Evaluation of the Technical Condition of the Turbine Unit During Diagnostics Using Fuzzy Information

G D Krokhin 1, E K Arakelyan 2, A I Pestunov 1, S V Mezin 2 and A E Kibireva 1

1 Novosibirsk State University of Economics and Management, Russia, 630099 Novosibirsk, Kamenskaya, 56
2 National Research University "MPEI», Russia, 111250 Moscow, Krasnokazarmennaya, 14

edik_arakelyan@inbox.ru

Abstract. The report is devoted to the problem of applying fuzzy set theory and fuzzy logic methods in models of diagnostics and assessment of the technical condition of TPP equipment using artificial intelligence methods. Are given here: description of fuzzy images; formation of features of fuzzy images; development of criteria for evaluating features; definition of dividing rules for fuzzy images; classification of fuzzy states of the power plant. The simulation algorithm is considered in relation to a heat and power unit with fuzzy input information and a statistical assessment of the adequacy of fuzzy models. The accuracy of the obtained mathematical model is estimated based on the estimation of the degree of dispersion of the obtained regression line relative to its mathematical model, while the adequacy criteria of 2 types ("R" and "D") are introduced, which help to integrally assess the proximity of mathematical models to the object under study using the selected measure.

1. Introduction

The main problem of evaluating and diagnosing the state of functioning power plants is to obtain diagnostic signs, among which it is necessary to recognize and identify the most informative. To solve this problem, [1-3] uses pattern recognition theory and its methods. To recognize fault state patterns, the measured features are classified, which are extracted during the experiment from the observed parameters of the power plant state characteristics (power, rarefaction, pressure, temperature, flow, etc.) and are represented as vectors corresponding to a separate mode. Thus, the state of the mechanism under the diagnosed load will be described by a matrix of feature vectors. Matrices of feature vectors of different states of the mechanism are compared with each other under the same load and similar states (states reduced to normative conditions) and compared with the matrix of reference (or normative) parameters of the state. As a result, all faulty states of the mechanism are separated, the boundaries between which are determined by discriminant functions. However, the pattern recognition theory does not provide specific rules for the separation of fuzzy (fuzzy) state images, which are usually manifested in the functional diagnostics of TPP power plants. The need to work with fuzzy images requires working out ways to separate them and solve the problems that arise in this case. To recognize fuzzy states based on vague features in the uncertainty space that occur in the operation of power plant equipment due to hidden defects, the following tasks are considered in this report:

1) description of fuzzy images;
2) formation of signs of fuzzy images;
3) development of criteria for evaluating features;
4) the definition of sharing rules for fuzzy images;
5) classification of fuzzy states of the power plant;
6) practical recommendations for the application of the developed methods.

2. Description of fuzzy images

Information about images of the state of a TPP’s functioning unit (or its elements) is represented as multidimensional vectors \((x_1, x_2, \ldots, x_n)\) with membership functions for each of the shared state images \(f_a, f_b\) (the case of the two-alternative hypothesis). To determine the membership function in this way, we use one of the algorithms for restoring functions of many variables from a finite sample. If the number of classes \(n\) in the description space \(X^n\) is more than two, various images arranged in pairs are possible, the difficulty of separating them can be estimated in advance by the maximum index of the degree of belonging to the intersection of fuzzy images

\[
M = \sup_{X} \min\{f_A(x), f_B(x)\},
\]

where \(f_a(x), f_b(x)\) - the membership functions of the images \(A\) and \(B\), respectively [4, 5].

For the case \(M > 0\) of mapping images to the parameter space, they overlap slightly (although in theory the images should not intersect).

In this regard, there is a problem of more effective (in the sense of reducing the zone of uncertainty) separation of images, for which the following solutions are proposed:

1. search for a solving rule that will assign objects to intersecting sets, according to their mathematical descriptions;
2. search for a mapping in accordance with which the space of descriptions of fuzzy images will be transformed into a space with less uncertainty.

3. Formation of signs of fuzzy images

The formulation of the problem of separating fuzzy images based on the hypothesis of compactness in the description space did not confirm the expected results. In this regard, it became necessary to search for signs of images that would describe them with less uncertainty.

In the course of computational experiments, the authors found that each attribute of aggregate states should be represented by a function of parameters of the description space (describing sets), i.e. it should contain all available information about the image of this state. Thus, diagnostic features must be found among the various functions of the description space. However, you must have additional characteristics in the form of membership functions for each of the parameters (attributes). Of course, it is not possible to get such information explicitly on a functioning object, so you need to get parameter characteristics indirectly.

We apply the recommendation [6], i.e. we perform an orthogonal projection operation for fuzzy sets on a certain hyperplane. We get an orthogonal shadow of a fuzzy set, which is characterized by the membership function. For a fuzzy set \(A\) estimates for shadows on three coordinate planes \((n = 3)\) will be determined by the following membership functions:

\[
\begin{align*}
f_{S(A)}(x_1, x_2) &= \sup_{x_3} f_{A}(x_1, x_2, x_3), \\
f_{S(A)}(x_1, x_3) &= \sup_{x_2} f_{A}(x_1, x_2, x_3), \\
f_{S(A)}(x_2, x_3) &= \sup_{x_1} f_{A}(x_1, x_2, x_3).
\end{align*}
\]

Similarly, estimates are obtained for the shadows of a fuzzy set \(B\) on coordinate hyperplanes. As a result of applying orthogonal design of fuzzy sets, we get their description through shadows on the subspace of the description space. In this case, a fuzzy shadow is a fuzzy relation whose dimension corresponds to the dimension of the subspace. Each element of the \(m\)-total fuzzy relation is a tuple of length \(m\). Each element of a relationship belongs to a fuzzy relationship with a specific value of the membership function. In this paper, this is considered as the fact of simultaneous appearance of elements of generating sets, and the value of the function - the function of belonging to the element of the relation as an estimate of the appearance of a trait. Thus, as a result, the conditions for belonging to
the class are met, and each of the selected shadows can be considered with confidence as a reliable sign of the image.

4. **Criteria for evaluating features**

Each element of $m$-th fuzzy relation is represented by a tuple of length $m$, which with a certain value of the membership function belongs to this fuzzy relation. Each tuple is a set of elements that generate a set (parameters) that map the Cartesian product of sets $(x_1, x_2, \ldots, x_n)$ in $L$, i.e.

$$R : X_1 \times X_2 \times \ldots \times X_n \rightarrow L.$$  \hspace{1cm} (3)

where $R$ – function (fuzzy relation), $L$– line segment [0; 1] of real line or structure (in general) [7, 8].

The set of linguistic variables and the set of $m$-dimensional vectors will be used as $L$.

This choice allows us to apply the well-developed apparatus of relation theory to analyze the properties of functional dependencies describing the operation of the energy mechanism [8], as well as concepts and methods widely used in the analysis of empirical data (including cluster analysis) [9-16].

The fuzzy relation can also be set using the fuzzy set membership function:

$$\mu_R : X_1 \times X_2 \times \ldots \times X_n \rightarrow L$$  \hspace{1cm} (4)

The tuple elements must all be present at the same time, otherwise the incomplete tuple will not belong to the fuzzy relation. Thus, for the case of fuzzy relations, all tuples of the $m$-th relation belong to the Cartesian product of generating sets, and each element of the relation belongs to a fuzzy relation with a certain value of the membership function.

As a result of this representation, the simultaneous appearance of tuple elements will be characterized by the membership function. Thus, each element of the obtained relation can be considered as the fact of simultaneous appearance of elements of generating sets, and the value of the membership function of the relation element can be considered as an estimate of the appearance of a trait. Such a sign, as a result, will be a sufficient sign. In other words, the object’s class membership conditions will be met, and each of the shadows can be considered with confidence as a sufficient attribute of the image.

5. **The definition of sharing rules for fuzzy images**

An object is assigned to one of the images using the "voting" procedure: the number of class $A$ and class $B$ attributes performed for this object is checked, and a decision is made on the majority of "votes" [17]. However, you must first perform feature recognition. To do this, consider the unary orthogonal shadow (Fig. 1).

Here for a certain number of objects of classes $A$ and $B$ the membership functions take values of at least a certain threshold $\alpha$ or $\beta$:

$$\Gamma_\alpha = \{ x \mid f_A(X) > \alpha \} \text{ or } \Gamma_\beta = \{ x \mid f_B(X) > \beta \}.$$

If we count from the origin, the condition $\alpha > f_B$ is met first, and then $\beta > f_A$. Moreover, on the set of objects whose functions belong to the set $A$ more than to the set $B$, you can specify the values of their differences: $(\alpha - f_B)$ and $(\beta > f_A)$, which will be performed on a subset of objects $X$.

As a result of this representation, it will be determined that the attribute has a certain threshold, which is exceeded and indicates the presence of the attribute. This flag is accepted if:

a) it has a significant threshold;

b) the threshold is repeated on a large number of objects of both classes.
And so, with the help of such characteristics, you can evaluate all the formed features and attribute the object to a particular image by the number of features. On the control object, the execution of attributes of each class is checked. If the object being checked falls into the zone of uncertainty on some attribute, then a failure is registered based on this attribute. This corresponds to a failure to meet the threshold for any of the images.

6. Classification of fuzzy states of a power plant

In [4, 5] Zadeh L. defined the membership function \( f_t \) as a function that characterizes the degree of confidence in the occurrence of an event \( y \) when \( x \) is observed. The function \( f_t(x) \) is defined for each \( x \) and satisfies the conditions:

\[
0 \leq f_t(x) \leq 1, \quad f^-_t(x) = 1 - f_t(x) .
\] (6)

When applying the membership function to an image recognition task Zadeh L. believes that training reports data about observations \( X_i, i = 1, 2, \ldots, k \) and value \( f_t(x) \), not just \( y \) or \( \bar{y} \) events.

Thus, we considering problem of classification for two events \( y_1 \) and \( y_2 \) by indirect observations \( (x_1, x_2, \ldots, x_n) = x \).

Let, according to the dichotomy condition, the events \( y_1 \) and \( y_2 \) be incompatible and form a complete set of events. Then we will denote \( y_1 \) by \( y \) and \( y_2 \) as \( \bar{y} \) (i.e. \( \bar{y} \) - negation \( y \)).

When diagnosing the state of a power plant by its elements, the obtained observations \( X \) form a set \( \Omega \), that is divided by the decision rule into two subsets \( \Omega_1 \) and \( \Omega_2 \), such that

\[
\Omega_1 \cup \Omega_2 = \Omega \quad \text{and} \quad \Omega_1 \cap \Omega_2 = \emptyset .
\] (7)

Denote by \( C_1, C_2, P(y), P(\bar{y}), P(x/y), P(x/\bar{y}) \), respectively: the errors of the obtained observation (of the first and second kind), the probabilities of events \( y \) and \( \bar{y} \), conditional densities of the probability of observation \( x \), write the Bayes T. rule in the form:

\[
\min_{\Omega_2} \int_{\Omega_1} \left[ C_1 P(y) P(x/y) - C_2 P(\bar{y}) P(x/\bar{y}) \right] dx .
\] (8)

Accepting that

\[
P(\bar{y}) = 1 - P(y) \quad \text{and} \quad P(\bar{y}/x) = 1 - P(y/x) ,
\] (9)

we get (8) as:

\[
\min_{\Omega_2} \int_{\Omega_1} P(x) \left[ (C_1 + C_2) P(y/x) - C_2 \right] dx .
\] (10)

From (10) it is clear that the minimum risk is achieved if to \( \Omega_2 \) are assigned all \( X \), for which is true the condition:

\[
p(y/x) < \frac{c_2}{c_1 + c_2} .
\] (11)

If \( f(x) = 0 \), we get the equation of the boundary between sets \( \Omega_1 \) and \( \Omega_2 \). In this case, the hypersurface \( f(x) = 0 \) must pass through all the points for which the condition is met

\[
p(y/x) = \frac{c_2}{c_1 + c_2} .
\] (12)

Since, by convention, the value of \( y \) takes only two values 1 and 0, \( P(y/x) \) is numerically equal to the mathematical expectation of the event \( y \) when \( x \) is observed, i.e. \( M(y/x) = P(y|x) \).

In \((n+1)\)-dimensional space \((x, y)\) \( M(y/x) \) defines the hypersurface of the regression \( y \) over \( x \). Therefore, we will rewrite (12) as

\[
M(y/x) = \frac{c_2}{c_1 + c_2} = \frac{\beta}{1 + \beta} , \quad \beta = \frac{C_2}{C_1} .
\] (13)
As a result, we obtained an equation for the hypersurface of a level in \((n+1)\)-dimensional space. The projection of this level hypersurface onto an \(n\)-dimensional space \(\Omega\) will define the hypersurface \(f(x) = 0\) separating \(\Omega_1\) and \(\Omega_2\) (Fig. 2).

\[f_y(x) - \alpha f_{\bar{y}}(x),\quad \text{where } \alpha \geq 0.\] (14)

Taking into account the conditions \(f_{\bar{y}}(x) = 1 - f_y(x)\) and equating (14) to zero, we get the equation:

\[f_y(x) = \frac{\alpha}{1 + \alpha},\] (15)

which can already be interpreted as the level hypersurface equation in \((n+1)\)-dimensional space. The projection of this hypersurface on an \(n\)-dimensional space \(\Omega\) will determine the hypersurface found by the Zadeh L. method that separates \(\Omega_1\) and \(\Omega_2\).

An equation for the hypersurface of a level in \((n+1)\)-dimensional space will define the hypersurface \(f(x) = 0\) separating \(\Omega_1\) and \(\Omega_2\) (Fig. 2).

**Figure 2.** Geometric interpretation of the concepts of image space and weight space [7].

Thus, in the normal formulation of the problem of recognizing two events, training only reports data about observations \(x_i, i = 1, 2, \ldots, k\) and value \(f_y(x_i)\), not just events \(y\) or \(\bar{y}\). Then, as a result of these arguments, the evaluation of the function \(f_y(x)\) is built, which is used in the work instead of the function \(f_{\bar{y}}(x)\). If the value \(x\) is observed, the decision is made depending on the sign of the function

\[f_y(x) - \alpha f_{\bar{y}}(x),\quad \text{where } \alpha \geq 0.\] (14)

Taking into account the conditions \(f_{\bar{y}}(x) = 1 - f_y(x)\) and equating (14) to zero, we get the equation:

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which can already be interpreted as the level hypersurface equation in \((n+1)\)-dimensional space. The projection of this hypersurface on an \(n\)-dimensional space \(\Omega\) will determine the hypersurface found by the Zadeh L. method that separates \(\Omega_1\) and \(\Omega_2\).

Based on the constraints that the membership function satisfies, it can be interpreted as a conditional mathematical expectation of the event \(y\) or as a conditional probability \(P(y/x)\).

As a result, the problem of pattern recognition using membership functions can be considered as a problem of reconstruction in \((n+1)\)-dimensional space of the regression surface \(M(y/x)\) for a particular sample \(x_i, i = 1, 2, \ldots, k\) and corresponding values \(P(y/x_i)\).

The hypersurface equation of level (15) defining the dividing hypersurface is written as:

\[M(y/x) = \frac{\alpha}{1 + \alpha}.\] (16)

From (13) and (16) it can be seen that if \(\alpha = \beta = C_2/C_1\), then they completely coincide, and, thus, it can be argued that the solution obtained using the membership function is Bayesian.

Thus, on the basis of the above, it is possible to classify the fuzzy states of the power plant using the Bayes T. rule to determine the risk of the decision being made.

### 7. Some practical results

The following models have been developed based on the application of fuzzy set theory and fuzzy logic methods in models for diagnostics and assessment of the state of power equipment at TPP [1-3]:

- A fuzzy model for identifying the state of power equipment, including such NON-factors in the input-output model of the controlled system as uncertainty in the content of the object structure parameters, inaccuracies in the output process measurements, etc. To account for NON-factors, fuzzy relations are introduced, which are integrated as the degree of belonging to the output signals. The model constructed in this way operates on the entire space of installation parameters in terms of a fuzzy relation that includes unrecorded uncertainty factors. The topology of space is introduced into the model using the concept of \(t\)-neighborhood of the system output;
- The necessary conditions for the design of a fuzzy controller, tested for pressure control in the condensers of the turbine unit, were obtained.
- The studied heat and power unit (turbo unit) is represented as a model, in which fuzzy parameters are introduced into the parametric space of its output signals. The parametric space was reduced to the metric space of parameters, which makes it possible to identify the entire system – the turbine unit.
- The analysis of modeling results with inaccurate input information was performed, and the statistical assessment of the adequacy of the obtained fuzzy models was carried out. The accuracy of the obtained mathematical model is estimated by estimating the degree of dispersion of the obtained regression line relative to its mathematical expectation. At the same time, 2 types of adequacy criteria ("R" and "D") are introduced, which help to integrally assess the proximity of mathematical models to the object under study using the selected measure.

8. References
[1] Krokhin G D 2008 Mathematical models of identification of the technical condition of turbo installations based on fuzzy information Abstract. Diss. on Doct. Degree. Irkutsk p 48.
[2] Krokhin G D, Mukhin V S, Sudnik Yu A 2010 Intellectual technologies in heat power engineering. Moscow: LLC "UMTS " Triada" p 170
[3] Arakelyan E K, Krokhin G D, Mukhin V S 2008 The concept of soft regulation of technical maintenance of TPP power units based on intelligent diagnostics Vestnik MPEI, no. 1. Moscow: MEI Publishing house pp 14-20
[4] Zadeh L A 1965 Fuzzy sets Information and control V.8 No.3 pp 338-353
[5] Zadeh L A 1966 Concept of state in the theory of systems General systems theory Edited by M. Mesarovich.- Moscow: Mir pp 49-65
[6] Zadeh, L A 1966 Shadows of fuzzy sets Problems with transmitting information no.1 pp 37-44
[7] Bellman R, Zadeh L 1976 Decision-making in vague conditions Issues of analysis and decision-making procedures Moscow: Mir pp 172-215
[8] Petrov B N, Ulanov G M, Goldenblat I I, Ulyanov S V 1978 Model theory in control processes. Moscow: Nauka p 224
[9] Kanel L N 1972 Review of systems for image structure analysis and development of classification algorithms in dialog mode TIIER, vol. 60 no. 10 pp 122-141
[10] Ayvazyan S A, Enyukov I S, Meshalkin L D 1983 Applied statistics: Fundamentals of modeling and primary data processing Reference edition Moscow: Finance and statistics p 471
[11] Ayvazyan S A, Enyukov I S, Meshalkin L D 1985 Applied statistics: The study of dependencies Reference edition M.: Finance and statistics p 487
[12] Ayvazyan S A, Bukhshtaber V M, Enyukov I S, Meshalkin L D 1989 Applied statistics: Classification and dimensionality reduction Reference edition Moscow: Finance and statistics p 607
[13] Manusov V, Krokhin G 1998 The Diagnosis of Thermal Power Station Turbine Plants States with Application of Fuzzy sets Theory XXX Kraftwekstechnisches Kolloquium Technische Universität, Dresden, Deutschland, PA6
[14] Grif M G 2002 Automation of design processes of functioning of human-machine systems based on probabilistic and fuzzy indicators The author's abstract Diss. On Doct. Degree Novosibirsk: NSTU p 35
[15] Gulyaev V A, Chaplygin V M, Kedrovsky I V 1986 Methods and tools for processing diagnostic information in real time. Kiev: Naukova Dumka p 224
[16] Kendall M, Stewart J A 1976 Multidimensional statistical analysis and time series, Moscow: Nauka p 736
[17] Classification and cluster, Under the ed. J. Van Raisin. 1980. Moscow: Mir p 389

Acknowledgments
The study was performed with support of Russian Science Foundation, grant № 19-19-00601.