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INVENTORY CLASSIFICATION USING MULTI – CRITERIA ABC ANALYSIS, NEURAL NETWORKS AND CLUSTER ANALYSIS

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Original scientific paper
The work presents a research on inventory ABC classification using various multi-criteria methods (AHP method and cluster analysis) and neural networks. For the real inventory sample data and previously conducted traditional ABC analysis the applications of the mentioned methods in inventory classification have also been investigated. The applied methods' obtained results have been used to evaluate their usage possibilities in real manufacturing environment. The investigations carried out in the present work create real conditions for a better inventory control and implementation of the results in the ERP system inventory module.

Keywords: *ABC analysis, AHP methodology, cluster analysis, inventory classification, neural networks*

Klasifikacija zaliha pomoću višekriterijske ABC analize, neuronskih mreža i klaster analize

Izvorni znanstveni članak
U radu je dano istraživanje ABC klasifikacije zaliha koristeći različite višekriterijske metode (AHP metoda i klaster analiza) te neuronske mreže. Za definirani realni podatkovni model zaliha i prethodno postavljeni model ABC analize, istražene su i primjene navedenih metoda u klasifikaciji zaliha. Kroz ostvarene rezultate primijenjenih metoda, procijenjene su mogućnosti njihova korištenja u realnom proizvodnom okruženju. Provedena istraživanja u ovom radu stvaraju dobru pretpostavku za bolje upravljanje zalihama te implementaciju rezultata u modulu zaliha ERP sustava.

Ključne riječi: *ABC analiza, AHP metodologija, klasifikacija zaliha, klaster analiza, neuronske mreže*

1 Introduction

Inventory control (inventory problem, inventory theory, inventory management problem, stock control) as a scientific and technical discipline helps in reaching a decision on the number of items (*how many?*) in stock and the time of placing an order (*when?*) for new quantities, taking into consideration several opposite demands. Inventory includes all material components that are not used at a particular time. In production companies these are most often inventories needed for own production – production inventories or finished (manufactured) goods intended for the market – market inventories. Therefore, inventories support production or are the result of production but they are also needed due to different intensity of both demand and supply [1 ÷ 3]. Stockout can result in production stoppage or impossibility of timely delivery of finished products to the customer, causing direct or indirect losses. Surplus stock gives certain security; higher supplies provide opportunity for reduced prices, production in larger series, but the surplus stock causes also considerable expenses due to the cost of storage and the capital investment.

Because of the surplus stock in most companies, great attention is given to the inventory classification into different classes or groups. Thus various management tools and ways of management are applied to those different groups. The ABC classification, based on the Pareto principle, is a frequently used analytical method for inventory classification into the three A, B and C groups. However, the traditional ABC classification considers only one criterion to classify inventory. Very often this criterion is annual cost usage obtained by multiplying annual requirements and unit price of the part's or the position's cost (item in stock). The other criteria, besides annual cost, are: time of delivery, item criticality, accessibility, unit price, penalties costs etc. Sometimes, one criterion only is not enough to reach a decision and the methods for multi-criteria decision making are therefore used [4]. Accordingly, the term multi-criteria inventory classification is used.

So many different methods for classifying inventory and taking into consideration multiple criteria have been used and developed. Among them, artificial intelligence methods like neural networks, fuzzy logic and genetic algorithms are applied. Min-Chun Yu [5] compared and tested the effectiveness of artificial-intelligence (AI)-based classification techniques and traditional multiple discriminant analysis (MDA) techniques. AI-based techniques include support vector machines (SVMs), back propagation networks (BPNs), and the k-nearest neighbour (k-NN) algorithm. The results of these investigations show that AI-based techniques demonstrate superior accuracy to MDA. The authors [6 ÷ 8] use neural networks to classify inventory. In the paper [6], unit price, ordering cost, demand range and lead time present input neurons. A, B and C classes present the output layer. As learning tools genetic algorithm and back propagation algorithm are used and compared. Chu et al. [9] have suggested a new inventory classification approach called ABC-fuzzy classification combining the traditional ABC with fuzzy classification.

In the papers [10, 11], AHP methodology has been used to classify inventory. Both quantitative and qualitative criteria can be taken into consideration. The authors [12] propose a modified version of an existent common weight data envelopment analysis (DEA) and then apply it for ABC inventory classification in the case where both quantitative and qualitative criteria exist. An improvement of nonlinear programming model for multiple criteria ABC inventory classification which determines a common set of weights for all the items is presented in article [13]. The authors [14] suggested a model based on the ranking by the distances from the positive and negative ideal solution. Bhattacharya et al. and Ferhan&Cengiz [15, 16] have used a TOPSIS method to classify inventories into classes.

For solving classification problems some authors have applied cluster analysis as a data analysis tool [17÷19].

Considering the above mentioned the main aim of this work which presents a continuation of previous research [7, 11] is to apply and compare different methods of inventory classification for the purpose of assembly of an agricultural machine. The traditional one-criterion ABC inventory classification is compared with the multi-criteria approach by the application of the AHP methodology, neural networks and cluster analysis.

For the multiple criteria inventory classification, four criteria are included. All the criteria are positively related to the importance level. The criteria are as follows [11]:

- Annual cost usage, €/year (calculated by multiplying the annual demand and the average unit price),
- Criticality factor (rated from 1 – noncritical to 5 – extremely critical),
- Lead time 1, working days – this is an interval from the ordering till the receiving of items for the development of a new product and start-up of batch production.
- Lead time 2, working days – this is an interval from the ordering till the receiving of items for the batch production when the new product is already developed. The lead time 2 is equal to or shorter than lead time 1, because the development phase is missing.

2 Inventory classification by the AHP methodology

AHP methodology is developed by Thomas Saaty [20, 21]. This methodology is based on the decomposition of the defined decision problem to the hierarchy structure which consists of the main goal at the top of the hierarchy followed by the *n* criteria and (or) sub-criteria (also sub-sub-criteria) and finally by the *m* alternatives at the bottom of the hierarchy. The goal presents the optimum solution of the decision problem. It can be the selection of the best alternative among many feasible alternatives. Also, the ranking of all alternatives can be performed, by obtaining the priorities. In this paper, the goal is to rank (classify) the stock keeping units (inventory) for the assembly of an agricultural machine. Criteria (sometimes called objectives or attributes) are the quantitative or qualitative data for evaluating the alternatives. In this paper, the selected criteria, according to the specificity of assembly problem, are listed and explained at the end of the section Introduction. The weights of the criteria present the relative importance of each criterion compared to the goal. Finally, alternatives present a group of feasible solutions of the decision problem. In this paper, alternatives are the stock keeping units for the assembly of an agricultural machine. Alternatives are evaluated against the set of criteria. Fig. 1 shows the AHP model for the inventory ranking, developed in [11].

Multiple criteria inventory classification was carried out by using the modified AHP methodology, which includes pair wise comparisons of criteria, but not the pair wise comparisons of alternatives. Criteria weights are derived from the pair wise comparisons according to the Saaty's scale [20, 21].

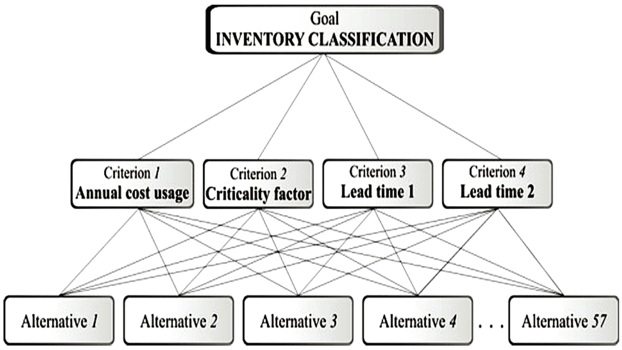

Figure 1 AHP model with 4 criteria and 57 alternatives

According to the pair wise comparisons, calculated weights of criteria are as follows: B_1=0,224 (the weight of the first criterion-annual cost usage), B_2=0,431 (the weight of the second criterion-criticality), B_3=0,138 (the weight of the third criterion-lead time 1) and B_4=0,207 (the weight of the fourth criterion-lead time 2) [11]. Because of large number of alternatives (57), pair wise comparisons of the alternatives are not performed (such as original AHP methodology). Instead of that, transformation of the criteria data of alternatives was made. In this way, all the criteria data were transformed to the 0 – 1 scale.

Scaled value of the *j*-th criterion (x^*_{ij}) for the *i*-th alternative was multiplied by the weighting factor (or simply weight) of the *j*-th criterion (B_j). The sum of multiplied scaled values and weighting factors across all of the criteria (so called weighted sum) presents the overall score for the alternative item. The alternative with the maximum score was on the top, while the alternative with the minimum score was on the bottom of the ranking scale [11].

3 Inventory classification by the neural network

The observed research belongs to the problems dealing with continuous input and output values i.e. problems connected with classification, thus the back-propagation neural network [22÷24] was applied [7].

In the given problem the model vector has three output variables – the classes A, B and C. Input variables were: annual cost usage, criticality factor, lead time 1 and lead time 2, previously described in part - Introduction of the paper. Variables with a value range for the proposed model are given in Tab. 1.

Table 1 Variables with a value range for the proposed model

No	Variable	Min. value	Max. value
1	Annual cost usage / €/year	0,07	2 327 500,00
2	Criticality / –	1	5
3	Lead time 1 / working days	1	60
4	Lead time 2 / working days	1	60

The RMS error (Root Mean Square error) is taken as a criterion for network validation.

The Delta rule is applied for network training. This rule is also called Widrow/Hoff rule or the minimum mean square rule which has become one of the basic rules in the training process of most neural networks.

In expression (Eq. 1) the formula for the Delta rule is given:

$$\Delta w_{ji} = \alpha \cdot y_{cj} \cdot \varepsilon_i , \tag{1}$$

where Δw_{ji} is the value of the difference in the weights of neuron *j* and neuron *i* realized in two steps (*k*-th and *k*-1), mathematically described by:

$$\Delta w_{ji} = \Delta w_{ji}^{k} - \Delta w_{ji}^{k-1} , \tag{2}$$

α is the rate (coefficient) of learning, y_{cj} is the output value of neuron *j* calculated according to transfer function, ε_i is the error given as:

$$\varepsilon_i = y_{ci} - y_{di} , \tag{3}$$

where y_{di} is the actual (desired) output. The error given by the expression (Eq. 3) returns to the network only rarely, other forms of error are used instead depending on the kind of work.

For most actual problems various rates of learning are used for various layers with a low rate of learning for the output layer. It is usual for the rate of learning to be set at a value anywhere in the interval between 0,05 and 0,5, the value decreasing during the learning process. While using the Delta rule algorithm the used data are to be selected from the training set at a random basis. Otherwise frequent oscillations and errors in the convergence of results can be expected. The transfer function used in this study is the Sigmoid function.

The study of the application of the back-propagation neural network was carried out for a defined data AHP model using the software NeuralWorks Professional II/PLUS [23, 24]. By alternating the attributes diverse architectures of neural networks were studied. The best network architecture generated the network output with 2,27 % rate of RMS error in the learning phase and 7,56 % in the validation phase.

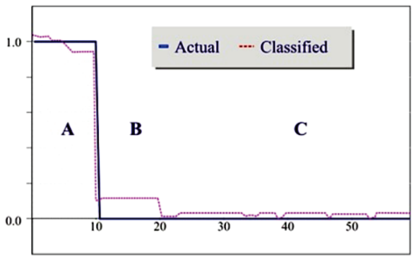

Figure 2 Presentation of actual and classified values given by neural network for the inventory class A [7]

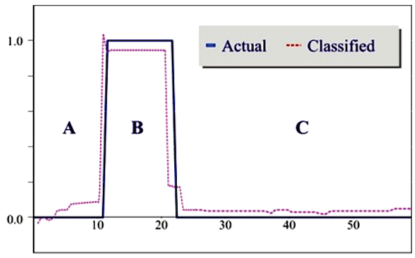

Figure 3 Presentation of actual and classified values given by neural network for the inventory class B [7]

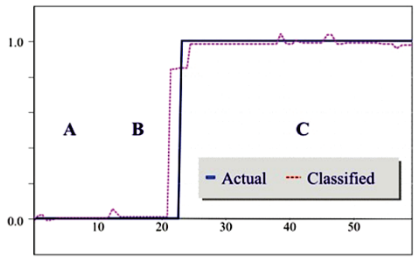

Figure 4 Presentation of actual and classified values given by neural network for the inventory class C [7]

The graphs in Figs. 2, 3 and 4 show the results obtained by the best network structure with regard to experimental results. The actual classes obtained by the AHP methodology and classified ones obtained by the trained neural network are shown. Every figure highlights only one class, as well as possible deviations in classification of appropriate class.

From Figs. 2, 3 and 4 it is obvious that the neural network acceptable classified items to the classes.

4 Inventory classification by the cluster analysis

4.1 Cluster analysis – general model

Cluster analysis makes it possible to group objects based on characteristic features. Besides objects grouping, variables grouping is also possible. Clusters are formed in the way that the objects within clusters are as similar as possible and the differences between clusters as big as possible i.e. the aim is to achieve homogeneity within clusters and heterogeneity between clusters.

The basic principle [25÷27] of the problem of clustering (based on determinants and by using the goal criteria function) the elements of the set $\mathcal{A} = \{a_1, \dots, a_m\}$ with m ≥ 2 elements, where is $a_i \in \mathbb{R}^n$, $i = 1, \dots, m$, into disjoint subsets $\pi_1, \dots, \pi_k$, $1 \le k \le m$, so that

- $\cup_{i=1}^{k} \pi_i = \mathcal{A}$ (each cluster element belongs to the defined set),
- $\pi_i \cap \pi_j = 0$, $i \ne j$ (different clusters cannot have common elements),
- $m_j := |\pi_j| \ge 1$, $j = 1, \dots, k$ (each cluster should contain at least one element).

The set $\mathcal{A}$ subsets $(\pi_1, \dots, \pi_k)$ will be marked with $\Pi = \{\pi_1, \dots, \pi_k\}$and called the set $\mathcal{A}$ partition while $(\pi_1, \dots, \pi_k)$ will be called clusters.

When defining the distance between objects the measures of nearness will be applied which are devided to the measures of similarity and the measures of difference. Two objects are said to be closer if the difference or distance between them is smaller and the similarity greater. The measures of similarity are most often applied with categorical variables (binary most often) while the measures of difference are most often applied with continuous variables.

To calculate differences between objects the measures of distance have been defined [28] and some of them are:

- The Euclidean distance - known as L_2 norm

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} = \|x - y\|_2^2 , \tag{4}$$

- The squared Euclidean distance

$$d(x, y) = \sum_{i=1}^{n} (x_i - y_i)^2 , \tag{5}$$

- The City – block (Manhattan) distance - known as L_1 norm

$$d(x,y)=\sum_{i=1}^{n}|x_i-y_i|=\|x-y\|_1 \,, \tag{6}$$

- The Chebychev distance

$$d(x,y)=\max|x_i-y_i| \,. \tag{7}$$

When measuring the obtained clusters'quality the goal criterion function is to be defined [27, 29÷31], and the most often used criterion function is the sum of the squared error that can be defined as:

$$\mathcal{F}(\Pi)=\sum_{j=1}^{k}\sum_{a_i\in\pi_j}\|c_j-a_i\|_2^2 \tag{8}$$

where $\|\cdot\|_2$ denotes the Euclidean (L_2) norm and $c_j=\frac{1}{|\pi_j|}\sum_{a_i\in\pi_j}a_i\,,\ j=1,\dots,k$ represents the centre of the cluster π_j.

The aim of the cluster algorithm is to find optimal partition Π^*, whose feature is that the sum of the cluster elements departure from the center is minimal, i.e. to find the partition which minimizes the goal function.

$$\mathcal{F}(\Pi^*)=\min_{\Pi\in P(\mathcal{A},k)}\mathcal{F}(\Pi). \tag{9}$$

In this way an attempt is made to make the distance within the clusters smaller and the distance between the clusters greater [32].

The searching problem of an optimal partition is a nonconvex and nonsmooth global optimization problem. Thereby the objective function can have a great number of independent variables (the number of clusters in the partition multiplied by the dimension of data-points). As exemplified by numerous examples, the number of local minima can be unexpectedly large [33]. In case we do not have a good initial approximation, what is usually recommended [34] are multi-run k-means algorithms with various random initializations.

The quality of data arranging in clusters is dependent on the kind of method and the structure of data. Different methods can demonstrate various complexities and separation of clusters. The clusterization methods are basically devided [29 ÷ 32] into hierarchical and non-hierarchical (partitional). A hierarchical method is suitable for analysis of smaller sets of data and clusters are presented graphically in the form of a decision tree – dendogram. As the number of clusters (A, B, C) used for the research in this work has been known in advance, a non-hierarchical method has been chosen (k-means algorithm). Different from the hierarchical methods it allows shifting of objects from the previously formed clusters. For the k-means method or algorithm a predetermined number of clusters k is necessary as well as the centroid for each cluster followed by the definition of the object distance from the cluster centroid (using one of the distance measures) and the object joining the nearest cluster. After that the new centroids within the cluster are to be calculated (both for the cluster the object was allocated to and the cluster the object was separated from). These steps are to be repeated until the optimality criterion is fulfilled [26 ÷ 30]. The k-means algorithm is the algorithm used most often due to its simplicity, speed and possibility of processing a large number of data.

4.2 Analysis of results

The aim of the analysis is to classify parts into clusters according to the share of determinants used in the analysis of the previously described methods. The cluster analysis, by the application of the k-means algorithm (for 3 clusters) has been conducted using the programme package STATISTICA. As the k-means algorithm converges towards the local minimum, the selection of initial cluster centroids playing in it a significant role, the mentioned algorithm has been started 250 times with different random initial approximations so as to find a solution as close as possible to the global optimum. The distance measures used are: the Euclidean distance, the squared Euclidean distance, the City-block (Manhattan) and the Chebychev distance. The solution with the least square error i.e. the least departure of the cluster elements from their centre is obtained using the squared Euclidean distance as a measure of difference. A good indicator of the classification suitability is the variance analysis which points to the existence of statistically important differences between the clusters formed. The classification is satisfactory if the variability within the clusters is as little as possible and between the clusters as great as possible. The value F is used to indicate to what degree a single, analysed variable makes difference between the clusters (Tab. 2).

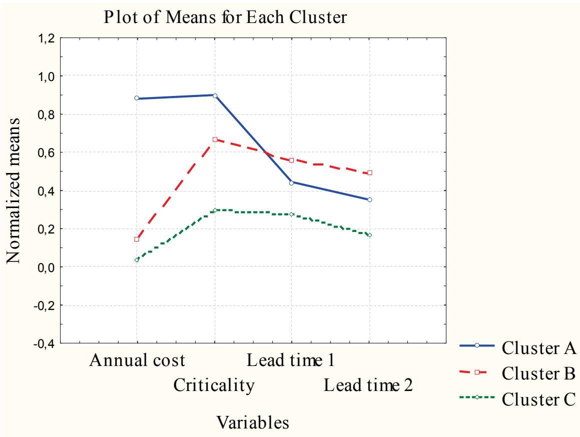

Figure 5 Diagram of mean values of all clusters per variables

The A, B and C clusters are defined based on the traditional ABC analysis which gives group A the greatest importance and group C the least importance. In the process group A includes 10 ÷ 20 % of the total number of parts but has the greatest share (70 ÷ 80 %) in overall annual cost. Group B has a share of 15 ÷ 20 % in overall annual cost while group C has 60 ÷ 70 % of the total number of parts but its share is the smallest (5 ÷ 10 %) in the overall annual cost [11]. Based on the diagram (Fig. 5) of the mean values of input variables for each cluster it can be seen that annual costs of the parts belonging to cluster A are considerably higher with regard to clusters B and C and that a smaller number of parts belongs to it (6), while the parts with the lowest annual costs and the greatest number of parts belong to cluster C (36).

Table 2 Analysis of variance for three clusters

Variable	Analysis of Variance							
	Sum of squares (*SS*) between clusters	Degrees of freedom (*df*)	Sum of squares (SS) within clusters	Degrees of freedom (*df*)	Mean square (*MS*) between clusters	Mean square (*MS*) within clusters	*F*	signif. *p*
Annual cost	3,704963	2	0,521100	54	1,852481	0,00965	191,9671	$2{,}86\times10^{-25}$
Criticality	2,723860	2	0,953333	54	1,36193	0,017654	77,1443	$1{,}48\times10^{-16}$
Lead time 1	0,918266	2	0,663117	54	0,459133	0,01228	37,3888	$6{,}44\times10^{-11}$
Lead time 2	1,166532	2	0,980316	54	0,583266	0,018154	32,1288	$6{,}43\times10^{-10}$

Table 3 Overview of parts classification by different methods

Item No.	Annual cost (transformed)	Criticality (transformed)	Lead time 1 (transformed)	Lead time 2 (transformed)	Group	Group	Group	Group
	$B_1 = 0{,}224$	$B_2 = 0{,}431$	$B_3 = 0{,}138$	$B_4 = 0{,}207$	ABC	AHP	NN	k-MA
26	0,920093	1	0,25	0,111111	A	A	A	A
48	0,530644	0,8	0,25	0,111111	A	A	A	A
52	0,960434	0,8	0,666667	0,666667	A	A	A	A
55	0,868891	0,8	0,333333	0,333333	A	A	A	A
56	1	1	0,583333	0,444444	A	A	A	A
57	1	1	0,583333	0,444444	A	A	A	A
5	0,028239	0,6	0,75	0,666667	C	B	B	B
6	0,033424	0,8	0,5	0,444444	C	A	A	B
7	0,022933	0,8	0,5	0,444444	C	B	B	B
12	0,041427	0,8	1	1	C	A	A	B
17	0,452983	0,4	0,5	0,444444	A	B	B	B
20	0,017378	0,6	0,5	0,444444	C	B	B	B
21	0,126455	0,6	0,5	0,444444	B	B	B	B
22	0,102405	0,6	0,5	0,444444	B	B	B	B
23	0,051978	0,6	0,5	0,444444	C	B	B	B
24	0,215671	0,8	0,5	0,444444	A	A	A	B
41	0,091234	0,8	0,583333	0,333333	B	A	B	B
45	0,345384	0,8	0,583333	0,333333	A	A	A	B
50	0,344143	0,6	0,5	0,444444	A	B	B	B
51	0,278821	0,6	0,5	0,444444	A	B	B	B
54	0,058029	0,6	0,5	0,555556	C	B	B	B
1	0,113576	0,2	0,25	0,111111	B	C	C	C
2	0,011792	0,2	0,25	0,111111	C	C	C	C
3	0,00404	0,2	0,5	0,444444	C	C	C	C
4	0,002327	0,2	0,083333	0,111111	C	C	C	C
8	0,001396	0,2	0,25	0,111111	C	C	C	C
9	0,006672	0,2	0,25	0,111111	C	C	C	C
10	0,006672	0,2	0,25	0,111111	C	C	C	C
11	0,007137	0,2	0,25	0,111111	C	C	C	C
13	0,096587	0,4	0,416667	0,333333	B	C	C	C
14	0,037238	0,2	0,25	0,222222	C	C	C	C
15	0,155625	0,6	0,25	0,111111	B	B	C	C
16	0,16059	0,6	0,25	0,111111	B	B	C	C
18	0,085493	0,6	0,25	0,111111	B	C	C	C
19	0,061521	0,4	0,416667	0,333333	B	C	C	C
25	0,016757	0,4	0,333333	0,333333	C	C	C	C
27	0,002638	0,4	0,25	0,111111	C	C	C	C
28	0,003569	0,4	0,25	0,111111	C	C	C	C
29	0,000776	0,4	0,25	0,111111	C	C	C	C
30	0,001862	0,4	0,25	0,111111	C	C	C	C
31	0,001164	0,4	0,25	0,111111	C	C	C	C
32	0,00031	0,2	0,25	0,111111	C	C	C	C
33	0,000621	0,2	0,25	0,111111	C	C	C	C
34	0,000155	0,2	0,25	0,111111	C	C	C	C
35	0,000155	0,2	0,25	0,111111	C	C	C	C
36	0,000059	0,2	0,333333	0,333333	C	C	C	C
37	0,000219	0,2	0,333333	0,333333	C	C	C	C
38	0,001396	0,2	0,25	0,111111	C	C	C	C
39	0,004655	0,2	0,25	0,111111	C	C	C	C
40	0,00031	0,2	0,25	0,111111	C	C	C	C
42	0,001396	0,2	0,25	0,111111	C	C	C	C
43	0,002483	0,4	0,25	0,111111	C	C	C	C
44	0,07851	0,2	0,166667	0,111111	B	C	C	C
46	0,088441	0,4	0,25	0,111111	B	C	C	C
47	0,029635	0,2	0,25	0,111111	C	C	C	C
49	0,054616	0,2	0,5	0,444444	C	C	C	C
53	0,085493	0,6	0,25	0,111111	B	C	C	C

ABC– Traditional ABC analysis; AHP–AHP methodology; NN– Neural networks; k-MA – k-means algorithm

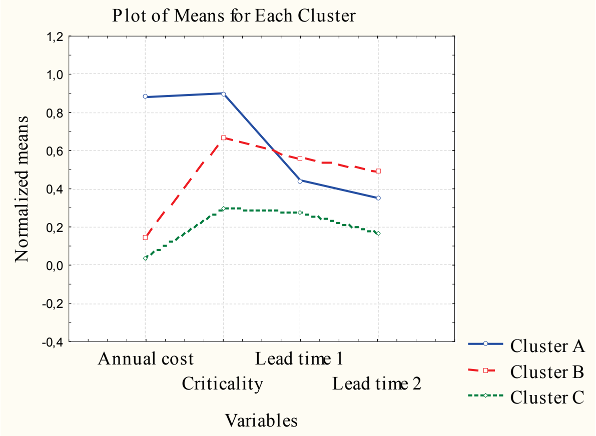

Figure 5 Diagram of mean values of all clusters per variables

The A, B and C clusters are defined based on the traditional ABC analysis which gives group A the greatest importance and group C the least importance. In the process group A includes 10 ÷ 20 % of the total number of parts but has the greatest share (70 ÷ 80 %) in overall annual cost. Group B has a share of 15 ÷ 20 % in overall annual cost while group C has 60 ÷ 70 % of the total number of parts but its share is the smallest (5 ÷ 10 %) in the overall annual cost [11]. Based on the diagram (Fig. 5) of the mean values of input variables for each cluster it can be seen that annual costs of the parts belonging to cluster A are considerably higher with regard to clusters B and C and that a smaller number of parts belongs to it (6), while the parts with the lowest annual costs and the greatest number of parts belong to cluster C (36).

Tab. 3 shows the results of clustering the parts applying the methods used in the work along with the presentation of the results of the traditional ABC method.

Tab. 3 also contains the data needed for the previously applied classifications.

The traditional ABC method is analysed using the same set of data and is given in work [11]. The standard ABC method uses one criterion (annual cost) while the methods used in the present work consider several criteria (Annual cost, Criticality, Lead time 1 and Lead time 2).

Analysis of the results given in Tab. 3 shows the results of classifying parts from the set of 57 elements in the following ways:

- as a result of the application of the AHP methodology the following classification is obtained: 11 elements of group A (19,3 %), 12 elements of group B (21,05 %) and 34 elements of group C (59,65 %);
- as a result of the application of the neural network method the following classification is obtained: 10 elements of group A (17,54 %), 11 elements of group B (19,3 %) and 36 elements of group C (63,16 %);
- Cluster analysis arranged the parts in the following way: 6 elements of the group – cluster A (10,52 %,), 15 elements of the group - cluster B (26,32 %), and 36 elements of the group - cluster C (63,16 %).

Analysis of the obtained results shows that the AHP methodology and the neural networks result in small deviation of the classification i.e. data arrangement. Application of the cluster analysis results in a small, but not significant, difference from the results obtained by the AHP methodology and the neural networks. The lowest level of error (dissipation of results) is obtained with classifying of the elements in group C, which is understandable as they represent the greatest number of elements in the observed set of elements for classification.

Fig. 6 displays graphical representation of comparison of the results obtained by the AHP methodology, neural networks and k-means algorithm considering 2 of the 4 analyzed variables (components).

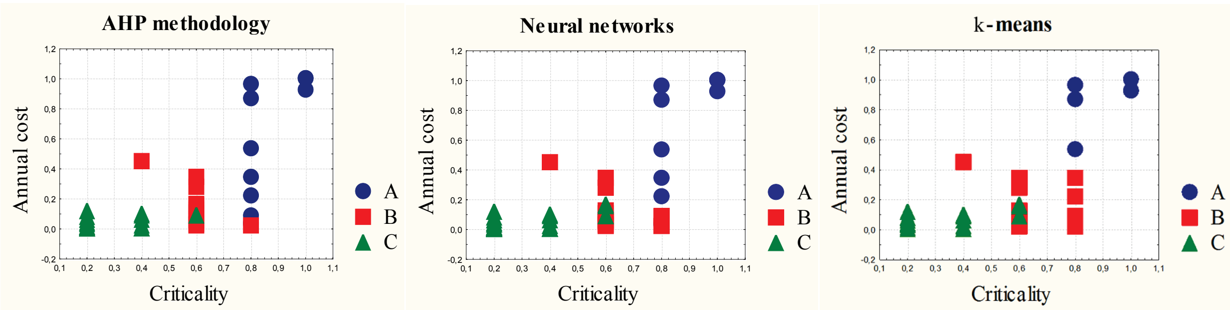

Figure 6 Graphical representation of the parts classification by different methods in the function of two variables

5 Conclusion

By comparing the results of neural network inventory classification with the original data AHP model, it can be concluded that neural network model predicted classes with acceptable accuracy, RMS error in learning phase amounts to 2,27 % and 7,56 % in the validation phase. It can be seen that the smallest error appears in classifying items to the class C because of the biggest sample data.

By comparing the results of the cluster analysis inventory classification (k-means algorithm) with the original AHP model data, it can be concluded that the k-means algorithm gives results with acceptable accuracy.

The AHP model, neural network model and cluster analysis model can be effectively implemented to inventory module of ERP systems. The real new inventory data from the ERP system can be used to enlarge the amount of sample data. It is to be expected that after learning and training the neural network will give better results i.e. smaller error. The enlarged data model will be a good basis for the testing and new adaptation of data so that better results of the cluster analysis (k-means algorithm) are to be expected.

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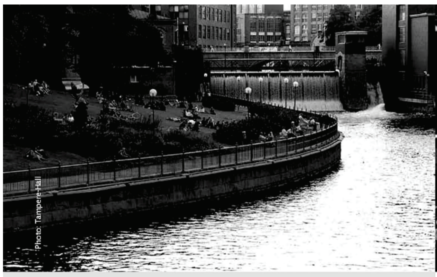

Nordic **Steel** 2015

Construction Conference

September 23-25, 2015
Tampere, Finland

First announcement and call for abstracts of 13th Nordic Steel Construction Conference (NSCC)

The Nordic Steel Construction Conference is an important forum for the presentation and discussion of new results in research and new ideas for products and structures. The Nordic Steel Construction Conference is an international event and of interest for everybody working with or interested in new materials, codes and applications in steel construction.

FCSA
Finnish Constructional Steelwork Association

Important dates

Dead line for abstracts 20.9.2014
Acceptance of abstracts 31.10.2014

Dead line for final paper (10 pages) and extended abstracts (2 pages) 31.12.2014.

Acceptance of final papers 31.1.2015
The final accepted full papers will be published on USB stick.
The 2 pages extended abstracts will be printed in the abstract proceeding volume.

Final program and early bird registration
(550€/participant, Banquet dinner 120€/participant)
begins 28.2.2015

Registration and abstracts

Standard registration
(650€/participant, Banquet dinner 120€/participant)
begins 30.4.2015.

Registration fee includes:
Badges and admission to all sessions, welcome reception, lunches, coffee breaks, final program and proceedings.

Abstract submission procedure
Abstracts length should be 200-300 words. The following information is required: List of authors with complete affiliation, corresponding author, keywords. Abstracts should be written in English in a Word file to be uploaded online: www.tut.fi/nscc-2015

Venue, hotels and how to get there
www.tamperehall.com

The Nordic Steel Construction Conference (NSCC) is a conference with proud traditions. The conference was held for the first time in Stockholm in 1970 and since then with about three years apart it has circulated between the Nordic countries. The last conference was held in Oslo in 2012 and gathered scientists, representatives of steel producers, steel wholesalers, contractors, consultants, architects, etc. Finland is responsible for the next event in 2015.

Last time the conference was organized in Finland in 2001 and the organizer was the Finnish Constructional Steelwork Association (FCSA). Now the baton once again has come to Finland. Also this time FCSA will be responsible for the administrative part of this event. This time Tampere University of Technology (TUT) takes the response of the scientific process.

It is a great pleasure for the Finnish Constructional Steelwork Association and the Tampere University of Technology to invite you to the 13:th Nordic Steel Construction Conference held in Tampere on September 23-25, 2015. The conference will be held at Tampere Hall, located in the heart of Tampere city centre. Tampere Hall is Scandinavia's largest Congress and Concert Centre.

The scientific process will be led by Professor Markku Heinisuo, TUT, the chairman of the Technical Committee and with Dr. Jari Mäkinen, the vice chairman. The technical committee is composed of leading steel professors and researchers from the Nordic countries and the rest of Europe.

The conference will attract participants representing both academia and industry from all parts of the world and there will be presentation of papers covering different aspects related to steel construction. You will hear and see many interesting presentations given by Key Note speakers, distinguished professors as well as by young PhD-students.

As a representative for the organizing and technical committee I want to take this opportunity to invite you to participate in this exciting international conference in Tampere 23-25. September 2015. I hope to see you!

Professor Markku Heinisuo, TUT

Scientific Committee

The committee will review both the abstracts and the final papers. The members are:

Prof. Markku Heinisuo, TUT - Chairman
Dr. Jari Mäkinen - Vice Chairman
Prof. Ove Lagerqvist, LTU
Prof.-em. Torsten Höglund, KTH
Prof. Milan Veljkovic, LTU
Prof. Luis Simões da Silva, University of Coimbra
Prof. David A. Nethercot, Imperial College
Prof. Jari Puttonen, Aalto University
Prof. Jeppe C Jönsson, Technical University of Denmark
Prof. Dan Dubina, University of Timisoara
Prof. Dr.-ing. Markus Feldmann, RWTH Aachen University
Prof. Jean-Marc Battini, KTH
Dir. Björn Aasen, Norconsult, Norway
Prof. Timo Björk, LUT
Prof. Mikko Malaska, University of Oulu
Prof. Reijo Kouhia, TUT

Organizers

The conference is organized by the Finnish Constructional Steelwork Association (FCSA) in co-operation with the Tampere University of Technology (TUT). Chairman for the conference is prof Markku Heinisuo, TUT. The Organizing Committee responsible for the arrangement consists of the following members:

Dr. Jari Mäkinen, TUT - Chairman
Prof. Markku Heinisuo, TUT
Dir. Markku Leino, FCSA
Dir. Jouko Kouhi, FCSA
Dir. Veikko Numminen, FCSA
Hanna Grönman, FCSA

Language and topics

The conference will be held in English and will mainly cover these topics:

- Bridges
- Connections
- Building Structures
- Stainless Steel Structures
- Composite Structures
- Fire Engineering
- Sustainable Engineering
- High Strength Steel
- Cold Formed Structures
- Building information models

Keynote lectures

Prof. Jean-Pierre Jaspart,
Liège University, Belgium
Component method as a general tool for the design of joints under various loading conditions

Univ.-Prof. Dr.-Ing. Peter Schaumann,
Leibniz Universität Hannover, Germany
Fire design of steel structures with intumescent coating

Prof. Milan Veljkovic,
Luleå tekniska universitet, Sweden
Use of higher strength steel in construction, opportunities and obstacles

Dr.Eng. Björn Aasen,
Norconsult AS, Norway
Execution of steel structures – recent developments and future trend

Rutger Gyllenram,
Kobolde & Partners AB, Sweden
Making sustainability work a key to your success

Dr. Jyrki Kesti,
Ruukki Construction Oy, Finland
Energy efficient solutions for steel structures

Dir. Heikki Haikonen,
Tekla Building & Construction
BIM solutions for design and site (prelim)