combinations C2, C3 and C4 are the combinations, in which one criterion is twice as important, as the other two and, at the same time, its impact on the final decision is the same as total impact of the remaining two criteria. The last three combinations indicate that two criteria are twice as important as the remaining one. The reason for such approach is to analyse, if any criterion should be more important than others in order to decrease the order-picking route and the order-picking time.

2.2. Construction of the applied methods

The steps of calculation of the TMAL method are as follows (Dmytrów, 2015):
1) The distance from the I/O point (x_1) was changed into the profit-type criterion by calculation of its inverse.
2) The value of each criterion must be normalised. In the article the quotient inversion was used:

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{n} x_{ij}^2}},$$ (2)

where x_{ij} – value of j-th criterion in the i-th alternative (location). There are much more normalisation formulas possible (Walesiak, 2016b: 10). The reason for selection of the above formula was to preserve the differences in the mean values and the variability.
3) The maximum normalised values created the so-called "perfect alternative" or the pattern.
4) Euclidean distances between the pattern and each location were calculated.
5) Mean weighed Euclidean distances from the pattern for each combination of weights were calculated.
6) The TMAL was calculated as the complement to unity from the ratio of mean weighed distance of each location, from the maximum value obtained in the previous step.
7) The TMAL values were sorted in the descending order.
8) The highest-ranking locations were selected until the demand for each product was satisfied.
     The Generalised Distance Measure (GDM) is based on the generalised correlation coefficient, considering the Pearson Product-Moment Correlation Coefficient and the Kendall τ correlation coefficient (Walesiak, 2016a: 51):

$$d_{ik} = \frac{1}{2} - \frac{\sum_{j=1}^{m} w_j a_{ikj} b_{kij} + \sum_{j=1}^{m} \sum_{l=1, l \neq i, k}^{n} w_j a_{ilj} b_{klj}}{2 \left[\sum_{j=1}^{m} \sum_{l=1}^{n} w_j a_{ilj}^2 \cdot \sum_{j=1}^{m} \sum_{l=1}^{n} w_j b_{klj}^2 \right]^{\frac{1}{2}}},$$ (3)

where:

d_{ik} − distance measure,

$i, k, l = 1, 2, …, n$ − number of the alternative (location),

$j = 1, 2, …, m$ − number of the criterion,

w_j − weight of the j-th criterion.

For variables measured on the interval or (and) ratio scale, the values of a and b are calculated by means of the following formulas:

$$\begin{aligned} a_{ipj} &= x_{ij} - x_{pj} \text{ for } p = k, l, \\ b_{krj} &= x_{kj} - x_{rj} \text{ for } r = i, l, \end{aligned}$$ (4)

where x_{ij} (x_{kj}, x_{ij}) − i-th (k-th, l-th) value of j-th criterion.

The steps of calculating the GDM are as follows (Walesiak, 2003: 137):

1. There is no need to change the loss-type criteria into the profit-type ones.
2. The values of each criterion were normalised by means of the formula (2).
3. The so-called "perfect alternative", or the pattern was created. For the loss-type criteria, the pattern values will be the minimum values within all alternatives. For the profit-type criteria, the pattern will be the maximum values within all alternatives.
4. The distances of each alternative (location) from the pattern by using the formula (3), applying the substitutions given by (4) were calculated.
5. The values of the GDM for the alternatives (locations) were sorted in the ascending order.
6. The highest-ranking locations were selected, until the demand for each product was satisfied.

The TOPSIS method was created by Hwang and Yoon (1981). In contrast to the TMAL and the GDM, where the reference point is the pattern, the TOPSIS method has two reference points – the pattern and anti-pattern. The steps of calculation of the TOPSIS measure are as follows:

1. The values of each criterion were normalised by means of the formula (2).
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 created.
3. The weighed distances of each i-th alternative (location) from the pattern (d_{i0}^+) and anti-pattern (d_{i0}^-) were calculated. For the TOPSIS method based on the

Euclidean distances, and the TOPSIS method based on the GDM distances, appropriate formulas were used.

4. On the basis of the distances from the pattern and anti-pattern, the synthetic measure for i-th alternative (location) was calculated:

$$q_i = \frac{d_{i0}^-}{d_{i0}^- + d_{i0}^+}. \tag{5}$$

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

2.3. Assumptions of the simulation experiment

The comparison of applied methods was conducted by means of the simulation experiment. Its assumptions are as follows:

1. A simple, rectangular warehouse was assumed.
2. The warehouse contained 1000 locations with one main aisle and 20 aisles within racks. Every rack contained 25 locations.
3. The warehouse utilised the ABC-class based storage system.
4. Every order consisted of ten products.
5. Every product was stored in four locations.
6. Available amounts of products in each location varied from a single unit to the amount that satisfied the demand twice.
7. For all applied methods and all combination of weights, 100 orders were generated.
8. For every picked product, every method and every combination of weights, ranking of locations was created.
9. For each method, the highest-ranking locations were selected until the satisfaction of demand.
10. After selection of locations, the picker's route was designated by means of the *s-shape* heuristics (De Koster, Le-Duc, Roodbergen, 2007: 19). The reason for using the *s-shape* heuristics is that it is one of the simplest and most widely used heuristics in order-picking (Tarczyński, 2013: 222).
11. For each route, its length was measured, and the order-picking time was calculated.
12. 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.

13. For each applied method, it was analysed by means of the one-way ANO-VA, if both the route lengths and picking times were significantly different (Domański, 2014: 55–56). Homogeneity of variances were checked by means of the Levene's test (Rozmus, 2012: 114).
14. If the null hypothesis was to be rejected, the pairwise comparisons were performed by means of the *post-hoc* Tukey's HSD test (Rozmus, 2012: 115).
15. The same procedure was applied for comparison of methods within each combination of weights.

3. Empirical results

3.1. Comparison of results for each combination of weights within each method

Mean route lengths and results of the ANOVA for all combinations of weights within all applied methods are presented in Table 3.

Table 3. Mean route lengths for every combination of weights within each method
(best results are underlined)

Method	C1	C2	C3	C4	C5	C6	C7
TMAL	211.82	208.88	219.58	221.88	219.12	229.00	217.06
	ANOVA $F = 1.170$, p-value = 0.321						
GDM	214.04	226.80	217.76	215.58	210.02	223.26	206.72
	ANOVA $F = 1.383$, p-value = 0.219						
TOPSIS – Euclidean distances	234.46	219.10	234.52	235.08	233.42	230.78	225.60
	ANOVA $F = 0.763$, p-value = 0.599						
TOPSIS – GDM distances	221.26	225.38	222.06	227.10	212.66	227.80	209.42
	ANOVA $F = 1.249$, p-value = 0.279						

Source: own elaboration

Table 3 shows that within each method, the differences between mean route lengths were not statistically significant. However, for the TMAL and the TOPSIS method with the Euclidean distances, the best results were obtained for the combination of weights C2 (0.5; 0.25; 0.25) – this means that the decision-maker should pay the most attention to the location's distance from the I/O point, while for the GDM and the TOPSIS method with the GDM distances, the best results were obtained for the combination of weights C7 (0.2; 0.4; 0.4) – it means that the decision-maker should pay the most attention to the degree of demand satisfaction and the number of other products in the neighbourhood of analysed location.

Mean order-picking times and results of the ANOVA for all combinations of weights within all applied methods are presented in Table 4.

Table 4. Mean order-picking times (in minutes) for every combination of weights within each method (best results are underlined, significant results are bolded)

Method	C1	C2	C3	C4	C5	C6	C7
TMAL	9:23	9:21	9:32	9:51	9:35	10:08	9:29
	ANOVA $F = 1.801$, p-value $= 0.096$						
GDM	9:25	9:53	9:25	9:35	9:15	9:51	9:08
	ANOVA $F = 1.994$, p-value $= 0.064$						
TOPSIS – Euclidean distances	10:34	10:04	10:35	10:32	10:31	10:25	10:12
	ANOVA $F = 0.726$, p-value $= 0.628$						
TOPSIS – GDM distances	9:40	9:50	9:35	10:02	9:17	9:60	9:09
	ANOVA $F = 2.407$, p-value $= 0.026$						

Source: own elaboration

The results obtained for the order-picking times are very similar to these for the route lengths. For the TMAL and the TOPSIS method with Euclidean distances the best results were obtained for the combination of weights C2 and for the GDM and the TOPSIS method with the GDM distances – for the combination C7. In most cases the differences were not statistically significant, with the exception of the results for the TOPSIS method with the GDM distances. The Tukey's test showed that the mean order-picking time obtained for the best combination of weights (C7) was significantly different from the time obtained for the worst combination of weights (C4).

3.2. Comparison of applied methods for every system of weights

The main goal of the article was the comparison of effectiveness of several linear ordering methods in selection of locations in the process of order-picking. Comparison of mean route lengths for each method and combination of weights are presented in Table 5.

Table 5. Mean route lengths for every method within each combination of weights (best results are underlined, significant results are bolded)

Combination of weights	TMAL	GDM	TOPSIS – Euclidean distances	TOPSIS – GDM distances
C1	**211.82**	214.04	234.46	221.26
	ANOVA $F = 2.799$, p-value $= 0.040$			
C2	208.88	226.80	219.10	225.38
	ANOVA $F = 1.660$, p-value $= 0.175$			
C3	219.58	217.76	234.52	222.06
	ANOVA $F = 1.509$, p-value $= 0.211$			
C4	221.88	215.58	235.08	227.10
	ANOVA $F = 1.734$, p-value $= 0.159$			

Combination of weights	TMAL	GDM	TOPSIS – Euclidean distances	TOPSIS – GDM distances
C5	219.12	<u>210.02</u>	233.42	212.66
	ANOVA $F = 2.540$, p-value = 0.056			
C6	229.00	<u>223.26</u>	230.78	227.80
	ANOVA $F = 0.231$, p-value = 0.875			
C7	217.06	<u>206.72</u>	225.60	209.42
	ANOVA $F = 1.807$, p-value = 0.145			

Source: own elaboration

Mean route lengths were also presented on Figure 1.
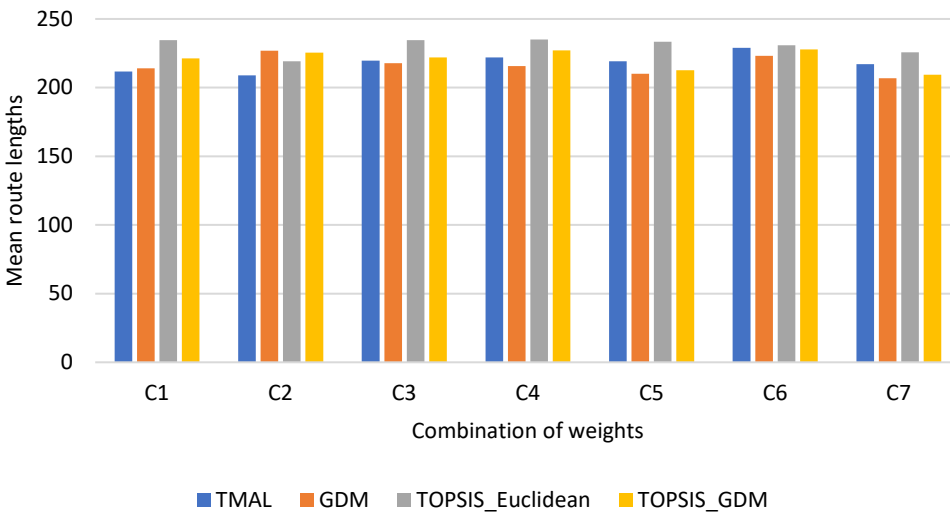
Figure 1. Mean route lengths for each method within each combination of weights
Source: own elaboration

For the combination of weights C1 (0.(3); 0.(3); 0.(3)) and C2 (0.5; 0.25; 0.25) the TMAL method of selection of locations generated the best results. For all remaining combinations the GDM used as the composite measure of development turned out to be the best method. The worst results were generally obtained by the TOPSIS method with Euclidean distances. The TOPSIS with GDM distances was generally the second or third best method. These results seem quite surprising because the TOPSIS method refers the object to both the pattern and anti-pattern, while the TMAL and GDM – only to the pattern. Only for the first combination of weights (C1) the mean route lengths were significantly different. The Tukey's test indicated that for the combination C1 the best result (for the TMAL method) was significantly different from the worst one (for the TOPSIS method with Euclidean distances). When comparing the best obtained result (the GDM for the combination C7) with the worst one (the TOPSIS with the Euclidean distances for the

combination C4), it turns out that the picker's route can be decreased on average by almost 30 units (over 12%), which is more than the aisle length.

Comparison of mean order-picking times for each method and combination of weights are presented in Table 6.

Table 6. Mean order-picking times (in minutes) for every method within each combination of weights (best results are underlined, significant results are bolded)

Combination of weights	TMAL	GDM	TOPSIS – Euclidean distances	TOPSIS – GDM distances
C1	**9:23**	9:25	10:34	9:40
	ANOVA $F = 6.727$, p-value = 0.0002			
C2	9:21	9:53	10:04	9:50
	ANOVA $F = 1.902$, p-value = 0.129			
C3	9:32	**9:25**	10:35	9:35
	ANOVA $F = 6.544$, p-value = 0.0003			
C4	9:51	**9:35**	10:32	10:02
	ANOVA $F = 3.430$, p-value = 0.017			
C5	9:35	**9:15**	10:31	9:17
	ANOVA $F = 6.993$, p-value = 0.0001			
C6	10:08	9:51	10:25	10:00
	ANOVA $F = 1.089$, p-value = 0.354			
C7	9:29	**9:08**	10:12	9:09
	ANOVA $F = 5.165$, p-value = 0.002			

Source: own elaboration

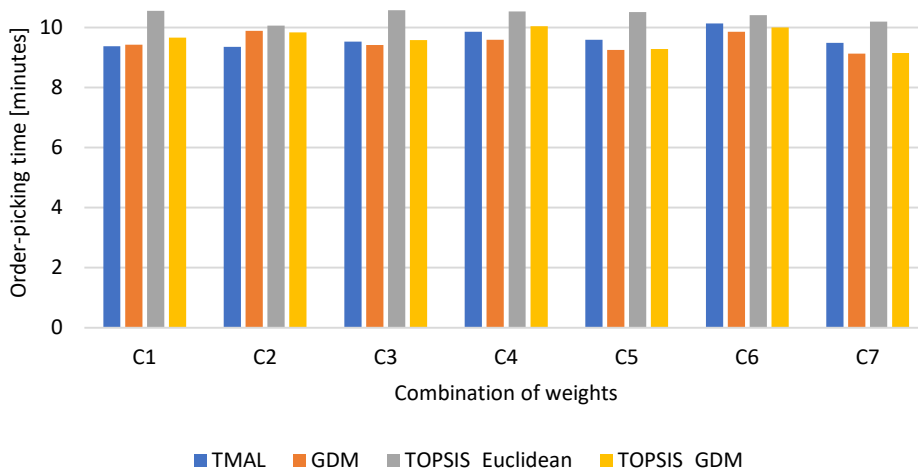Mean order-picking times were also presented on Figure 2.

Figure 2. Mean order-picking times (in minutes) for every method within each combination of weights

Source: own elaboration

As for the route length, for the combinations C1 and C2 the best results were obtained for the TMAL method. The GDM used as the composite measure of development was the best method for all other combinations of weights. The TOPSIS with the Euclidean distances was again the worst method – for all combinations of weights it yielded the longest order-picking times. However, for all combinations of weights, except for C2 and C6, the differences between results obtained by various methods were statistically significant. The best result was obtained by the GDM used as the composite measure of development for the combination C7 and the worst – by the TOPSIS method with Euclidean distances for the combination C3. The mean order-picking time obtained by the best method was shorter than the one obtained by the worst method by almost one and a half minute, or by almost 14%.

4. Conclusions

In the article, several linear ordering methods were used as multiple-criteria decision-making techniques. There were the TMAL method (based on the Hellwig's Composite Measure of Development), Generalised Distance Measure used as the composite measure of development and the TOPSIS method, based on the Euclidean and GDM distances. For every method, seven combinations of weights applied to three criteria, were used. For every method and every combination of weights, 100 orders were generated. Each order consisted of 10 products, of which each product was placed in four different locations. The products' storage system was the ABC-class. Locations to be visited were selected for each product by means of the applied methods. After selection of locations, the route was designated by means of the *s-shape* heuristics.

The first comparison was made within each method with respect to applied combination of weights. The differences between mean route lengths and mean order-picking times were generally not statistically significant (see Tables 3 and 4). The exception was the TOPSIS method with the GDM distances for the picking time – within this method the combination of weights C7 (0.2; 0.4; 0.4) was the best and generated significantly better results than the worst combination – C4 (0.25; 0.25; 0.5). For the TMAL and the TOPSIS method with the Euclidean distances, the best results were obtained for the combination of weights (0.5; 0.25; 0.25) – this means that the decision-maker should pay the most attention to the location's distance from the I/O point. For the GDM and the TOPSIS method with the GDM distances, the best results were obtained for the combination of weights (0.2; 0.4; 0.4) – this means that the decision-maker should pay the most attention to the degree of demand satisfaction and the number of other products in the neighbourhood of analysed location.

When comparing methods for every combination of weights, for both route length and order-picking times, for the combinations of weights C1 and C2, the

TMAL method turned out to be the best one (see Tables 5 and 6 and Figures 1 and 2). For other combinations of weights, for both the route length and order-picking times, the GDM used as the composite measure of development was the best method. Except for the combination C1, the differences in route lengths were not statistically significant. When we analyse the order-picking time, the differences between results obtained by means of the applied methods were generally statistically significant. For both the route length and order-picking time, the best choice was the GDM for the combination of weights (0.2; 0.4; 0.4). This means that the decision-maker should select locations by means of the Generalised Distance Measure, and that the two criteria: the degree of demand satisfaction and number of other picked products in the neighbourhood of analysed location should be more important than the distance from the I/O point. However, it is worth noting that these results were obtained for the ABC-class based storage and rectangular warehouse with one main aisle and should not be generalised on other storage strategies and warehouse types.

Although applying the ABC-class based storage itself optimises the order-picking process in comparison to the random storage strategy, applying the appropriate method of selection of locations with certain combination of weights can further improve the order-picking route length and time. When we compare the best result with the worst one, we can decrease the mean route length by 12% and the order-picking time by almost 14%. This means that each picker could pick one additional order during one hour and for the whole 8-hours working day – eight additional orders. Obtained results show that there is still room for improvement, even after applying optimised storage systems.

Future research in this area will include:
1. Performing similar analysis for allocation of products with accordance to across-aisle strategy.
2. Comparison of other heuristics for the designation of the picker's route (*return*, *midpoint*, *largest gap*, or *combined*).
3. Applying other criteria, such as storage level in the high storage warehouse, storage time or the existence (or not) of the complete packages at every location.
4. Trial of selection of the best method and the best combination of weights for various types of warehouses.

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Porównanie kilku metod porządkowania liniowego do wyboru lokalizacji w procesie kompletacji przy zastosowaniu metod symulacyjnych

Streszczenie: Przy przechowywaniu współdzielonym wybór lokalizacji, z których należy pobrać produkty podczas procesu kompletacji, nie jest sprawą oczywistą. Każdą lokalizację, w której znajduje się produkt do skompletowania zamówienia, można opisać za pomocą wielu zmiennych, na przykład: czasu przechowywania produktu, odległości od punktu odkładczego, stopnia zaspokojenia zapotrzebowania czy liczby innych produktów w zleceniu, znajdujących się w sąsiedztwie badanej lokalizacji. Tak więc „atrakcyjność" każdej lokalizacji z punktu widzenia kompletacji badanego zlecenia można opisać za pomocą zmiennej syntetycznej, na podstawie której tworzymy ranking tych lokalizacji. Dla każdego produktu wybiera się lokalizacje będące najwyżej w rankingu, a następnie wyznacza się trasę, którą ma pokonać magazynier. W artykule zostały porównane wyniki uzyskane za pomocą kilku metod klasyfikacji: Taksonomicznej Miary Atrakcyjności Lokalizacji, opartej na Syntetycznym Mierniku Rozwoju Hellwiga, metody TOPSIS oraz Uogólnionej Miary Odległości.

Słowa kluczowe: Taksonomiczna Miara Atrakcyjności Lokalizacji, metoda TOPSIS, Uogólniona Miara Odległości, kompletacja, metody symulacyjne

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