

Effectiveness of Product Storage Policy According to Classification Criteria and Warehouse Size

Augustyn Lorenc

Assistant Professor
Cracow University of Technology
Poland

Tone Lerher

Professor
University of Maribor
Slovenia

The paper focuses on identifying the influence of warehouse size to effectiveness of products storage policy. In the paper different storage policy was analysed. To evaluate the effectiveness of selected order-picking warehouses the dedicated software for simulation of orders picking process was used. The effectiveness of product allocation planning was evaluated by the total time that is needed for the order-picking process. For the route planning it was assumed that the nearest product was appointed as next to pick. In our research, a discrete event simulation analysis by using special software called PickupSimulo was performed. In this research different warehouse sizes were investigated. The layout ranged from 2.188 m² to 22.021 m².

Based on the simulation study it is possible to support warehouse managers for choosing the best products storage policy. This will reduce retrieval time and improve the effectiveness of order picking.

Keywords: warehousing, storage policy, product classification methods, retrieval, simulation, performance analysis.

1. INTRODUCTION

The warehouse is main element of transport system, which join several stages of products movement in transport chain. It is a point in which many processes related with transportation and transshipment of cargos take place. Those processes could include: product picking, preparation to delivery, consolidation and others like information flow.

The global market allows for a competition of local enterprises as well as of those who have their localizations on other continents. It is so because more and more enterprises decide to sell their products with the use of the Internet. It results in smaller and smaller orders and their irregular frequencies. This is why the proper design of the warehouse layout and product distribution constitutes a serious challenge to enterprises.

The most important factors that influence the competitiveness of warehouses are time and cost. If the storage process is chosen at random or is improper, then it affects three types of the costs which refer to movement, waiting time and transport. It happens, for example, when high in demand products are stored in the most distant part of the warehouse and those rarely in need are at the closest distance to the completion and packing zone. Hence, the time, distance and internal transport costs become higher. The number of employees and transport devices also increases [1].

2. STATE OF THE ART

One of the main processes taking place in warehouses is order picking [13]. It is a comprehensive process, because it joins correlated elements like: information flow, transport mode, routing, stocking system and cargos. During that process, actions listed above take place:

- preparation of transport units for picking, aimed to fast and direct access to cargos,
- orders picking, which is manual picking of products specified in picking list,
- verification of quantity, aimed to confirm completeness of transport units with picking list (products type and quantity),
- packing and formation of transport units. Packing is aiming to protecting cargos against harmful effects of environment and products effect to environment. Packing also helps to increase control of groupage. Transport units formation helps to increase effectiveness of using transport modes and easily moving, identification and handling,
- moving to dispatch zone and shipment.

The paper focuses on identifying the influence of warehouse size to effectiveness of products storage policy. In most research studies this correlation is usually neglected. In the paper different storage policy was analysed. The main aim of the research done for this paper was to find out the dependence of the effectiveness of different storage policy on the warehouse size. When reviewing the latest research papers in this area, a significant research gap was found. Literature review shows that most researchers focus their attention on the layout planning for racks and product allocation problem taking into account just product attributes or pickup routing problem.

According to the research presented in the paper [8] decisions to manage order picking can be classified into

Received: Juny 2018, Accepted: November 2018

Correspondence to: PhD Augustyn Lorenc
Cracow University of Technology
al. Jana Pawla II 37, 31-864 Cracow, Poland
E-mail: alorenc@pk.edu.pl

doi:

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FME Transactions (2019) 47, 142-150 **142**

strategic, tactical and operational decisions. Strategic management decisions refer to policies and plans for using the resources in order to fulfill the long term competitive strategy. Examples of strategic decisions are the layout of the storage area (i.e., shape, number of warehouse blocks and depot location), as well as the selection of storage systems, in particular the level of automation and the material handling equipment to retrieve items. Typical strategic decisions are discussed in [6] and [14]. At the tactical level, decisions are taken that impact the medium term. The determination of the resource dimensions, like storage capacity and the size of pick zones, is an example of a tactical decision. Finally, operational decisions typically concern daily operations like batch formation and job assignment. Decisions of operational nature should be considered within the constraints set by the strategic and tactical decisions. Van den Berg [3], and [11] give an overview of methods and techniques for planning tactical and operational warehouse problems. Gong and De Koster (2011) focus on tactical and operational decisions, using stochastic methods to model and analyze warehouse operations, while [10] focus on layout and control decisions to manage manually operated order picking systems. The paper [8] provides a state-of-the-art and classifies recent order picking planning literature, in particular studies that combine multiple tactical and operational planning problems.

Picking causes the most problems and difficulties and it is one of the key factors for efficiency of many logistics facilities [17]. The goods moving constitutes half of the total order completion time. Therefore, the shortening of picking time in the warehouse is a priority task for almost every logistics company. Its final duration depends, among other things, on the level of the warehouse automation, the applied storage system, and the way of order completion [12]. It is important that the ordered load is properly completed in terms of assortment and quantity, and that it has reached the release zone on time (delivery deadline has not been exceeded). If a given enterprise still wants to stay competitive, each process which takes place in the warehouse should be analysed and, first of all, the time of the goods movement has to be decreased [9], [18].

Process of picking orders deserves special attention due to resources needs and costs, which can be between 37% and 55% of total costs of warehousing [2]. Taking into consideration related process, i.e. packing and loading, it could be even 61% of total costs [1]. Categorization of warehouse costs, in Pareto-Lorenz diagram is showed in figure 1.

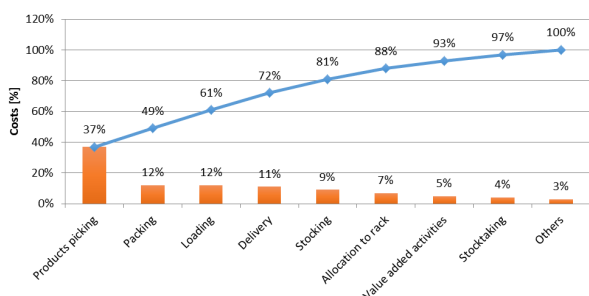


Figure 1. The percentage participation of the individual activities costs and total cost of warehousing, based on [2]

Nowadays, product classification methods are used to plan distribution of products in the warehouse. The methods rely on assigning products to groups of various ranks. Then the products are located in the warehouse in such a way that the shortest time of access to certain positions which are most significant is provided. Classical methods of product classification are the following analyses: ABC, XYZ and Index COI [20].

In the article the most frequently used methods of product classification: Activity Based Costing (ABC) analysis and Cube-per-Order (COI) are employed together with the most common criteria: product frequency – represented by picking frequency, the number of items sold – total number of pieces of the same product (SKU), weight and volume of products [7] [19].

ABC analysis is the most common analysis that enables products classification. Since it is a single criterion analysis, it is not possible to consider simultaneously several input parameters. The classical ABC analysis allows the division of products into three groups with the percentage participation equal to: A – 80%, B – 15%, C – 5%. Some modifications of this analysis are also used. They comprise more groups with adequately corrected percentage participation. However, the analysis can be done several times with a different property as the criterion each time, which can be followed by a synthesis of results adopting relevant weights for each criterion (analysis result) [20]. This analysis is usually performed after the following criteria [16], [5]:

- the value of sales or profit on sales,
- products picking frequency,
- amount of products picked,
- products weight and volume.

Index COI (Cube-per-Order Index) is the simplest method of products classification. An analysis done using this method is a two-criteria analysis in which the product size and demand are adopted as the criteria [4]. The product size can be understood as its volume or weight, while the demand as the amount of product picking (frequency) or mean demand [15].

3. METHODOLOGY: GENERAL ASSUMPTIONS

The aim of the research is to identify the impact of warehouse size on the picking effectiveness resulting from the application of products storage policy. The evaluation of warehouse processes / operation effectiveness can be made using a few criteria, i.e. time of orders picking, route length, chattiness (employees' work-performance, costs and transport modes). In this paper, the time of orders picking was adopted as the criterion of effectiveness evaluation. On this basis, the methods which help to reduce picking time were examined.

Because of the biggest costs of product picking, the effectiveness of it should be performed. Generally it is possible thanks to indicators, which are presented in the next part of that paper. That indicators does not reflect the whole information about processes of picking, and cannot be used to predict time of picking after changing of product allocation in warehouse. Because of that a mathematical model for orders picking simulation was

formulated. This model can imitate a real picking process in warehouse with a high degree of similarity. To do that, method based on simulation of orders picking process instead of classic indicators was used. Based on generated orders picking list, picking route was appointed.

To evaluate the effectiveness of the orders picking process in cases of product allocation based on the product storage policy, a mathematical model was developed. This model can imitate the real picking process in a warehouse with a high similarity. For this reason instead of classic indicators a method based on the simulation of orders picking process was employed. In the applied method of picking process simulation the following assumptions were made:

- the warehouse structure can be described in a matrix form,
- all orders are picked by order pickers using VNA trucks, moving in the products storage zone,
- products of significantly different weight and size can be stored in the warehouse,
- dedicated zones for products storage are permitted.

To describe the warehouse structure an incidence matrix was employed. Consequently, the warehouse storage area structure can be written in the form of transition matrix W:

$$W = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1y} \\ r_{21} & r_{22} & \dots & r_{2y} \\ \vdots & \vdots & \ddots & \vdots \\ r_{x1} & r_{x2} & \dots & r_{xy} \end{bmatrix} \quad (1)$$

For example W matrix can describe the position of racks and rows in warehouse (figure 2). That matrix represents just storage area excluding delivery and shipping area.

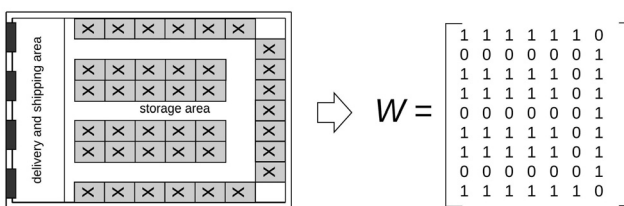


Figure 2. Structure representation by W matrix

The values in matrix W is used to calculate the values in matrix P. This matrix represents the total time of all processes for complete the order – the travel, picking item (t_i), lifting (t_z), turning during picking (t_t), turning during movement (t_a) acceleration and deceleration of VNA truck (t_s). The total time is calculated from the current coordinates to any location in the warehouse (t_p), which is described by formula (2).

$$\sum_{p=1}^q t_p(x, y, z) = 2t_s + t_{lp}(D_{lr} \cdot (x_1 - x_2 - c_l(x_1 - x_2)) + d_{cr} \cdot c_l(x_1 - x_2)) + t_{lp}(D_{wr} \cdot (y_1 - y_2 - c_w(y_1 - y_2)) + d_{cr} \cdot c_w(y_1 - y_2)) + 2t_s \cdot t_a + t_z + t_t + t_i \quad (2)$$

In the presented research each aisle width (d_{cr}) was the same. To plan the order picking route the method of finding the nearest location determinate by $t_{min}(l)$ off product was used. The order of picking product is represented by the matrix P. Each rows of the matrix contains the coordinates of next nearest position of product relative to actual position of picker. The routing planning algorithm can be described by formulas (3):

$$t_{min}(l) = \min_{l \in O} \forall t_p(x, y, z)$$

$$\text{for } \min(t_{min}(l)) \rightarrow \overline{N}(l) = (x, y, z) \quad (3)$$

$$P = \sum_{l=1}^{la} \overline{N}(l)$$

The example of described method is showed in the figure 3.

The planning of products allocation following the applied storage policy consisted in establishing in the storage space separate subzones dedicated to the storage of products of a given category.

These zones were established so that the number of racks for the storage of products of a given category was relevant to the demand for the products of the given class. Moreover, it is essential that the zone be created such that the accessibility time (t_d) to each place is the shortest possible, which can presented by (4):

$$\forall_{r \in K} t_d \leq \forall_{r \in K+1} t_d \text{ where } K \in \{1, 2, 3\} \quad (4)$$

The algorithm also minimize the total time of picking products from the order. The algorithm for the order picking time calculation used in our simulation is presented graphically in Figure 4.

Products were distributed in the warehouse by the designation of a space of the shortest accessibility time from the parking area. Most closest location is reserved for the most frequent products, next location for the second frequent products. It is described by minimize target function (5):

$$\min : F(t_p) = \sum_{p=1}^q t_p(x, y, z) \quad (5)$$

For the optimal route search the Artificial Neural Network, and presented assumptions were used. For discussed simulation, the following division of training data sets was made: 70% of the collection – training data, 15% of the collection – validation data, 15% of the collection – testing data. During data preparation, the following Matlab functions were applied: Mapminmax, Removeconstantrows. Selection of ANN structure is performed by the system on the basis of the method of successive approximation. The choice of the network structure was made by assessing the mean square error (MSE). On the basis of performed simulation, the system has decided that the best results have been obtained by multilayer unidirectional feedforward type network consisting of 3 hidden layers. In the first hidden layer, 10 neurons were used, in the second, 20, and in the third, 5. In all hidden layers, the tangential activation function was applied. Feedforward networks are the most commonly used and the most useful.

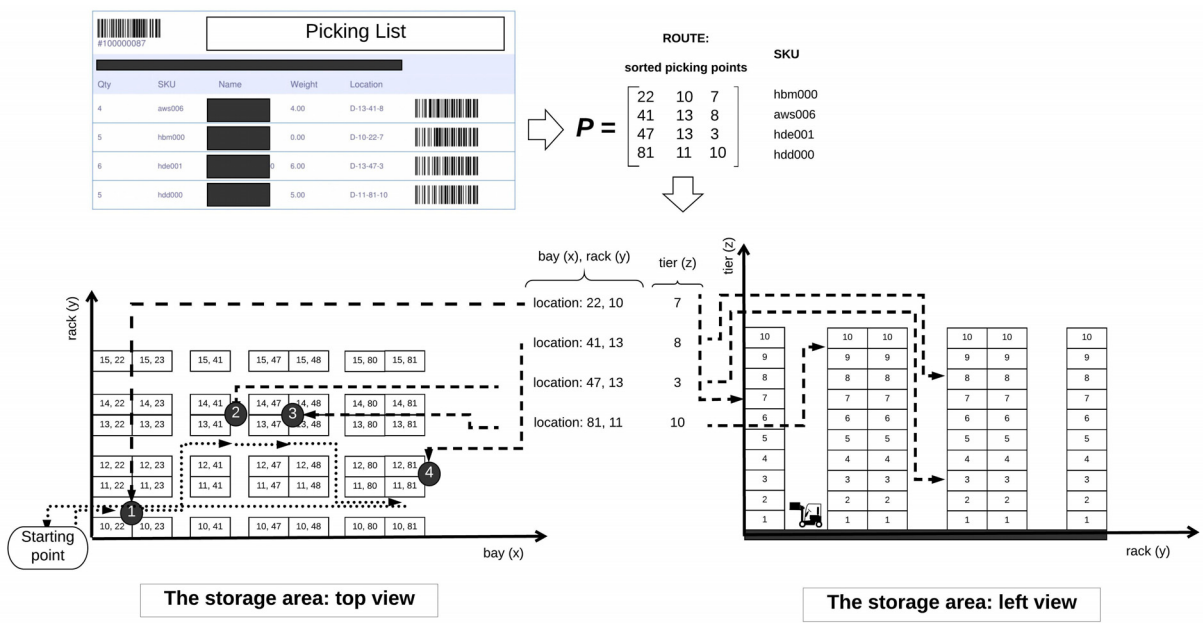


Figure 3. Example of picking route calculation based on picking list

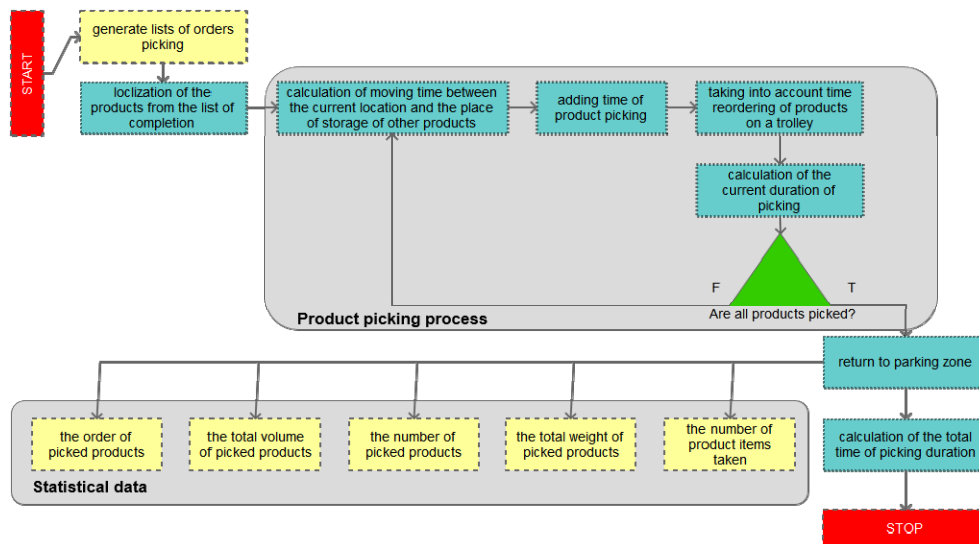


Figure 4. Algorithm for calculation of products picking time

On the basis of the orders picking model, the authors developed a computer application called PickupSimulo. It was written in PHP 5.3 and HTML 4.0 using relational database MySQL 5.6. This solution enables the use of large data collections, clear presentation of results and easy modification of input parameters. Furthermore, the application enables integration with Matlab software. The application has a module structure composed of four main modules: data preparation, classification and simulation, data exchange with Matlab software (export and import) as well as artificial neural networks (not used in the present research).

4. CASE STUDY

In our simulation model represented the most common warehousing system with double was used. We used the layout ranging from 2188 m² to 22021 m². For each cases five tier racks were used. As the stock keeping unit the carton boxes was used. The average SKU was assumed as 96% of warehouse capacity. The

PickupSimulo program was used to perform simulations for five warehouses of different size (2188, 7149, 12491, 17225 and 22021 m²). The parameters of the warehouses are presented in Table 1.

Table 1. Differences between analyzed variants

	Variant				
	I	II	III	IV	V
Width [m]	53,0	100,7	119,3	137,8	159,0
Length [m]	41,3	71,0	104,8	125,0	138,5
Area of storage [m ²]	2188	7149	12491	17225	22021
Warehouse capacity [SKU]	3410	10035	18835	23435	31035
Average stock keeping unit	2700	9376	17696	21589	28276
Number of aisles	10	19	23	26	30
Number of storage racks	20	38	46	52	60
Number of bay in each rack	28	50	75	90	100

For order picking the VNA truck was used. That type of forklift need the aisle width between 1.6 to 2.3 meters. The analysed company use also counter-balance truck so the aisle width in that case is 3.5 m. Because of that the same width was use in simulations. The speed of VNA truck was determined on real cases that enabled the determination of the VNA truck operating speed range. Furthermore, acceleration and braking times, or slowing down at turns were included as penalties. To perform the simulations the mean VNA truck speed was adopted at $v_x = 1.39$ m/s. The minimum speed on a straight section was $v_x = 0.97$ m/s, and the maximum $v_x = 1.81$ m/s. The standard deviation was 0.246. The picking always is begin in dispatch zone, the VNA truck is traveling to the racks for pick the products from order according to the planned route. In each rack the picker is lifted to proper tier and pick the SKU from it. Next the picker is lowering down and go to the next location of product from list. The histogram of real speed of VNA truck from the company of analysed case is presented in Figure 5.

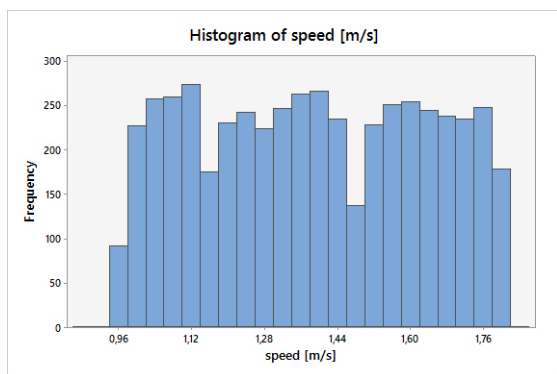


Figure 5. Histogram of VNA truck speed for simulation results

In practical terms, we can state with 95 % confidence that the actual mean speed [m/s] is somewhere between $v_x = 1.37$ and $v_x = 1.39$, while the true standard deviation is somewhere between 0.241 and 0.250.

For manual picking of one small package the 10 seconds as average time was assumed. For bigger products with weight over 5 and under 18 kilos that time was assumed as 20 seconds, and for picking SKU the 65 seconds was assumed – as avege total time for one location of lifting, product picking, and lowering down.

The size of racks the following dimensions were assumed: 1.34 m - width of bay rack, 0.9 depth of rack bay, and 1.5 height of one tier.

To generate the research data the actual picking lists from an FMCG warehouse were used. The variant III represent the real warehouse size and structure. Base on that, the other variants were prepared by scale the warehouse parameters. In all variants the same type of racks and storage equipment was used. The scaling method is presented in figure 6.

The warehouse stocks average 2700 types of product. The most common 120 picking lists was used as input data, six lists from each given day in one month. These lists reflected the most common cases, so the data was reliable and representative. The picking lists reflected the representative period / time interval during which there was no seasonality that might disturb

the test results. In that picking list the SKU identifier was given with the name of product, quantity, position, weight and barcode. The typical picking in that warehouse can be determined as:

- from 3 to 10 order lines per order,
- from 1 to 60 number of products per order line,
- from 30 to 80 picking lists per day,
- the weight of the product from 0.1 kg to 20 kg,
- the volume of the product from 0.05 m³ to 1.0 m³.

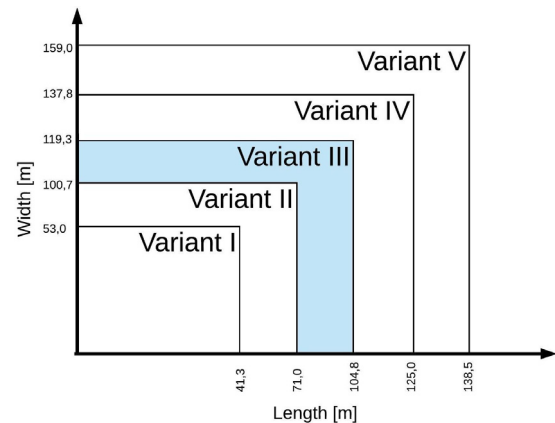


Figure 6. The scaling of warehouse size base on real warehouse size – variant III

Because it was not possible to get more picking lists, those 120 picking lists were used to generate others. That was run to see whether the simulation results would differ with different numbers of picking lists. The simulations were performed every 100 cases in the interval of 100 to 3000. The statistical analysis proved that above 1000 picking lists the growth of their number has no impact on the simulation result. Consequently, it was decided that to make the simulations valid statistically, 1000 picking lists should be used. Prior to the simulations the data were checked for the risk of occurrence of repetitions. Such cases were eliminated so that they did not affect the simulation result more than other cases.

After preparing the simulation model for calculation picking time, the model was compared with results for those of 120 picking lists. The model showed that results of simulation is correlated with real result by 0,96 coefficient of similarity. It proves that the model can be used for simulations.

For the variants presented in Table 1 products classification was done. Base on formula (5) products allocation in the storage area was planned. The next stage of the research was the simulation of products picking process following the model presented in methodology. Each simulation was performed for 1000 picking lists. For each variant the same picking list was used to proper compare of cases. The average time of orders picking referred to the method and classification criterion applied as well as the warehouse size is shown in Figure 7.

The products picking time resulting from the simulations for two warehouse areas (2188 m², 7149 m²) and nine variants of products allocation was a basis for deriving linear functions identifying the orders picking time increase depending on the warehouse area. It can be notice that generally for variant I, II, and III the picking time trend is going in straight line. It shows that picking time is proportional to the warehouse size.

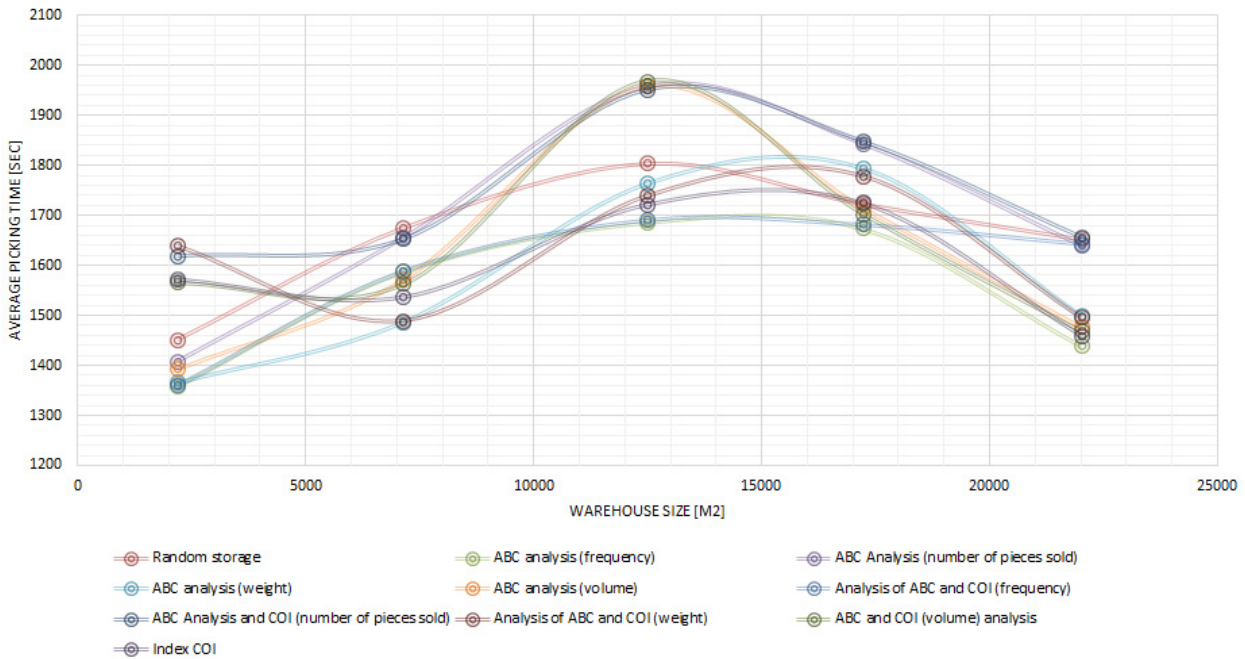


Figure 7. Average picking time depending on the warehouse size and storage policy

Because of that the conclusion is that for small warehouse size the chosen method did not shorten the order picking time, so it does not matter which method will be chosen. The simulations indicate that the picking time decreases for warehouse size larger than 10000 m2, so for that space the storage policy should be implemented. The effectiveness of storage policy and criterion depends on many factors, but generally the ABC analysis by product frequency gives the best results according to other methods.

This function, in turn, was a basis for the forecast of picking time increase. The results of this simulation for each storage policy and products allocation are tabulated in Table 2.

Table 2. Simulation of picking time depending on variants

	Avg Picking time [sec]				
	I	II	III	IV	V
Random storage	1451	1675	1804	1723	1652
ABC analysis (frequency)	1358	1587	1686	1673	1439
ABC Analysis (number of pieces sold)	1408	1655	1958	1843	1639
ABC analysis (weight)	1365	1486	1763	1793	1499
ABC analysis (volume)	1393	1572	1959	1716	1477
Analysis of ABC and COI (frequency)	1361	1589	1690	1681	1643
ABC Analysis and COI (number of pieces sold)	1618	1653	1951	1848	1656
Analysis of ABC and COI (weight)	1638	1489	1739	1778	1495
ABC and COI (volume) analysis	1565	1563	1968	1703	1468
Index COI	1572	1536	1722	1725	1459

For each variant the best results were marked by dark green colour. By light green the results lower than average were marked. It shows that ABC storage policy by criterion of frequency generally give the best results. The histogram of picking time for simulation of order picking by ABC storage policy by criterion of frequency for all variants is presented in figure 8.

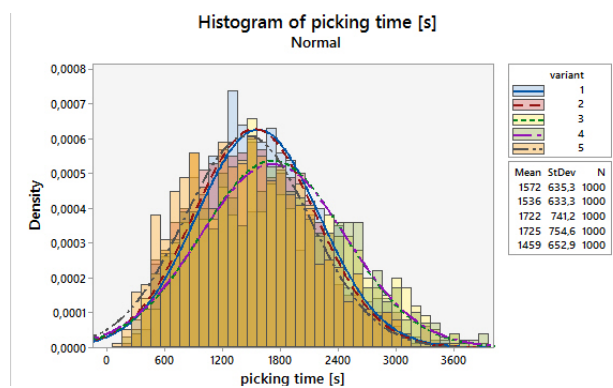


Figure 8. Histogram of picking time for simulation of order picking by ABC storage policy (criterion of frequency)

The most favourable results were obtained for the ABC analysis according to the frequency criterion. For these variant detailed statistical analyses are presented and the results are shown in figure 9 and figure 10.

The scatter plot represents all results from simulation. The box-and-whisker plot present that results in consistent form. The whole rectangle presents lower and upper quartile. The line inside that rectangle presents median value for results. The vertical line under and over the rectangle represent the lowest and the highest results. The points marked by stars present individual results that can be treated as outstanding from typical. Those rare results should be not used for formulating a conclusion.

For all the methods statistical tests were done to determine whether the results for particular warehouse sizes differ from one another. The most favourable results were obtained for the ABC classification according to products frequency. The results were further analysed statistically. Table 3 shows various statistics for each of the five columns of data.

The ANOVA analysis divides the difference between the data into two parts: between-group part and within-group part. ANOVA analysis proved that for

each variant the results are statistically different. That analysis is one of the most typical one. The F-ratio, which in this case equals 48,68 is a ratio of the between-group estimate to the within-group estimate. Since the P-value of the F-test is less than 0,05, there is a statistically significant difference between the means of the five variables at the 5% significance level. The ANOVA analysis prove that there is correlation between the warehouse size and effectiveness of storage policy.

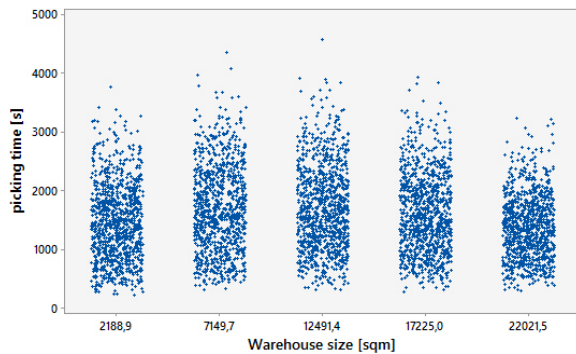


Figure 9. Scatterplot for orders picking time depending on warehouse size for ABC storage policy by frequency criterion

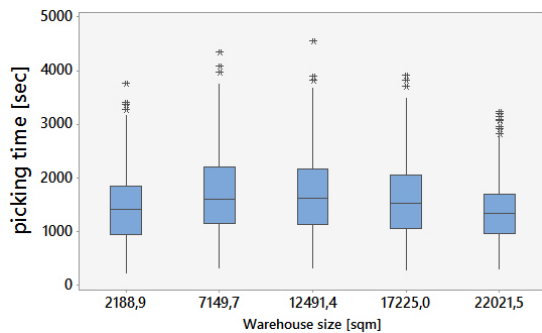


Figure 10. Box-and-whisker plot for orders picking time depending on warehouse size for ABC storage policy by frequency criterion

Table 3. Summary statistics for ABC storage policy by frequency according to picking time [sec]

Area of storage [m ²]	Average picking time [sec]	Standard deviation	Coeff. of variation	Min.	Max.	Range
2188	1358	643,6	44%	198,0	3753	3555
7149	1587	718,5	42%	303,0	4342	4039
12491	1686	716,8	42%	290,0	4549	4259
17225	1673	665,1	41%	265,0	3905	3640
22021	1439	529,8	39%	272,0	3224	2952

To compare the mean values the Tukey HSD test was done. That test enable to divide different results and identify the similar one. A multiple range test by Tukey HSD for 95% confidence interval was done.

Table 4. Results of ANOVA analysis for ABC storage policy by frequency

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Between groups	8,44E7	4	2,110E7	48,68	0,000
Within groups	2,16E9	4995	433523		
Total (Corr.)	2,24E9	4999			

Table 4 applies a multiple comparison procedure to determine which means are significantly different from which other.

Table 4. Multiple Range Tests for picking time [sec] by area of storage [m²] ABC storage policy by frequency

Variant	Area of storage [sqm]	Mean	Homogeneous group		
I	2188	1438		x	
II	7149	1673			x
III	12491	1685			x
IV	17225	1587		x	
V	22021	1357	x		

In table 4 the bottom half of the output shows the estimated difference between each pair of the means. Four homogenous groups are identified using columns of X's. Within each column the levels containing X's form a group of means within which there are no statistically significant differences. The method currently being used to discriminate among the means is Tukey's honestly significant difference (HSD) procedure. With this method there is a 5 % risk of calling one or more pairs significantly different when their actual difference equals 0. If the "x" in homogeneous group is in the same column it means that variants give the similar results. That case appears just for variant II and III. It also prove that for that warehouse size the order picking policy does not matter. The analyses have proved that there is a statistical dependence of picking time on warehouse area size but just for storage area bigger than 12000 m².

5. CONCLUSIONS

The simulations indicate that the picking time decreases for warehouse size larger than 10000 m², so for that space the storage policy should be implemented. The effectiveness of storage policy and criterion depends on many factors, but generally the ABC analysis by product frequency give the best results according to other methods. For small warehouse size the chosen method did not shorten the order picking time, so it does not matter which method will be chosen. The results of research presented may be a reliable basis helpful in the selection of products storage policy when planning products allocation in a warehouse. Moreover, the computer programs developed may be used for the evaluation of potential solutions prior to their practical implementation in a warehouse, which will, consequently, result in reducing the risk of implementing an ineffective solution. The research results are, therefore, of significant importance for warehouse management.

Based on the simulation study it is possible to support warehouse managers for choosing the best products storage policy. Therefore, our research is an example of a good practice, and facilitates the choice of optimal product classification method, which may help to avoid the need of analyses of the effectiveness of each products classification method to choose an optimal one. Companies that decide to use the class-based storage system will be able (based on their warehouse size) to choose the best storage policy using our research model. Taking the above into account, we

are convinced, that this will reduce retrieval time and improve the effectiveness of order picking.

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NOMENCLATURE

r	location in the rack; takes the value $r(x,y) \in \{0,1\}$, with $r(x,y) = 0$ for aisles
$t_p(x,y,z)$	time between locations within the warehouse for order line (p)
y	warehouse row
x	bay number in a rack location (y)
z	stock tier
t_{lp}	time required for movement on a straight section of 1 meter
t_a	sum of time required to turn during movement
t_s	sum of accelerate and decelerate speed of VNA truck
D_{wr}	rack bay depth (of one pallet space)
D_{lr}	length of a rack bay
d_{cr}	width of an aisle
$c_l(x)$	number aisles along warehouse to rack x
$c_w(y)$	number of aisles across the warehouse to rack y
t_z	sum of time of the forks lifting up and lowering down to a stocking tier (z)
t_t	sum of time of turning VNA truck during picking process
t_i	sum of time of pick items from rack during picking process
O	order list
l	order line with product description correlated with product identifier (ID) and nearest location in storage area (x,y,z)
la	total number of lines in order
N	vector with coordinates of the nearest product relative to actual position of picker
P	matrix with coordinates of all product lines optimized by time reduction
K	inventory storage category

ЕФИКАСНОСТ ПОЛИТИКЕ СКЛАДИШТЕЊА ПРОИЗВОДА ПРЕМА КРИТЕРИЈУМУ КЛАСИФИКАЦИЈЕ И ДИМЕНЗИЈАМА СКЛАДИШТА

А. Лоренц, Т. Лерхер

Рад се бави утицајем димензија складишта на ефикасност политике складиштења производа. У раду

се анализира другачија политика складиштења. У циљу евалуације ефикасности изабраног складишта коришћен је одговарајући софтер за симулацију процеса поруџбине и узимања робе. Процена ефикасности планирања процеса дистрибуције извршена је на основу укупног времена потребног за реализацију процеса од поруџбине до узимања робе из складишта. При планирању руте пошло се од претпоставке да је најближи производ био следећи кога

је требало узети. Анализа дискретне симулације догађаја је извршена коришћењем специјалног софтвера PickupSimulo. Истраживање је обухватило складишта различите површине: $2\,188\text{m}^2$ – $22\,021\text{m}^2$. Резултати симулације могу да буду од користи руководиоцима складишта при избору најбоље политике складиштења производа. Тиме се редукује време узимања производа и побољшава ефикасност извршења поруџбине.