M5P	5.086	4.359	4.178	4.087	4.428	3
REP	5.229	4.339	4.291	4.211	4.518	5
Fuzzy (own)	**5.085**	**4.3908**	**4.1169**	**4.1111**	**4.4271**	**2**

Conclusions

In a competitive work with experimental data based on fuzzy identification technology the forecasting was received models of gas turbine power plant. Models take into account the following factors: outdoor temperature, vacuum exhaust; pressure environment; humidity. Comparison with other technologies not collective synthesis models from paper demonstrates that the fuzzy technology dominates the other 14 the accuracy of identification.

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FUZZY CLASSIFIER LEARNING BY MAIN COMPETITORS METHOD

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The classification problem lies in the assignment an object to one of preassigned classes. It is implemented by analyzing the attributes of the classified object. Various engineering, management, economic, political, medical, sport, and other problems are reduced to classification. Fuzzy classifiers, namely, those using fuzzy sets during functioning or learning, have recently become more and more popular. The application of fuzzy sets for classification problems is presented in for the first time. At present, classifiers based on logic inference in terms of production rules, the antecedents of which contain the fuzzy terms “low,” “average,” “high,” and so on, are most popular. Each rule describes an area of factor space, wherein the objects belong to one class. Since the borders of these areas are fuzzy, one object can belong to several classes but with different degrees.

To increase the correctness, the fuzzy classifier is learned by experimental data. During learning, the rule semantics remains constant, and the membership functions of fuzzy terms and weights of rules are modified. The learning is reduced to solving the optimization problem with continuous controllable variables. The main goal of learning to provide the minimum distance between the experimental data and the fuzzy inference results. This distance is called the learning criterion can be defined differently.

We propose a new criterion for fuzzy classifier learning that taking into account only the main competitors – the alternatives with the highest membership degrees. In the case of correct classification is necessary to maximize the difference between the membership grades to the winner-class (*win*) and to the class with the second rank (*vicewin*). In the case of wrong classification is necessary to minimize the difference between the winner-class membership grade and to the right decision.

It is assumed that the training set M of pairs of "input - output" is known:

$$\left(\mathbf{X}_r, y_r\right), \quad r=\overline{1, M} \qquad 1)$$

where $\mathbf{X}_r$ denotes the vector of informative features (attributes) of the classification *r*-th object; y_r is label of the class for *r*-th object, which is selected from the following set $\{d_1, d_2, ..., d_m\}$.

Let us denote $F\left(\mathbf{X}_r\right) \in \{l_1, l_2, ..., l_m\}$ – the classification result over the fuzzy rule base for the input vector $\mathbf{X}_r$ of the *r*-th row of the sample (1). Then the learning criterion of the sample (1) is written as follows:

$$Crit_4 = \sum_{r=\overline{1, M}} \Delta_r, \qquad (2)$$

where $$\Delta_r = \begin{cases} p \cdot \dfrac{\mu_{win_r} - \mu_{y_r}}{\mu_{win_r}}, & if \;\; y_r \neq win_r \\ \dfrac{\mu_{vicewin_r} - \mu_{win_r}}{\mu_{win_r}}, & if \;\; y_r = win_r \end{cases}.$$

By μ denotes membership degree and through *p* denotes a penalty factor. Formula (2) is illustrated in Fig. 1.

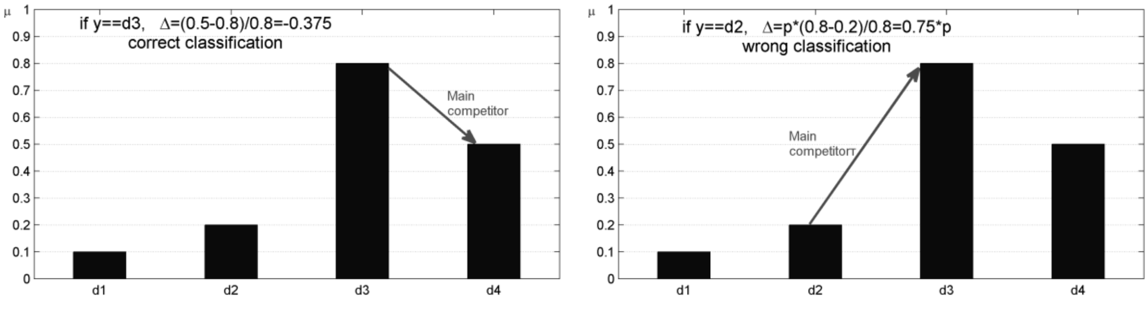

Fig. 1. To formula (2)

The problem of recognition the grape type from which a wine is made is considered. The database Wine Dataset from UCI Machine Learning Repository contains the results of chemical analysis over 13 factors of 178 samples of Italian wine made in the same region. One of three types of grape is pointed for each sample. The learning set is formed from rows of a database with the boundary values from 13 attributes. Let us include all the odd rows of database into the learning set. The rest data are put to the test set. As a result, a learning set from 100 rows and a test set from 78 rows are obtained. Let us project the fuzzy classifier of wine with the following inputs: flavonoids, color intensity, and proline. The knowledge base contains 5 rules.

Statistics of fuzzy classifier learning is shown in Fig. 2. In addition to the criterion (2) were checked criterions from [1]: $Crit_1$ – misclassification rate; $Crit_2$ – the distance between the desired fuzzy output and real fuzzy output; $Crit_3$ – extended form of $Crit_2$ by weighted by the penalty factor in the case of an incorrect decision. For each criterion, 1000 experiments on the fuzzy model learning were carried out. We used 2 fuzzy models, the t-norms in which are implemented by the operation of minimum and the product, respectively. Experiments have shown (Fig. 2), that the new criterion considering only the main competitors provides the best correctness of learning.

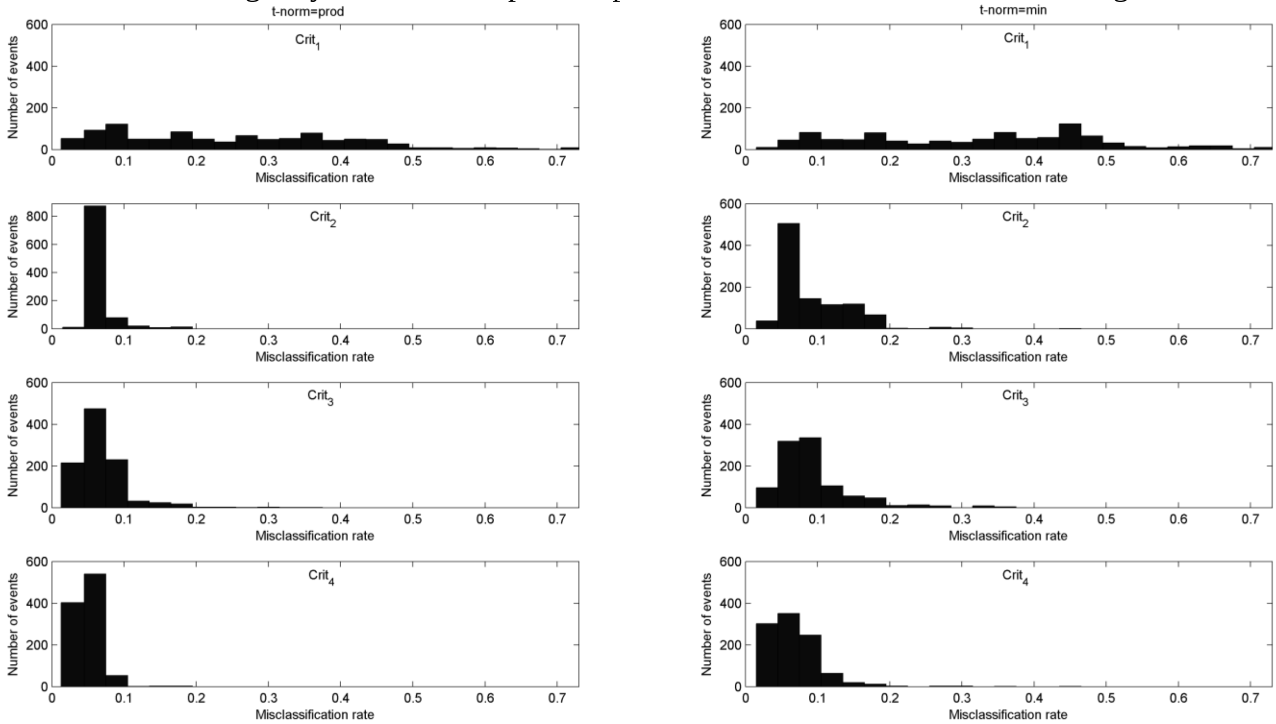

Fig. 2. Testing classifiers trained on different criteria

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