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This Publication has to be referred as:

Malakov, I. & Topalova, I. (2009). System Development of Representative Criteria for Choosing an Optimal Variant of Technical Product (2009). 1335-1337, *Annals of DAAAM for 2009 & Proceedings of the 20th International DAAAM Symposium*, ISBN 978-3-901509-70-4, ISSN 1726-9679, pp 668, Editor B[ranko] Katalinic, Published by DAAAM International, Vienna, Austria 2009

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SYSTEM DEVELOPMENT OF REPRESENTATIVE CRITERIA FOR CHOOSING AN OPTIMAL VARIANT OF TECHNICAL PRODUCT

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Abstract: *Setting up a system of criteria that generalizes all requirements for picking up the optimal among variants turns out to be an essential problem in the way of designing technical products. The goal of the research is the development of a method for setting up the criteria system and easy optimizing it through generalizing under different indications. The proposed research for optimal design of technical products uses cluster method application for generalizing the number of criteria. It is represented and tested applying self-organized feature maps (SOFMs). Because of changing the parameters of SOFM - the achieved results show easy adaptation to changes in input criteria. The main advantage is the fast work of the SOFM; full lack of a subjective error; easy adaptation to changes in input criteria and to changes in the requirements concerning the significance of the generalized criteria.*

Key words: *design, technical product, cluster analysis, neural network, self-organized map*

1. INTRODUCTION

A crucial task when designing technical devices is to define a system of criteria for choosing the optimal variant, since the ultimate decision's features rely heavily upon them. According to many authors (Pahl & Beitz, 1997) this is a rather sophisticated problem stumbling on lots of complications: multiple criteria for evaluating alternating variants, all of which are to be analyzed and subsequently reduced in number; contradicting requirements and rules for the final decision making etc. One of the approaches views the task as a multi-criteria optimization problem, another one suggests to weigh all criteria in order to eliminate those with less significance, a third one considers the correlations among the criteria. Shortcoming of the first approach is the lack of common indices for choosing the optimal variant; the second approach is too subjective when deciding upon the least significant criteria, while the third approach involves too much calculations. Very suitable for decreasing the number of criteria is the well-developed cluster analysis. Most used is the hierarchical cluster analysis along with the K-average method, which has the shortcoming of being too subjective when defining the number of clusters. The application of self-organizing neural networks - Feature Maps for cluster analysis has many advantages over other methods because of networks adaptability and realizing all steps of hierarchical cluster analysis automatically in many iterations. Another very important advantage is that changing some of the parameters of the network could influence reducing or increasing the generalization degree of the criteria. All the mentioned advantages of applying self-organizing neural networks make their application a preferable tool for solving the represented problem.

2. REQUIREMENTS TOWARDS THE SYSTEM OF CRITERIA

1. **Generalization**, i. e. the criteria should cover all requirements and common terms of the performed task and

reflect every vital feature of the matched alternatives.

2. **Minimalism**, i.e. the system should include the least permissible number of criteria since any excessive one would increase the costs of dealing with the problem.

3. **Unity**, i. e. the criteria system should enable comparative assessment of separate features for all alternative variants of the designed product.

4. **Feasibility**, i. e. the choice of criteria should relate to both the available information pack and the possibility of calculating their values.

5. **Reliability**, i. e. maximum compatibility between the features quality ratio within the product and their analytic presentation through target functions.

6. **Orthogonality**, i. e. all criteria should be independent and never applied for evaluation of the same features in alternative variants.

7. **Synonymity**, i. e. the chosen criteria should be straight functions of the object parameters and their formulations should exclude any possibility of misinterpretations.

8. **Responsiveness** to changes in the control parameters, i. e. small changes in the numeric values of studied parameters should lead to relatively big changes in the criteria values.

9. **Simplicity**, i. e. the criteria should be plainly formulated and easy to understand.

10. **Operativeness**, i. e. the system of criteria should provide possibilities for actualization (adding/ reducing of criteria) along the decision making process.

3. METHOD FOR SETTING UP THE CRITERIA SYSTEM

The method encompasses a number of steps (Boyadjiev at al., 2005): **Step 1:** A commission of experts is gathered $E = \{E_j\}$, $j = 1 \div n$, under consideration of certain rules for picking up the experts.

Step 2: A system of initial criteria is set up on the basis of a list of requirements towards the designed product and the pursued objectives $F^0 = \{f_k\}$, $k \in K_0$.

Step 3: The upholding of rules and requirements as listed above is tested. Subsequently some of the initial criteria are eliminated and a new system of criteria emerges: $F^1 = \{f_k\}$, $k \in K_1$, $K_1 \subseteq K_0$, $F^1 \subseteq F^0$.

Step 4: Patterns and indices for grouping the criteria into clusters along with evaluation scales for those indices are selected. The simplest way to do the grouping is by applying a single pattern, e. g. similarity.

Step 5: The experts $E = \{E_j\}$, $j = 1 \div n$ perform a consecutive assessment of all criteria pairs of the multitude $F^1 = \{f_k\}$, $k \in K_1$ sticking to the selected patterns and scales and thus determine the related evaluation values. All obtained results are recorded in a matrix of binary matching $\bar{p} = [\bar{p}_{(t,s)j}]_{h \times n}$, where $\bar{p}_{(t,s)j}$ embodies the value for the criteria pair f_t and f_s , $f_t, f_s \in F^1$ given by expert j , while $h = 0,5k(k-1)$ means the number of matched criteria pairings.

Step 6: The average binary evaluation value for each criteria pair is defined using the equation:

$$\hat{\rho}_{(r,s)} = \frac{1}{n} \sum_{j=1}^n \bar{\rho}_{(r,s)j} \quad (1)$$

Step 7: The consensus in the experts' statements is tested with one of the usual methods. A low level of consensus needs going back to Step 5. Otherwise follows Step 8.

Step 8: After completing step 5 the number (h) of initial couples of Criteria are already defined. The structure of the self-organized Kohonen network is defined (Akoka 1992) and the input vector of couples of Criteria is applied to the network input neurons.

Step 9: Training of the network and analysis of the achieved end clusters. If the system of the criteria is approved by the head of the project as good one – go to Step 10. If no, then change the neighborhood parameter of the network. Give them a smaller/greater value to respectively reduce/increase the generalization degree of the criteria.

Step 10: The head of the project approves the achieved generalized criteria.

4. METHOD APPLICATION AND RESULTS

The objective of unsupervised learning is to find the natural structure inherent in the input data (Bickel & Scheffer 2004). There are a number of unsupervised learning schemes, including competitive learning, adaptive resonance theory and Self-Organising Feature Maps (SOFMs). A well known type of SOFM is a Kohonen network. The objective of a Kohonen network is to map input vectors (patterns) of arbitrary dimension N onto a discrete map with 1 or 2 dimensions. A Kohonen network is composed of a grid of output units and N input units (NewFrame 2005). In our research we operate with 9 different criteria (h = 36 couples) and after fulfillment of Step 5 we achieve the initial calculated distance (Fig.1) for each couple. The values of distances between the criteria in the 36 couples form the 36 input neuron values. The initial distances are calculated applying only one indication. The winning output unit is simply the unit with the weight vector that has the smallest Euclidean distance to the input pattern. The neighbourhood of a unit is defined as all units within some distance of that unit on the map (not in weight space). The parameter of greatest importance concerning the generalization degree of the criteria is the *neighborhood* (N) parameter of the SOFM. The results of clustering with a 5x5 map and N = 0.6

	Initial defined couples	Initial calculated distance
1	C1-2	7.10
2	C1-3	7.00
3	C1-4	9.10
4	C1-5	6.95
5	C1-6	9.25
6	C1-7	9.10
7	C1-8	7.20
8	C1-9	6.90
9	C2-3	8.20
10	C2-4	8.10
11	C2-5	1.10
12	C2-6	1.00
13	C2-7	9.15
14	C2-8	3.90
15	C2-9	9.10
16	C3-4	9.25
17	C3-5	9.10

Fig.1. Part of the input neuron h=36 couples of criteria

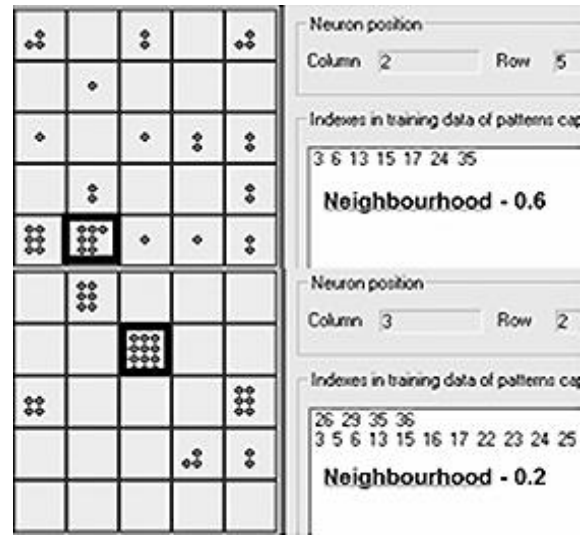


Fig.2. Clusters achieved with N = 0.6 and N = 0.2

respectively N = 0.2 are shown in Fig.2. The parameter N could be changed each time the experts are not confident (Step 10) with the result of the generalization of the criteria. Obviously the smaller the N parameter the greater the generalization degree of the criteria. The main advantage is the fast work of the SOFM; full lack of a subjective error; easy adaptation to changes in input criteria and to changes in the requirements concerning the significance of the generalized criteria; good visualization of the results and thereby good conditions for easy analysis.

5. CONCLUSION

The proposed new method for optimal design of technical products with cluster method application for choosing the number of criteria is represented and tested applying SOFMs. Changing the network parameter N gives advantages in easy adaptation to changes in input criteria and to changes in the requirements concerning the significance of the generalized criteria, achieved at the end of training the network. The fast work of the SOFM and full lack of a subjective error makes the method rather preferable over traditional cluster analysis methods. As *future research* the change of neighborhood parameter in SOFM may be accomplished automatically giving it a small increasing/decreasing step in order to accelerate the end decision and make it possible to implement the method in real time working systems. As the initial distances are calculated applying only one indication, in further research the method will be tested with many SOFM applying input vectors (couples of Criteria) calculated for different indications. The generalized criteria of each SOFM could be finally generalized applying a common SOFM.

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