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THE SIMULATION MODEL OF WAREHOUSE SPACES APPLYING MATHEMATICAL-STATISTICAL METHODS

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Abstract
This article explores the use of cluster analysis in designing warehouse spaces. Drawing on theoretical insights from cluster analysis and an examination of the supply processes in selected industrial enterprises, it introduces an algorithm for applying hierarchical clustering methods to the design of storage systems across various industrial production environments. The proposed methodology is experimentally validated, demonstrating its practical application as a mathematical-statistical approach for designing warehouse spaces in companies.
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Key Words: Mathematical-Statistical Methods, Modelling, Warehouse, Dendrogram

1. INTRODUCTION

Among the mathematical methods, cluster analysis was used to create the model. Cluster analysis involves methods that sort cases into groups that are homogeneous within themselves and heterogeneous between different groups [1]. Halkidi and Vazirgiannis (2001) define cluster analysis as a multivariate technique designed to categorize objects into distinct groups known as clusters. It is a frequently used statistical method, as demonstrated by various references in the literature [2-6].

We have a data matrix X with dimensions $n \times p$, where n represents the number of objects and p denotes the number of variables (attributes or features). Additionally, we consider a partition $S^{(k)}$ that divides these n objects into k distinct clusters, represented as $S^{(k)} = \{C_1, C_2, C_3, ..., C_k\}$, while applies [7]:

$$C_i \neq \emptyset,\ i = 1, \dots, k, \tag{1}$$

$$\text{and } \bigcup_{i=1}^{k} C_i \text{ encompasses the entire dataset} \tag{2}$$

Given a set of objects $o = \{A_1, A_2, ..., A_n\}$ and a specific dissimilarity coefficient D, a subset p of these objects o is considered a cluster if the following condition is met [8]:

$$\max_{i,j} D\left(A_i; A_j\right) < \min_{k,l} D\left(A_k; A_l\right), \tag{3}$$

$$\text{where } A_i, A_j, A_l \in o \text{ and } A_k \notin p. \tag{4}$$

2. MATERIAL AND METHODS

The current literature presents numerous clustering algorithms, many of which are implemented in specialized software tools. One of the most commonly referenced classifications of "traditional" clustering methods, as indicated in most sources, is the distinction between hierarchical and non-hierarchical clustering techniques.

Hierarchical clustering methods organize analysed objects into a structured hierarchy of clusters. This hierarchy is made up of distinct, non-empty subsets of the original object set. A key feature of hierarchical clustering is that it produces a series of decompositions where each one refines or builds upon the previous or subsequent decomposition [9].

Hierarchical clustering methods are classified according to the method of creation of decompositions as follows [9]:

1. *Agglomerative methods* start by treating each object as its own cluster. In the next steps, the most similar clusters are gradually merged until a specified quality criterion is met. These methods create a sequence of cluster decompositions for the object set O, from $S^{(0)}$ to $S^{(n-1)}$. Each cluster $C_i^{(k)}$ in step $S^{(k)}$ is assigned a non-negative value $C_i^{(k)}$:
   - The decomposition of a set of objects $S^{(0)}$ is made up of its individual objects, i.e. single-element clusters $C_i^{(0)}$ and each single-element cluster $C_i^{(0)}$ has a number $h(C_i^{(k)}) = 0$ for $i = 1, 2, ..., l0$.
   - Let a decomposition $S^{(k)} = \{C_1^{(k)}, C_2^{(k)}, \dots, C_{lk}^{(k)}\}$ is in the k^{th} step and clusters are assigned numbers $h(C_i^{(k)})$ for $i = 1, 2, ..., l_k$. From the clusters, we select the pair that has the minimum value of the dissimilarity coefficient D, i.e. they are the most similar. These clusters merge and build single cluster. The other clusters pass to the next decomposition unchanged.
2. *Divisional methods* – begin by considering all objects as part of one overarching cluster at the start of the clustering process. This cluster is then divided into smaller clusters.

Table I describes the advantages and disadvantages of individual hierarchical methods of cluster analysis [10].

Table I: Advantages and disadvantages of hierarchical cluster analysis method [10].

	Advantages	Disadvantages
Agglomerative hierarchical methods	- Clustering is an intuitive and popular classification approach, with results typically displayed in a dendrogram. - It allows for easy interpretation by hierarchical relationships. - Moreover, it does not require the user to predefine the number of clusters.	- There is no single "correct" clustering algorithm, as results can vary significantly depending on the chosen algorithm and the method of measuring similarity. - It is not efficient for handling large datasets. - Additionally, the computation can be slow.
Divisional hierarchical methods	- The monothetic method offers a straightforward key for classifying other samples. - It allows for easy interpretation of results. - Divisional techniques are better suited for very large datasets compared to agglomerative techniques. It identifies hierarchical relationships. - Additionally, it does not require the selection of the number of clusters.	- The monothetic method is not very robust. - The polythetic method fails to provide a simple key for adding new samples to a specific group. - It is inefficient when dealing with large datasets. - It can be computationally slow.

In the presented article, one of the hierarchical methods is used to create a simulation model, specifically **Ward's method**. Ward's method, also known as the method of "minimizing the increase of the error of the sum of squares," focuses on optimizing the homogeneity of clusters based on a specific criterion: minimizing the increase in the error of the sum of squares of deviations of cluster points from their mean (centroid). This distinguishes it from other hierarchical clustering methods, which typically optimize the distance between clusters.

At each clustering level, the loss of information is assessed, represented as the increase in the total within-group sum of squares of deviations from the mean *ESS* value for each cluster.

Clusters are then merged in such a way that results in the least increase in the sum of squares error. Essentially, this method aims to minimize intra-cluster variance. The increment of the *ESS* function is calculated using the following relation [10]:

$$\Delta ESS(A_i, A_j) = \frac{1}{2} d_{ES}(A_i, A_j),\ A_i, A_j \in o,\ i, j = 1, 2, ..., n \tag{5}$$

Non-hierarchical methods of cluster analysis categorize objects into a predetermined number of distinct clusters. These methods can be classified into two types [11]:

- Fixed clustering methods – where the assignment of an object to a cluster is clear-cut.
- Fuzzy cluster analysis – which assesses the degree to which objects belong to clusters.

Table II outlines the advantages and disadvantages of the various non-hierarchical methods of cluster analysis [11].

Table II: Advantages and disadvantages of non-hierarchical cluster analysis methods [11].

Advantages	Disadvantages
- Non-hierarchical methods may be more appropriate than hierarchical techniques for larger datasets or when there is no inherent hierarchical structure in the data. - These methods are computationally fast. - They can effectively handle large files.	- The user must specify the number of groups *K* in advance. - If the estimated number of clusters is incorrect, the method may yield inaccurate results. - It does not establish relationships between clusters; *k*-means clustering relies on Euclidean distances, which can be problematic if Euclidean distance is not the most suitable metric.

3. RESULTS AND DISCUSSION

The presented article deals with the application of cluster analysis in the design of layout in the warehouse in order to make the process more efficient. The theoretical basis of cluster analysis was the basis for the design of the cluster analysis application algorithm in the design of the storage system, which is shown in Fig. 1.

The choice of the dissimilarity measure and the clustering method has a significant influence on the results of the cluster analysis. The dissimilarity measure determines how the similarity between objects is measured, which strongly influences the grouping and arrangement of the clusters. Similarly, the partitioning method determines how the objects are assigned to the clusters, which is crucial for the structure and organization of the storage areas. A conscious selection of these parameters thus contributes significantly to the efficiency and accuracy of the warehouse layout.

The proposed algorithm for the application of cluster analysis methods in warehouse stocks is experimentally verified in practice in the following part of the article. Verification of the proposed methodology is applied to stocks of finished products of three selected companies. For the cluster analysis of the stock of finished products, we will start from the analysis of the shipment of products by individual customers for past periods or from the expedition plan for future periods. Due to the extensiveness of the issue of cluster analysis, in this chapter, the squared Euclidean distance is used to express similarity (distance), and Ward's method is chosen from the hierarchical methods of cluster analysis.

The output of the cluster analysis is the dendrogram of finished products for the selected production company from the automotive industry shown in Fig. 2. A dendrogram graphically represents various distinct groups of objects.

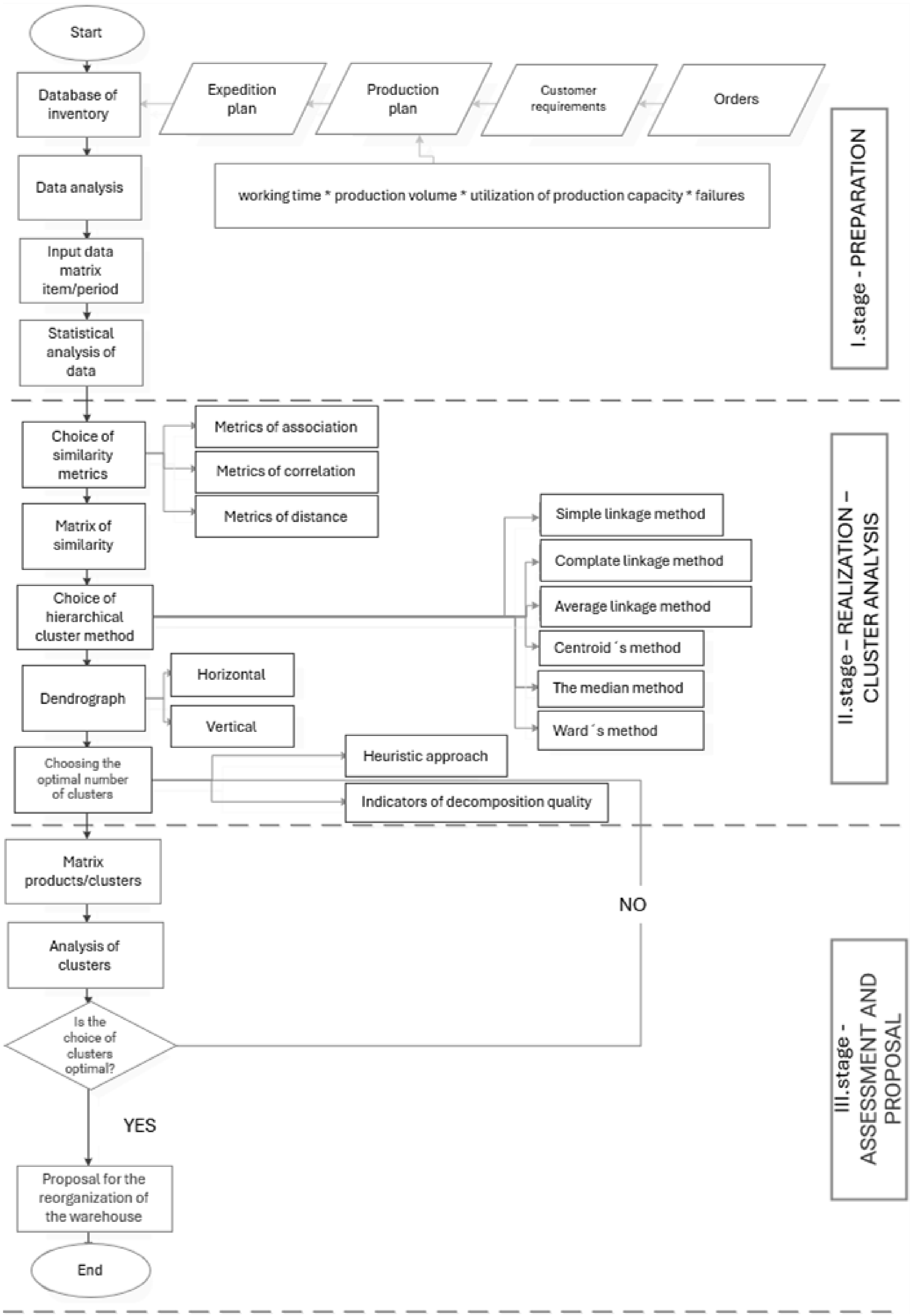


Figure 1: Algorithm of cluster analysis application in warehouse optimization.

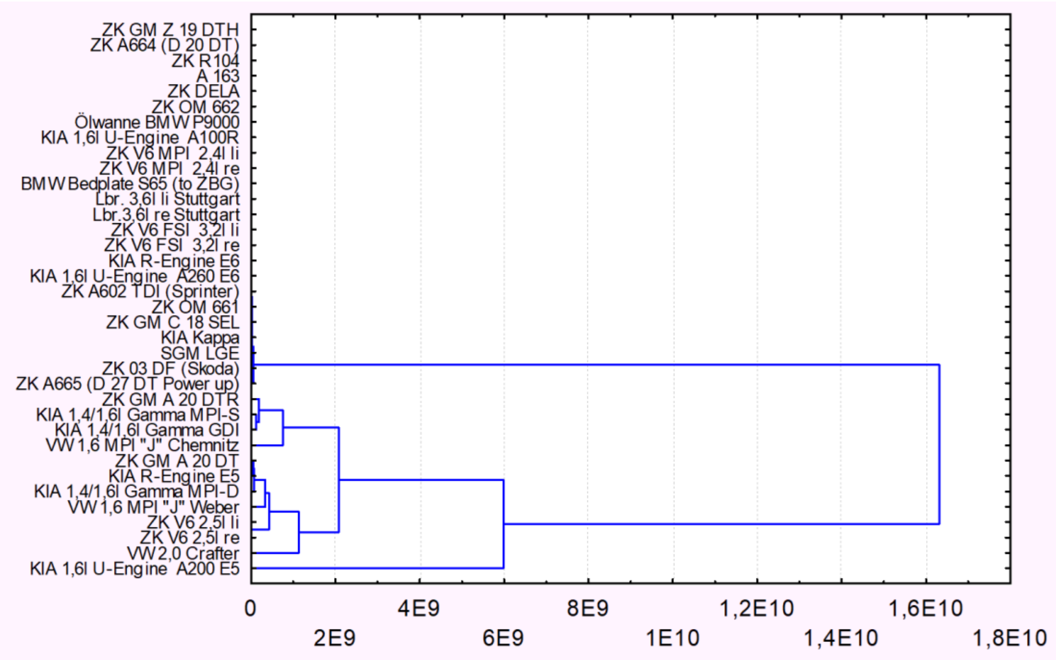


Figure 2: Dendrogram cluster analysis from the automotive industry.

Fig. 3 shows the individual step-by-step process of merging objects in the statistical software STATISTICA CZ. The given values represent the selected measure of distance – the squared Euclidean distance.

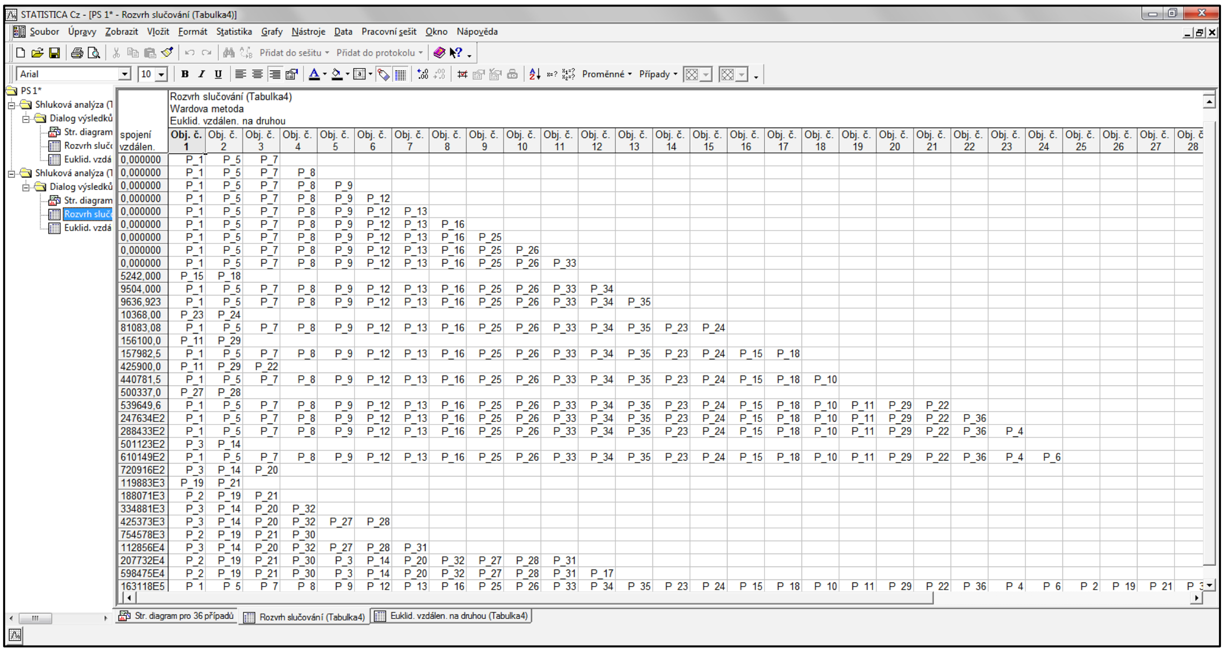


Figure 3: The clustering schedule of objects from the automotive industry (print Screen from software STATISTICA CZ).

We consider the optimal number of clusters to be 3 clusters. The arrangement of finished products in the warehouse based on the resulting clusters was taken into account when designing the layout of the finished goods warehouse, which is shown in 3D form in Fig. 4. In this case, cluster analysis was applied in a warehouse of finished products of the foundry industry.

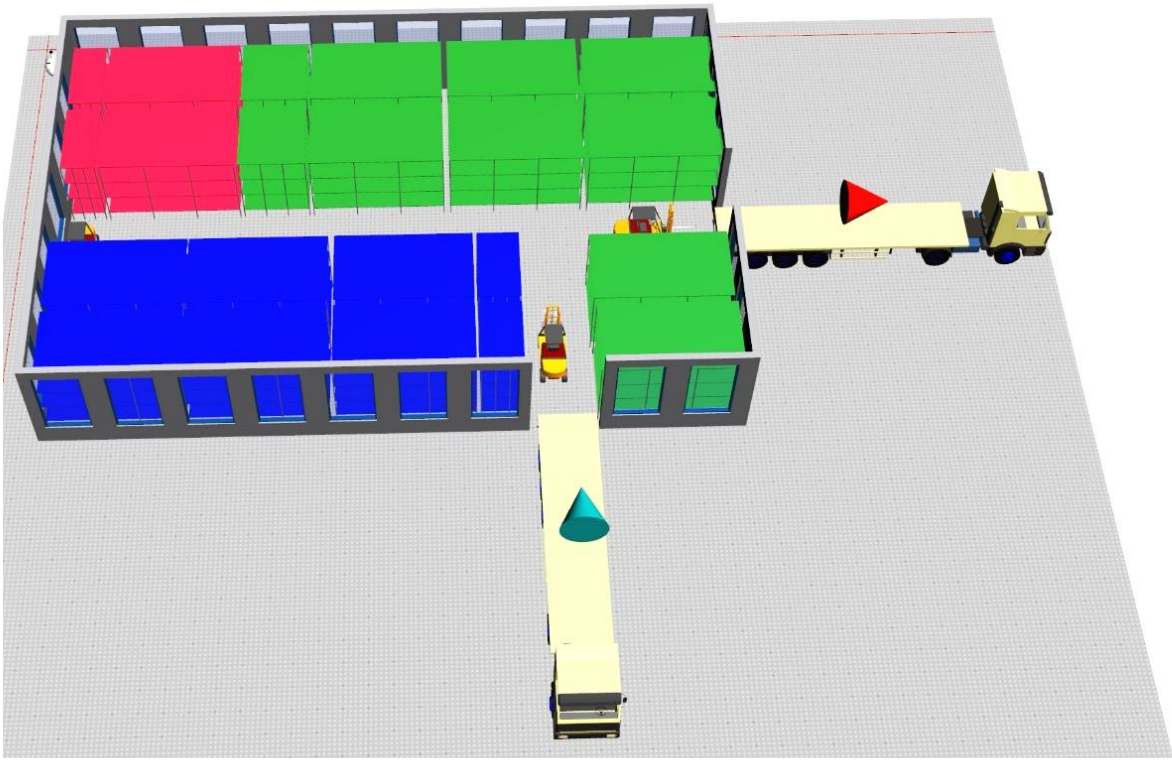


Figure 4: 3D layout of the warehouse of finished products of a company from the automotive industry.

Cluster analysis was also applied in the design of the layout of finished products in woodworking production. The result is the dendrogram shown in Fig. 5. We consider three clusters to be the optimal number of clusters. The classification of objects into clusters is used in the layout design shown in Fig. 7.

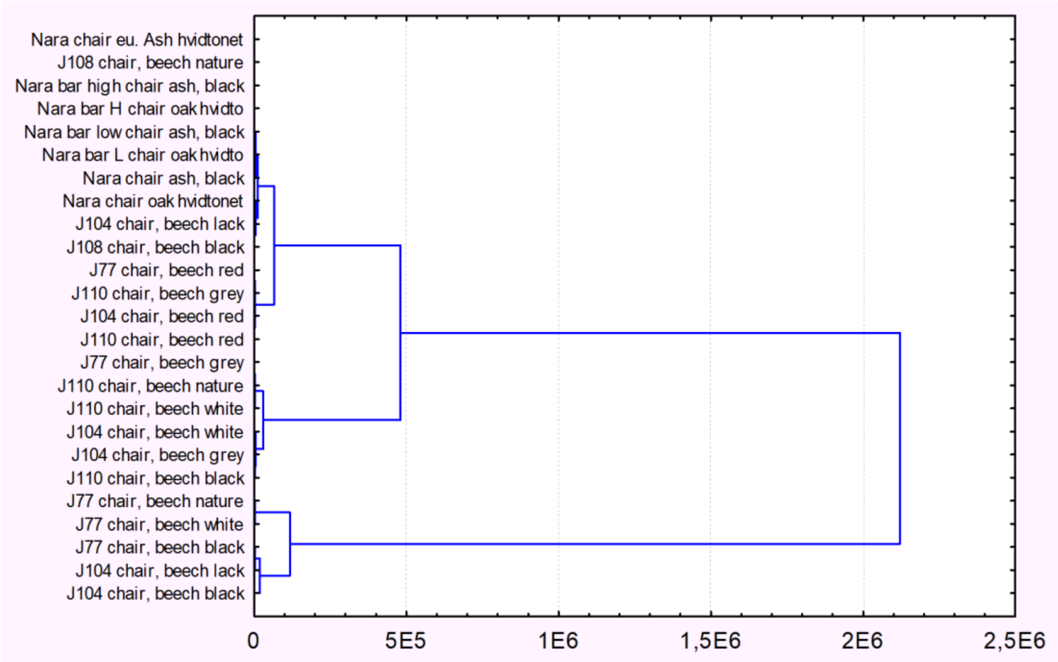
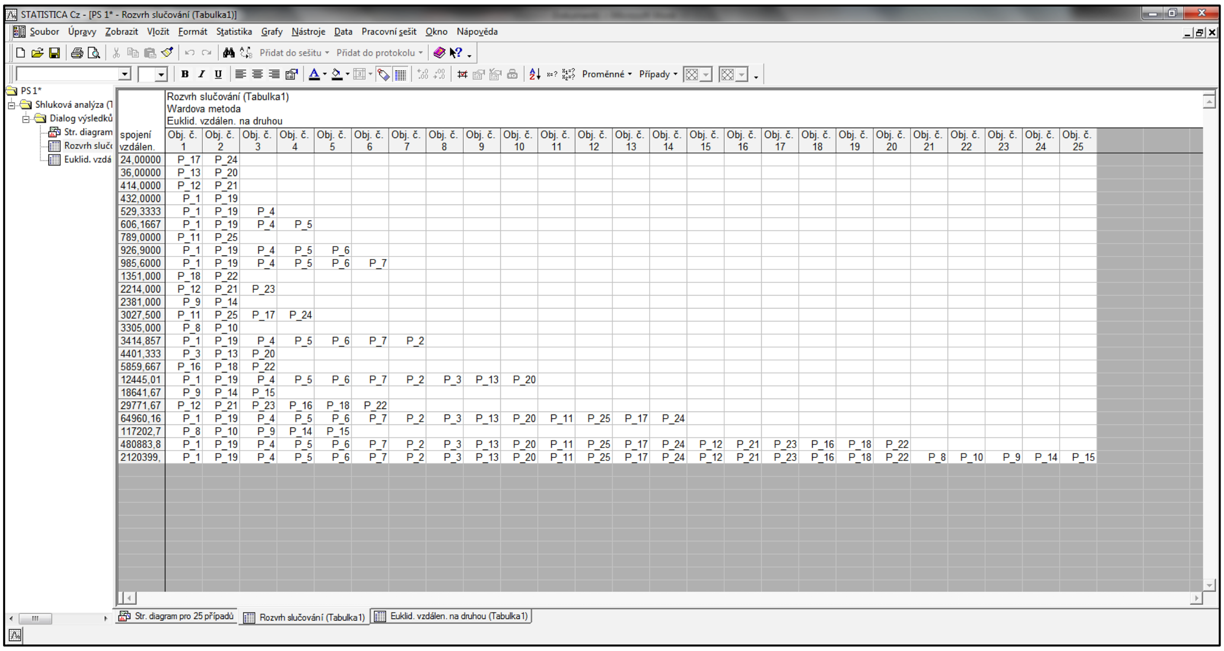


Figure 5: Dendrogram cluster analysis from woodworking industry.

The schedule of cluster analysis for objects from the woodworking industry is showed in Fig. 6.



Rozvrh slučování (Tabulka1)
Wardova metoda
Euklid. vzdálen. na druhou

spojení vzdálen.	Obj. č. 1	Obj. č. 2	Obj. č. 3	Obj. č. 4	Obj. č. 5	Obj. č. 6	Obj. č. 7	Obj. č. 8	Obj. č. 9	Obj. č. 10	Obj. č. 11	Obj. č. 12	Obj. č. 13	Obj. č. 14	Obj. č. 15	Obj. č. 16	Obj. č. 17	Obj. č. 18	Obj. č. 19	Obj. č. 20	Obj. č. 21	Obj. č. 22	Obj. č. 23	Obj. č. 24	Obj. č. 25
24,00000	P_17	P_24																							
36,00000	P_13	P_20																							
414,0000	P_12	P_21																							
432,0000	P_1	P_19																							
529,3333	P_1	P_19	P_4																						
606,1667	P_1	P_19	P_4	P_5																					
789,0000	P_11	P_25																							
926,9000	P_1	P_19	P_4	P_5	P_6																				
985,6000	P_1	P_19	P_4	P_5	P_6	P_7																			
1351,000	P_18	P_22																							
2214,000	P_12	P_21	P_23																						
2381,000	P_9	P_14																							
3027,500	P_11	P_25	P_17	P_24																					
3305,000	P_8	P_10																							
3414,857	P_1	P_19	P_4	P_5	P_6	P_7	P_2																		
4401,333	P_3	P_13	P_20																						
5859,667	P_16	P_18	P_22																						
12445,01	P_1	P_19	P_4	P_5	P_6	P_7	P_2	P_3	P_13	P_20															
18641,67	P_9	P_14	P_15																						
29771,67	P_12	P_21	P_23	P_16	P_18	P_22																			
64960,16	P_1	P_19	P_4	P_5	P_6	P_7	P_2	P_3	P_13	P_20	P_11	P_25	P_17	P_24											
117202,7	P_8	P_10	P_9	P_14	P_15																				
480883,8	P_1	P_19	P_4	P_5	P_6	P_7	P_2	P_3	P_13	P_20	P_11	P_25	P_17	P_24	P_12	P_21	P_23	P_16	P_18	P_22					
2120399,	P_1	P_19	P_4	P_5	P_6	P_7	P_2	P_3	P_13	P_20	P_11	P_25	P_17	P_24	P_12	P_21	P_23	P_16	P_18	P_22	P_8	P_10	P_9	P_14	P_15

Figure 6: The clustering schedule of objects from woodworking industry (print Screen from software STATISTICA CZ).

Based on the heuristic approach of selecting the optimal number of clusters are created these clusters. It was confirmed that the proposed methodology of applying cluster analysis in the supply process is correct and the use of cluster analysis in the creation of groups (clusters) of supplies has its justification, because clusters are created on the basis of similarity, in our case the similarity of the shipment to the customer, which is the main criterion in the creation product groups towards customers. The most shipped products should be placed closest to the exit. These criteria were taken into account in the 3D design of the selected distribution warehouse (Fig. 7).

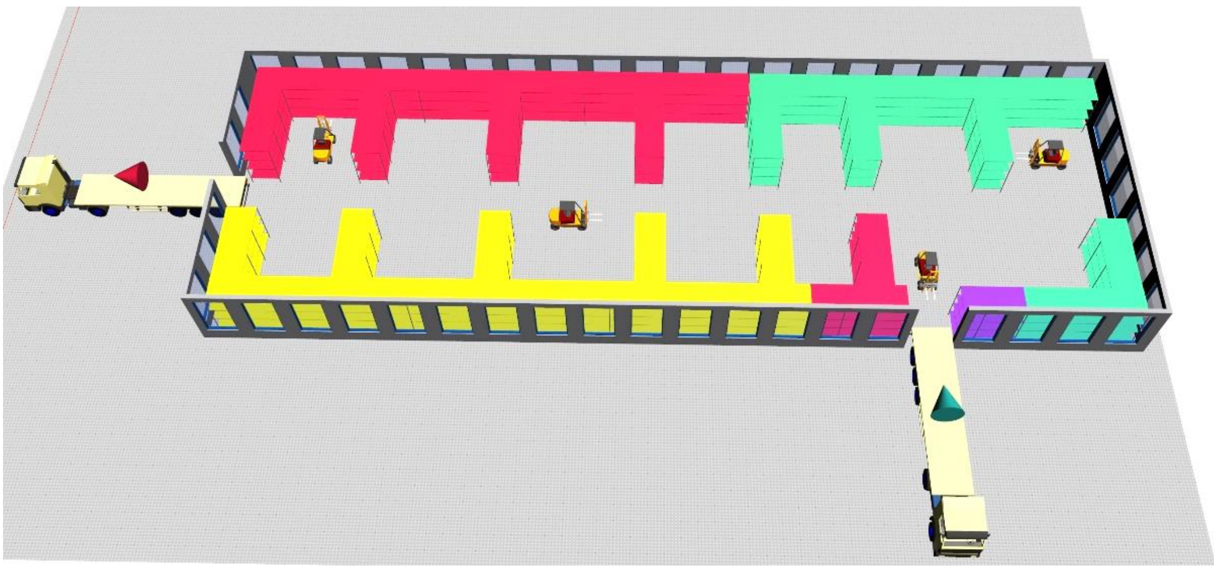


Figure 7: 3D layout of the warehouse of finished products of a company from the woodworking industry.

The proposed algorithm was applied to the data matrix of data on the dispatch of hygiene products in the selected manufacturing enterprise.

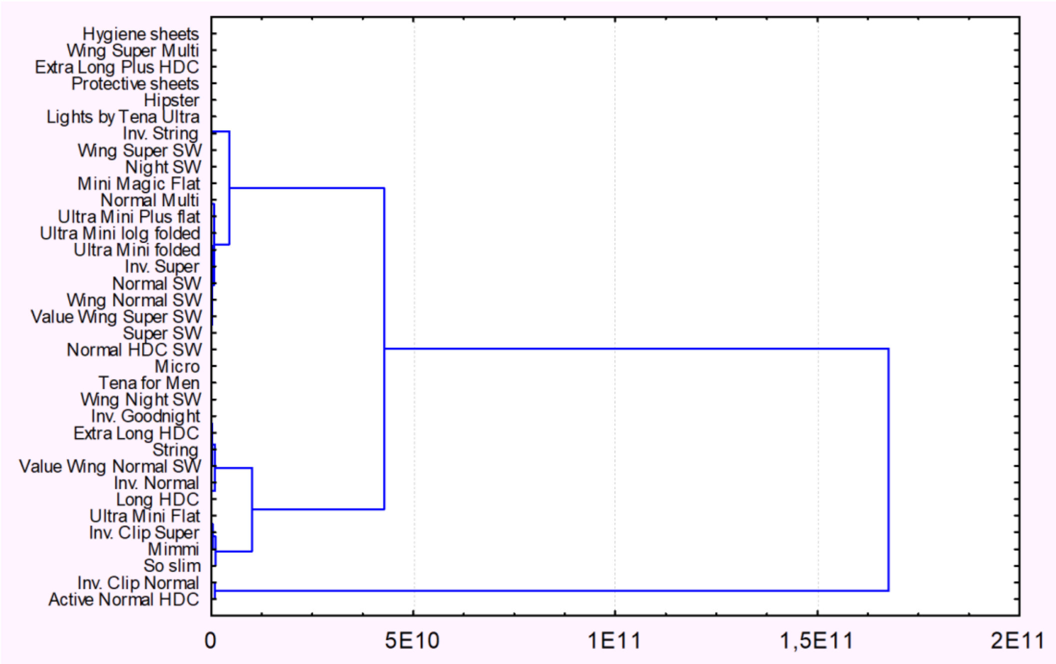


Figure 8: Dendrogram cluster analysis of hygiene products.

In Fig. 9 is the clustering schedule of hygiene products which corresponds to the dendrogram shown above.

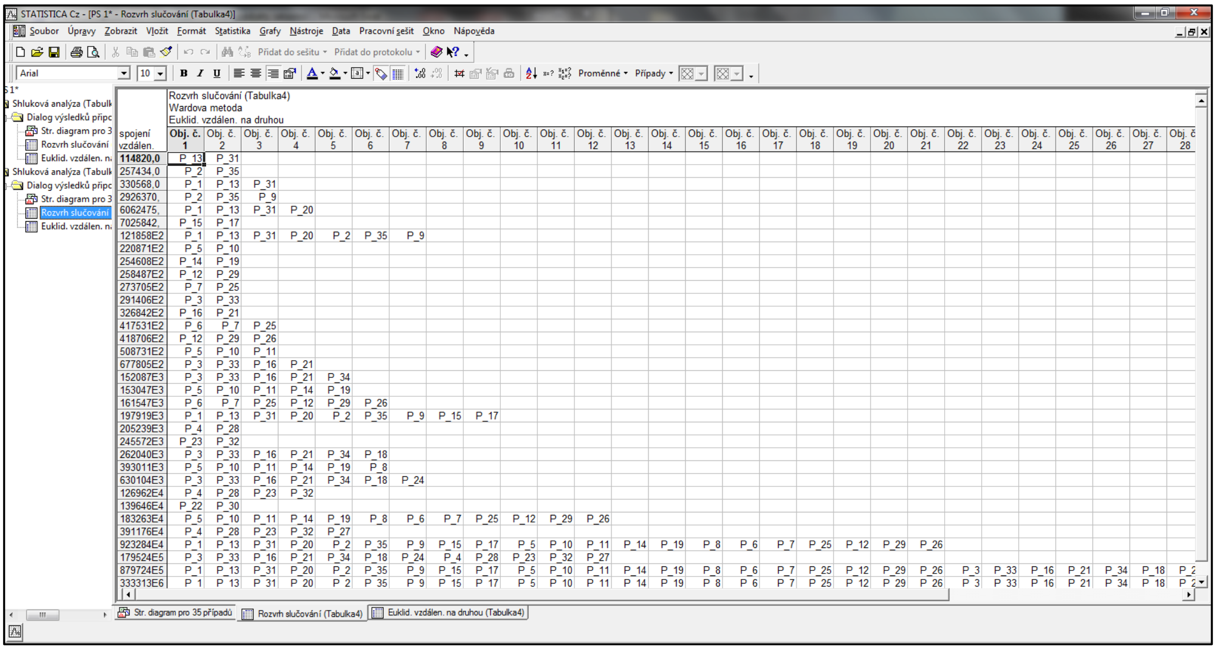


Figure 9: The clustering schedule of hygiene products (print Screen from software STATISTICA CZ).

The results of cluster analysis are the basis for reorganisation in the warehouse of hygiene products. The 3D layout of the warehouse was designed for this company (Fig. 10).

Using the modelling and simulation as a scientific method we can obtain knowledge and information about the examined system and its elements. The model created represents the examined system either real, existing or idealised, simplified or existent. The simulation works with the created model, which represents e.g. computer form of the examined system [12-14]. By working with such a model it is possible to obtain information about the actual system and its behaviour.

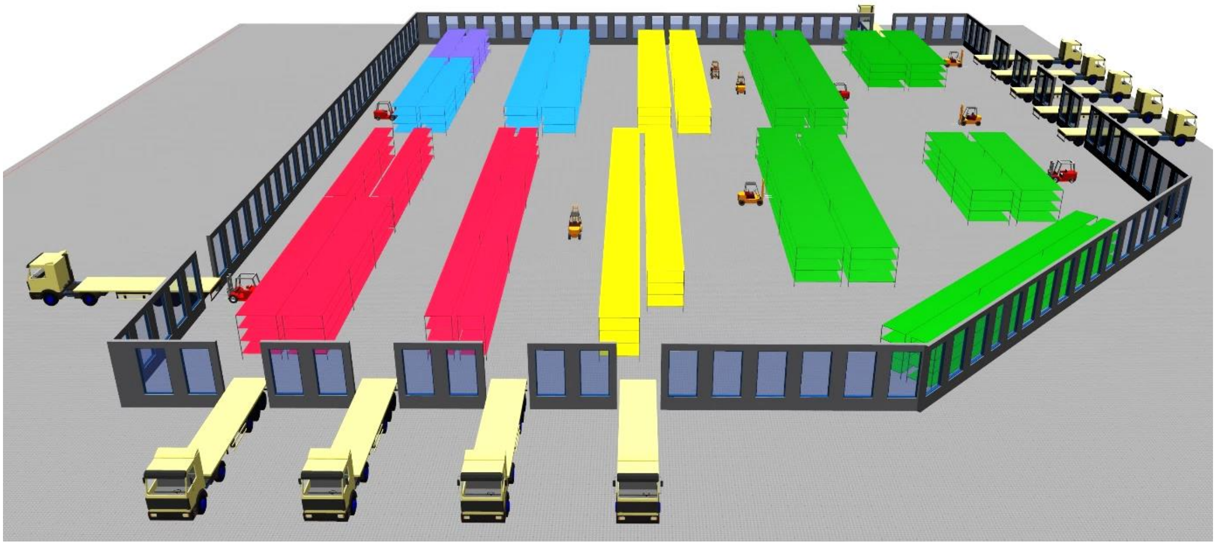


Figure 10: 3D layout of the warehouse of hygiene products.

The basic principle of simulation consists in simplified representation of the real system by its simulation model describing only those properties of the real system of interest. After verifying and validating the simulation model, the experimenter makes a set of simulation experiments using the simulation model [15, 16]. In the framework of these simulation experiments he suggests various "improvements" of the simulated system and verifies their impact on the modelled system. The results of these experiments are applied back to the real system to improve its properties. Simulation is not a tool that allows you to get an optimal solution directly. In the case of computer simulation, the model becomes a computer program in the final form, which should capture the structure of the modelled system, its dynamics and its probability character. There are several reasons to give simulation a preference between gaining experimentation experience and a real system [6-9]. In particular, it is cheaper and more variable, it allows to explore non-existing objects and systems, it is safe for the examined system, it allows to record all changes in the state of the system. In the process of creating the model structure, it is important to have perfect knowledge of the studied systems, especially the interrelationships between entities, state variables and systems with each other. A precisely built model with a well-defined structure is a basic condition for a properly performed simulation. Almost all general scientific methods are used in the modelling process [17-20].

To achieve effective simulation and modelling in manufacturing systems, it is essential to utilize sophisticated tools that facilitate accurate representation and analysis. One such powerful tool is the Siemens Tecnomatix Plant Simulation software, which aligns with the principles of simulation described above. Siemens Tecnomatix Plant Simulation software is a powerful tool for modelling, simulating, visualizing, and analysing manufacturing systems and logistics processes with the goal of optimizing material flow and resource utilization at all levels of production planning. The software facilitates the creation of clear, 3D hierarchical models of manufacturing plants, production lines, and operations, enabling fast and efficient modelling of both discrete and continuous manufacturing processes. This is achieved through a robust object-oriented architecture and a range of modelling functions. Additionally, the software allows for the assembly and 3D visualization of models using built-in libraries or external CAD data, providing flexibility in model design. Siemens Tecnomatix Plant Simulation also offers realistic visualization of large 3D simulation models, ensuring simulation requirements are met, while providing detailed data analysis to support decision-making and process optimization.

The knowledge contained in the article is compatible and integrable with various innovative tools and methods and applicable in various areas of scientific research [21].

We assume the direction of further research in the following areas:

- connection of the designed algorithm for stock classification with the information system used in the analysed company and also with automatic identification systems used in logistics (e.g. barcode scanners),
- incorporation of the proposed algorithm of application of cluster analysis methods in storage into software intended for modelling and simulation of business processes (e.g. Siemens Tecnomatix Plant Simulation),
- extension of the algorithm with detailed elements and restrictions resulting from real production conditions in the search for an optimal solution for the arrangement of warehouse stocks.

The presented contribution, in addition to proposing simulation models for three heterogeneous warehouses, is expanded to include a methodology for the application of cluster analysis in designing a warehouse simulation model, which can be applied to the design of warehouses of various natures. This methodology can be modified depending on the type of warehouse, storage conditions, or other criteria [22-25].

Decision support models for warehouse management systems are based on a multi-criteria decision-making process. These facts have been elaborated in articles [26, 27] and proven in case studies. The mentioned studies can be considered as inspirational for further research related to the search for an optimal warehouse management system.

4. CONCLUSION

The market is characterized by management by the "invisible hand of the market" and companies strive to achieve synergy between their own requirements and market requirements in the form of customer needs. In order for a company to achieve success on the market in an enormously competitive environment, it must strive to achieve advantages compared to other companies, primarily in the form of quality manufactured products, flexible responses to changes in demand, speed of delivery, and this can only be achieved through a process of continuous improvement. For this reason, companies increasingly focus on optimizing internal processes. One of the goals is increasing the efficiency of storage in the company and rationalizing all related activities. For this reason, an algorithm for the application of cluster analysis methods in storage was proposed.

The core of cluster analysis is the expression of similarity, the squared Euclidean distance was used in the article, which is the most used measure of similarity, and Ward's method was used from cluster analysis methods, which differs from other hierarchical methods of cluster analysis in that the criterion for creating clusters is not the distance of objects or of clusters, but minimizing the increase of the error of the sum of squares of the deviations of the cluster points from (the centroid). To select the optimal number of clusters, a heuristic approach was used in the work, i.e. choosing the optimal number of clusters depends on the subjective judgment of the solver, his experience and knowledge.

Based on the results of cluster analysis using the procedure outlined in the proposed algorithm, a proposal for warehouse inventory arrangement is developed. The methodology for applying cluster analysis methods contributes to improving the efficiency of supply processes towards customers. Furthermore, the proposed algorithm demonstrates potential applicability in various areas of intra-company production and non-production processes, offering broad flexibility for optimization across different operational domains.

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