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METHOD FOR EVALUATING TECHNICAL CONDITION OF AGGREGATES BASED ON ARTIFICIAL INTELLIGENCE

Purpose. Enhancing operational efficiency of natural gas pumping units by applying artificial intelligence methods to assess their technical condition.

Methodology. The artificial neural networks theory, in particular, the counter-propagation network with two layers of Kohonen and Grossberg, was used to recognize aggregate states. The structure choice and calculation of the separation line coefficients was carried out using genetic algorithms.

Findings. The task of evaluating the aggregate technical state is formed as a pattern recognition task. An analysis of literary sources has shown that the problem of pattern recognition relates to difficult-to-formulize tasks, and their solution requires new approaches, based on artificial intelligence methods. The artificial neural networks of counter propagation are proposed to use for recognizing the aggregate technical states. The article shows advisability of using the LVQ-network type, which has two layers of Kohonen and Grossberg in its composition, for this assessment. The efficiency of the network is confirmed by a test case. A genetic algorithm that allows choosing both the polynomial structure and its parameters is used to construct a diving line separating one class of signs from another. The technical condition of the lubricating system of the natural gas pumping aggregate is estimated, as an example of the developed methodology application.

Originality. The AI-based method for assessing the technical state of gas-pumping units has been further developed to evaluate their state in operating mode and, based on this, develop effective algorithms for optimal loading of parallel operating aggregates.

Practical value. Algorithmic and software testing was developed on the test case, based on the proposed method for assessing the aggregate technical condition. The proposed method, which effectively solves the problem of partitioning the signs planes into classes each of which characterizes its certain state, has been shown as an example of the technical state evaluation of the gas turbine engine lubrication system.

Keywords: *pattern recognition, technical condition, neural network, genetic algorithm, gas pumping unit*

Introduction. It is necessary to attribute certain features (objects) to one or another cashier when solving a number of practical tasks. Such problems arise, for example, in drilling [1], the production of synthetic materials [2], technical diagnostics [3], and others.

Pattern recognition tasks are difficult to formulize, and their solution requires the development of new methods and approaches using intelligent technologies. It is necessary to determine the feature by which one or another object can be attributed to a certain class for a successful solution of such tasks. In this case, the uncertainties of the images that need to be recognized should be taken into account.

Pattern recognition tasks are of two types, classification and clustering. Classification of images means the process by which the whole set of images having different properties (attributes) is divided into non-intersecting classes. Classification is carried out by means of training when the assignment of objects to a particular class is carried out according to reference samples.

In contrast to the classification, with clustering, the number of classes (clusters) which should be divided into a set of images is unknown in advance. Clustering allows one to structure the input data and characterize the status of a particular object by exploring each cluster. The purpose of the work is to improve the method for constructing separate curves between classes on the basis of genetic algorithms.

Literature review. The problem of pattern recognition is one of the most complex tasks of cybernetics [4]. Methods for pattern recognition can be divided into two groups, classification and clustering. The essence of the classification is [5, 6] that a set of objects is investigated. Each object of this set is characterized by a certain number of signs. It is assumed, that it is possible to submit a certain number of subsets that do not intersect. There is a finite set of objects and it is known which classes they belong to. It is necessary to range an object in a certain class based on a set of signs of the object.

In the case when the object to be classified is to be submitted as a vector whose components are valid numbers, mathematical methods of classification are used.

The object recognition signs can be deterministic and stochastic. Recognition with deterministic features occurs by matching two vectors. One of them is the precedent of another representing the object. The norm of the difference between

vectors in the Euclidean space is used as a measure of the object belonging to a certain class [5]. If the signs of an object are given in a binary code, then the criterion of belonging to a particular class can be Heming's distance [6].

In most cases, feature vector components are distorted by obstacles, which prompts the use of statistical methods, in particular, Bayesian ones [7]. The Bayesian method provides effective recognition in the case where objects signs distribution laws that must be Gaussian are known [8, 9].

The image recognition method, which is based on linear statistical estimation of incoming statistics nonlinear functional transformations, is proposed in cases where the hypothesis of the normal law of distribution of features of the object is not confirmed [10]. This method is close to the class of nonlinear parametric methods that work according to the "nearest neighbor" rule [9]. The statistical methods of pattern recognition should include a method called the nuclear method of reference vectors [11]. The essence of the method is in the effective overview of models and finding of a compromise between the degree of conformity of data models and their complexity. Calculating it reduces to solving finite dimensional problems of quadratic optimization with the number of variables equal to the number of observations [12]. The size of such a task can be quite large, which is a significant drawback of the method. Clustering, unlike classification, where the number of classes of object recognition is known, assumes that the number of clusters is unknown.

The process of separating the image set into clusters is based on minimization of a certain partition quality criterion, which may be [6]: the mean square distance between the images in the cluster; mean square distance between images belonging to different classes; indicators based on the notion of the matrix of distances; minimum and maximum dispersion, and others.

An efficient solution of the clustering problem can be obtained using neural networks such as Kohonen and Grossberg [13, 14].

The estimation of aggregate technical state using methods of artificial intelligence. Parameters of the technical system (the unit) change over the time, as a result of natural aging and wear. Such a change can be used to determine its technical state.

A certain technical condition of a unit, for example, "good", "normal", "satisfactory", is characterized by some set of signs (images). The set of such images forms n-dimensional image space, whose coordinates are indicators of the unit technical state.

Let us assume that for each node of the unit the basic technological parameters, which indirectly characterize its technical condition, are determined. We will mark them through $x_1^{(h)}$ and $x_2^{(h)}$, $h = \overline{1, q}$, where q is the number of nodes of the units. For each node of the unit, we construct a plane of signs (Fig. 1) and, let some classes be distinguished in this plane,
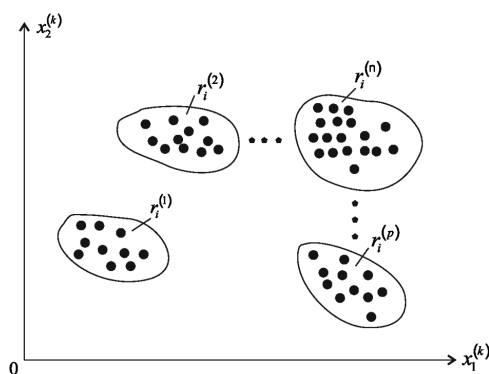
each of which characterizes a certain technical state of the selected node of a unit. For each class we assign a certain rating [15] $r_i^{(v)}, v = \overline{1, p}$, where p – the number of classes on which the plane of the unit node signs is broken. The least value of the rating $\min_v : r_i^{(v)} = 1$ is assigned to a class that characterizes the state of the node, for example, "good", while $\max_v : r_i^{(v)} = p$ is assigned to the rating that is associated with the worst technical condition of the assembly unit. Then the technical condition of the unit will be evaluated by the value

$$t_c = \sum_{h=1}^{q} t_c^{(h)}, \qquad (1)$$

where $t_c^{(h)} \in \{1, p\}$ is the rating of the technical condition of the ith node of the unit.

The assessment of the unit technical condition is carried out by observing its work over a period of time. At the same time it is necessary to exclude stops and launches of the unit from the observations. As a result, they receive the data array about the operation of each unit node. In the specified coordinates of signs, a plane of unit node signs, which must be divided into classes, is formed.

An effective tool to split planes into classes is artificial neural networks, in particular, neural networks of counter production. Such networks are called Learning Vector Quantization Network (LVQ-network) and have inbuilt input layer of neurons and layers of neurons of Kohonen and Grossberg. LVQ-network has two layers with serial communications. In the network operation mode, the input vector is fed to its input $\overline{x}$ and the output vector $\overline{y}$ is formed. The Kohonen network layer functions in accordance with the rule "winner takes it all". If input to the layer Kohonen submit a vector $\overline{x}$, then the output will have a signal that is formed in accordance with the following relationship

$$\overline{s} = W\overline{x},$$

where W is the matrix of weight coefficients.

It should be noted that j^{th} line of the matrix W is a vector of the weights $\overline{w}_j$ j^{th} neuron.

In the process of learning the Kohonen layer, a vector $\overline{x}$, which is scalarly multiplied by the weight vector $\overline{w}_j$ of all neurons, enters its input. A scalar product is a measure of similarity between an input vector $\overline{x}$ and a vector of neuron weights $\overline{w}_j$. The neuron, for which the condition $\max : \overline{x}^T \overline{w}_j$ is fulfilled, becomes a "winner" and its scales approach the components of the input vector $\overline{x}$. The Kohonen layer is taught by the following rule

$$\overline{w}_{new} = \overline{w}_{old} + \eta (\overline{x} - \overline{w}_{old}) \lim_{x \to \infty},$$

where $\overline{w}_{new}$ is the new weight value that connects the input component of the vector $\overline{x}$ with the winner neuron; $\overline{w}_{old}$ is the previous value of the same weight; η is the coefficient that determines the speed of training.

The outputs of the Kohonen layer are applied to the inputs of the Grossberg layer neurons. Then, each weighting factor is corrected only when it is connected to the neuron of the Kohonen layer with a non-zero output. There is a task of constructing a separate line that separates one class from another, after dividing the nodes set of a unit into a certain number of classes. Assume that q classes are obtained as a result of technical state evaluating of the unit node. It is necessary to build a dividing line between z and $z - 1$ classes. Let the classes z and $z - 1$ be placed respectively N_o and N_w images. Then the dividing line between these classes can be obtained by minimizing the functionality [17]

Fig. 1. The feature area of the ith node of the unit

$$F(\bar{a}) = \frac{1}{N_o}\sum_{i=1}^{N_o}\left(f\left(\bar{x}^{oi},\bar{a}\right)-1\right)^2 + \frac{1}{N_w}\sum_{j=1}^{N_w}\left(f\left(\bar{x}^{wj},\bar{a}\right)+1\right)^2, \quad (2)$$

where $f\left(\bar{x},\bar{a}\right)$ is equation of the dividing line; $\bar{a}$ — is the vector of the dividing line parameters.

When the condition is met $f\left(\bar{x}^{oi},\bar{a}\right)\approx 1$, vector $\bar{x}^{oi}$ will belong to the class $z-1$. Where $f\left(\bar{x}^{wj},\bar{a}\right)\approx -1$ vector $\bar{x}^{wj}$ will belong to the class z. The fulfillment of the last two conditions provides a minimum of functional (2). If the structure of the function is known $f\left(\bar{x},\bar{a}\right)$, then the equation of the dividing line $f\left(\bar{x},\bar{a}\right)=0$ will be obtained by defining its parameters as components of vector $\bar{a}$, from $\min_{\bar{a}}: F(\bar{a})$ condition.

The function $f\left(\bar{x},\bar{a}\right)$ is linear with respect to its parameters

$$f\left(\bar{a},\bar{x}\right) = \sum_{\rho=0}^{m-1} a_\rho \varphi_\rho\left(\bar{x}\right), \quad (3)$$

where $\varphi_p\left(\bar{x}\right)$ — is known functions of vector argument $\bar{x}$.

Formula (3) is written in the form of a scalar product of two vectors $\bar{a}$ and $\bar{\varphi}\left(\bar{x}\right)$. We obtain

$$f\left(\bar{a},\bar{x}\right) = \bar{a}^T\bar{\varphi}\left(\bar{x}\right).$$

Substituting the value $f\left(\bar{a},\bar{x}\right)$ in (2), we will get

$$F(\bar{a}) = \frac{1}{N_o}\sum_{i=1}^{N_o}\left(\bar{a}^T\bar{\varphi}\left(\bar{x}^{oi}\right)-1\right)^2 + \frac{1}{N_w}\sum_{j=1}^{N_w}\left(\bar{a}^T\bar{\varphi}\left(\bar{x}^{wj}\right)+1\right)^2. \quad (4)$$

Minimizing the functional (4) for a vector argument $\bar{a}$, the following vector-matrix equation is obtained

$$A\bar{a} = \bar{b}, \quad (5)$$

where

$$A = \frac{1}{N_o}\sum_{i=1}^{N_o}A\left(\bar{x}^{oi}\right) + \frac{1}{N_w}\sum_{j=1}^{N_w}A\left(\bar{x}^{wj}\right); \quad (6)$$

$$A\left(\bar{x}^{oi}\right) = \begin{bmatrix} \alpha_{00}\left(\bar{x}^{oi}\right) & \alpha_{01}\left(\bar{x}^{oi}\right) & \cdots & \alpha_{0,m-1}\left(\bar{x}^{oi}\right) \\ \alpha_{10}\left(\bar{x}^{oi}\right) & \alpha_{11}\left(\bar{x}^{oi}\right) & & \alpha_{1,m-1}\left(\bar{x}^{oi}\right) \\ \cdots & \cdots & \cdots & \cdots \\ \alpha_{m-1,0}\left(\bar{x}^{oi}\right) & \alpha_{m-1,1}\left(\bar{x}^{oi}\right) & \cdots & \alpha_{m-1,m-1}\left(\bar{x}^{oi}\right) \end{bmatrix};$$

$$A\left(\bar{x}^{wj}\right) = \begin{bmatrix} \alpha_{00}\left(\bar{x}^{wj}\right) & \alpha_{01}\left(\bar{x}^{wj}\right) & \cdots & \alpha_{0,m-1}\left(\bar{x}^{wj}\right) \\ \alpha_{10}\left(\bar{x}^{wj}\right) & \alpha_{11}\left(\bar{x}^{wj}\right) & \cdots & \alpha_{1,m-1}\left(\bar{x}^{wj}\right) \\ \cdots & \cdots & \cdots & \cdots \\ \alpha_{m-1,0}\left(\bar{x}^{wj}\right) & \alpha_{m-1,1}\left(\bar{x}^{wj}\right) & \cdots & \alpha_{m-1,m-1}\left(\bar{x}^{wj}\right) \end{bmatrix};$$

$$\bar{b} = \frac{1}{N_o}\sum_{i=1}^{N_o}\bar{\varphi}\left(\bar{x}^{oi}\right) - \frac{1}{N_w}\sum_{j=1}^{N_w}\bar{\varphi}\left(\bar{x}^{wj}\right).$$

Elements of matrices $A\left(\bar{x}^{oi}\right)$ and $A\left(\bar{x}^{wj}\right)$ are calculated by the following formula

$$\alpha_{kl} = \varphi_k\left(\bar{x}\right)\varphi_l\left(\bar{x}\right), \quad k,l = \overline{0,m-1}. \quad (7)$$

In formula (3), functions $\varphi_\rho\left(\bar{x}\right)$ are chosen in a power polynomial form. Then

$$f\left(\bar{a},\bar{x}\right) = \sum_{\rho=0}^{m-1} a_\rho \prod_{\nu=1}^{m_t} x_\nu^{s_{\nu\rho}}, \quad (8)$$

$$\sum_{\nu=1}^{m_t} s_{\nu\rho} \le r_1; \quad r_1 \text{ — is the degree of polynomial (8).}$$

The number of polynomial members (8) is calculated by the following formula [18]

$$m = \frac{\left(m_t + r_1\right)!}{m_t! r_1!}. \quad (9)$$

When choosing a function $\varphi_\rho\left(\bar{x}\right)$ in the regressions form, formula (7) takes the following form

$$\alpha_{kl}\left(\bar{x}^{oi}\right) = \prod_{\nu=1}^{m_t} x_\nu^{(oi)(s_{\nu k}+s_{\nu l})};$$

$$\alpha_{kl}\left(\bar{x}^{wj}\right) = \prod_{\nu=1}^{m_t} x_\nu^{(wj)(s_{\nu k}+s_{\nu l})}, \quad k,l = \overline{0,m-1}, \quad (10)$$

and the vector $\bar{b}$ components will be as follows

$$b_k = \frac{1}{N_o}\sum_{i=1}^{N_o}\prod_{\nu=1}^{m_t} x_\nu^{(oi)s_{\nu k}} - \frac{1}{N_w}\sum_{j=1}^{N_w}\prod_{\nu=1}^{m_t} x_\nu^{(wj)s_{\nu k}}, \quad k = \overline{0,m-1}. \quad (11)$$

The dividing line can be constructed on the sign plane after determining the coefficients of the polynomial (8), by solving the matrix equation (6).

The dividing line (8) constructed in such a way has a significant disadvantage [17]. The essence of this disadvantage is that almost always the object placement density in a class further from the border is greater than that at the very border. To improve the dividing line process quality, it is important to consider the fact that objects, located closer to the dividing line, have a greater impact on it than objects located further away from it.

In order to provide a lesser impact of objects when they are separated from the dividing line, the following weight function is proposed in [17]

$$W(f) = e^{-\frac{f^{2\beta}}{\gamma}}, \quad (12)$$

where $f = f\left(\bar{x},\bar{a}\right)$; β and γ are the coefficients, selected based on the results of the computational experiment.

Considering the weight function (12) allows writing functional (2) in the following form

$$F(\bar{a}) = \frac{1}{\sum_{i=1}^{N_o}W\left(f\left(\bar{x}^{oi},\bar{a}\right)\right)}\sum_{i=1}^{N_o}W\left(f\left(\bar{x}^{oi},\bar{a}\right)\right)\left(f\left(\bar{x}^{oi},\bar{a}\right)-1\right)^2 +$$
$$+ \frac{1}{\sum_{i=1}^{N_o}W\left(f\left(\bar{x}^{wj},\bar{a}\right)\right)}\sum_{j=1}^{N_w}W\left(f\left(\bar{x}^{wj},\bar{a}\right)\right)\left(f\left(\bar{x}^{wj},\bar{a}\right)+1\right)^2. \quad (13)$$

In the case $\beta = 0$ where the weight function (11) is identically equal to one, the functional (2) is obtained.

As previously, the function $f\left(\bar{x},\bar{a}\right)$ is chosen as a polynomial (8).

The solution of the problem of constructing the dividing line requires not only the determination of the polynomial coefficients (8), but also its structure. The problem of the dividing line equation synthesis will be solved on the genetic algorithms theory basis. The polynomial coefficient (8) will assign a unit if it is included in the regression equation (8) or zero in the opposite case. An ordered sequence of zeros and units that are associated with the corresponding coefficients of the polynomial (8) will be created. Such an ordered sequence in the theory of genetic algorithms is called a chromosome, and its atomic element (1 or 0) is called a gene. Functional (13), which is to be minimized, will be a fitness function. The task

will be set by natural selection to find such a chromosome, which will fit the least value of the fitness function (13).

The algorithm to solve the given task consists of such a sequence of steps.

Step 1. Initialization. To choose the power of the polynomial (8), that will determine the set of possible equations of the separation line from the set of polynomial powers r_1. The initial population P is randomly generated from I chromosomes of length m each, where m is calculated by the formula (9).

Step 2. Evaluation of chromosome fitness in a population P. Another chromosome is selected from the population. In accordance with the selected chromosome, a polynomial (8) of degree r_1 is formed, which will contain m_1 units and $m - m_1$ zeros. The polynomial formed in such a way is included in the fitness function (13), which is minimized by the parameters a_ρ, $\rho \in \{1 \dots m_1\}$. The fitness function (13) is nonlinear with respect to the parameters a_ρ. To minimize it, the deformed polygon method is selected (Nelder-Mead method) [19]. The initial approximation $\overline{a}^{(0)}$ is the value obtained as a result of solving the matrix equation (5). Thus, performing step 2 allows determining the value of fitness function (13) for each chromosome in the population P.

Step 3. Checking the algorithm stop condition. In the fitness function values (13), obtained in step 2, the least value is selected $F(\overline{a}^*) = \min_{a_\rho} : F(\overline{a})$. If the condition $\left| F(\overline{a}^*) \right| \leq \varepsilon$ is met, where ε is a positive number that determines the accuracy of the problem solving, then the calculations are completed. The calculations may also be stopped in those cases where the fitness function (13) has not been reduced or the algorithm has performed a given number of steps.

In the case of not fulfilling any of three conditions, the transition to the next step takes place.

Step 4. Chromosome selection. The selection of those chromosomes that will participate in the creation of a new population is carried out by the calculated values in the second step. Such selection is based on the principle of natural selection, when chromosomes with the least value of the fitness function participate in the creation of a new population (13).

To select such chromosomes in this algorithm, the tournament method [20] was used. In the tournament method, selected chromosomes are divided into subgroups of 2−3 chromosome pairs in each subgroup.

Step 5. Formation of a new population of descendants. A new population of chromosomes is formed by the operators of crossing and mutation. The crossing operator is performed much more often than the mutation operator. The likelihood of the crossing operator P_c execution lies within $[0.5 \dots 1.0]$, and the probability of the mutation operator P_m is $[0 \dots 0.1]$.

Crossing is performed on groups of chromosomes, which are formed in the fourth step. A random number P_N is generated from the interval $[0 \dots 1]$ and, if the condition $P_c \leq P_N$ is met, then the selected pair of chromosomes crosses. Otherwise, chromosome crossing does not occur. Crossing is performed as follows. The crossed point (locus) L is randomly played for the selected pair of chromosomes. Value L is an integer that must satisfy the condition $0 \leq L \leq m - 2$. In the first chromosome, genes at positions $[L + 1 \dots m]$ are replaced by genes of the second chromosome, and in the second chromosome, genes at positions $[L + 1 \dots m]$ are replaced by genes of the first chromosome (Fig. 2).
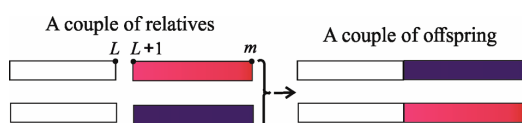

Fig. 2. The process of creating a new pair of chromosomes under the action of the crossing operator

To implement the mutation process, a random number is generated from the interval $[0 \dots 1]$ and if it belongs to the interval $[0 \dots 0.1]$, the mutation operator is applied to the selected chromosome from the relatives pool. The effect of the mutation operator is to randomly select the locus of the chromosome L, and the gene in position L changes its value to the opposite (from 1 to 0 and vice versa).

As a result of executing crossing and mutation operators, the population of relatives is replaced by the population of descendants. After step 5, the transition to step 2 occurs.

The aggregate technical condition estimating algorithm testing by artificial intelligence methods. To check the effectiveness of the developed algorithm, a test that mimics the technical condition of an assembly unit was developed. It was assumed that the state of the node is characterized by three classes. The number of objects in each class is 100. The coordinates of the objects x_1 and x_2 are also randomly generated on the feature plane. Each coordinate is a random variable distributed by the law of uniform density

$$p(x_i) = \begin{cases} \dfrac{1}{b-a}, & a < x_i < b \\ 0, & x_i < a \\ 0, & x_i > b \end{cases}, \qquad (14)$$

where $i = 1, 2$.

Table 1 contains parameters of density function $p(x_i)$.

Five random values distributed by the law (14), were generated for each coordinate x_i, and its average value was calculated. It should be noted that even the sum of three proportionally uniformly distributed random variables results in a distribution close to normal [5]. Thus, there are reasons to believe that the values x_1 and x_2 in each class are distributed according to a law that is close to normal. Fig. 3 reproduces the simulation results obtained in accordance with Table 1.

With the help of the LVQ-network, many features (Fig. 4) were divided into three classes (Fig. 4). The centers of the classes are denoted by Figs. 1, 2, and 3. The following network parameters were selected: the number of neurons is 3; the Kohonen layer learning coefficient is 0.01; the coefficient of "fairness" is 0.001; the number of training cycles is 1000.

The result of an attributes array partitioning into classes by the LVQ-network is shown in Fig. 4.

Dividing lines that separate classes from each other are constructed using a genetic algorithm that minimizes fitness (13). A polynomial of the second degree was selected. Other parameters of the algorithm were as follows: the number of chromosomes in the population is 100; the maximum number of iterations of the genetic algorithm is 10; the probability of crossing is $0.5 \leq P_c \leq 1$; the probability of a mutation is $0 \leq P_m \leq 0.1$; the number of chromosome pairs in a subgroup is 3; accuracy of solving the problem is 0.01; parameters that govern the rate of a function decline at a distance from zero are $\alpha = 1$, and $\beta = 500$.

The dividing line between the first and second classes (Fig. 5) is described by the following equation

Table 1

Parameters of density function

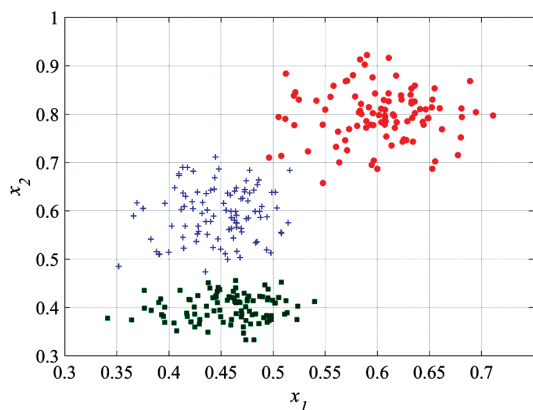| Classes	Values	Parameters $p(x_i)$	
		a	b
Class - 1	x_1	0.3	0.6
	x_2	0.4	0.8
Class - 2	x_1	0.3	0.6
	x_2	0.3	0.5
Class - 3	x_1	0.4	0.8
	x_2	0.58	1.0

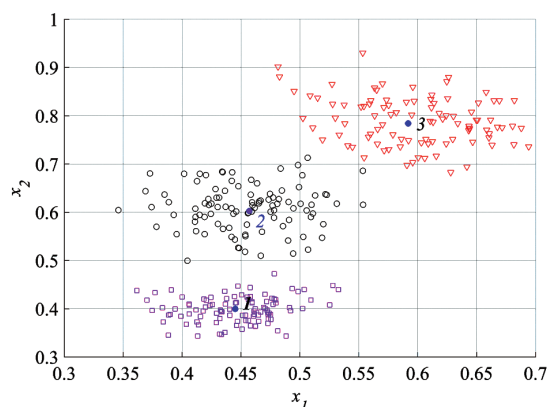*Fig. 3. Simulation modeling of feature classes*

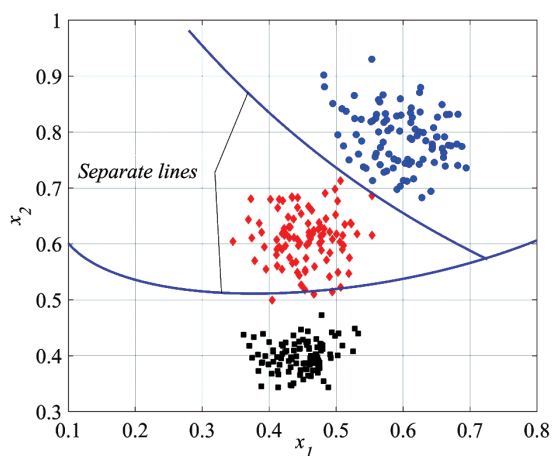*Fig. 4. Division of features set into classes*

Fig. 5. Division of attributes set into classes by dividing lines

$$a_1 + a_2 x_1 + a_3 x_2 + a_4 x_1 x_2 + a_5 x_2^2 = 0,$$

where $a_1 = -8.1351$; $a_2 = 24.4044$; $a_3 = -4.5066$; $a_4 = 6.6658$; $a_5 = -19.0694$.

The second dividing line, that separates the first class from the third, is described by the following equation

$$a_1 + a_2 x_1 x_2 + a_3 x_2^2 = 0,$$

where $a_1 = -3.3863$; $a_2 = 6.9372$; $a_3 = 1.5359$.

Analysis of Fig. 5 shows that there was an error-free division between the first and third classes, and when the first and second classes were divided, three objects from the first class went to the second class.

Thus, the test case has shown that the pattern recognition method on the artificial intelligence basis enables to synthesize

an effective algorithm and the corresponding software for the division of the signs set into classes.

Technical condition assessment of a lubricating system of a gas-pumping unit. As an example of applying a method for assessing the technical condition of aggregates, consider the lubrication system of the gas-pumping unit (GPU). In order to drive centrifugal superchargers of natural gas, in most cases, gas turbine engines (GTE) are used in GPU.

The GTE lubrication system has a reservoir, filter, and cooler. The oil under pressure is pumped through the lubrication system and returned to the tank for re-use.

The lubrication system in the GTE plays two important functions [21]: ensuring lubrication between rotating and stationary surfaces and diverting heat (cooling effect) from these surfaces. The designs of the lubrication systems should consider the type of bearing, bearing load, the temperature and the viscosity of the oil. Bearings which carry the rotor shaft of the GTE are of two types: hydraulic and antifriction. In a hydrodynamic bearing, slip friction changes into a fluid slip; antifriction bearings operate on the principle of rolling friction.

Thus, the technical state of the lubrication system largely depends on the effective and trouble-free operation of the GPU in general [22].

To assess the technical state of the lubrication system of the GTE it is important to highlight those features that carry the maximum information about its state.

There is no general theory of formalized definition of characteristics [23]. Choosing a set of attributes often depends on the experience and intuition of the expert.

In order to obtain material for assessing the technical condition of lubrication GTE, experimental studies were conducted at the compressor station Dolinsky Board linear gas mains SE "Prykarpattransgas" where centrifugal supercharger GPA-TS1-16S/76-1,4 gas turbine engine HH-90L2 are installed.

The experimental material analysis showed [24] that the pressure in the system and the oil temperature at the engine
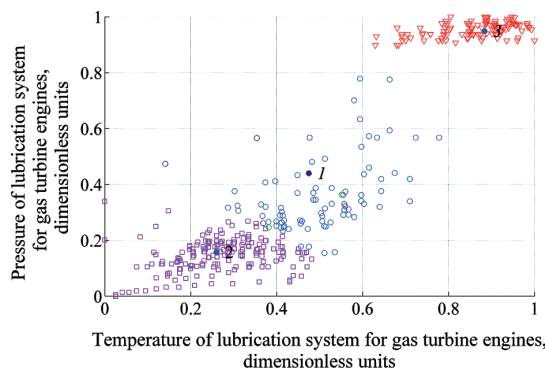

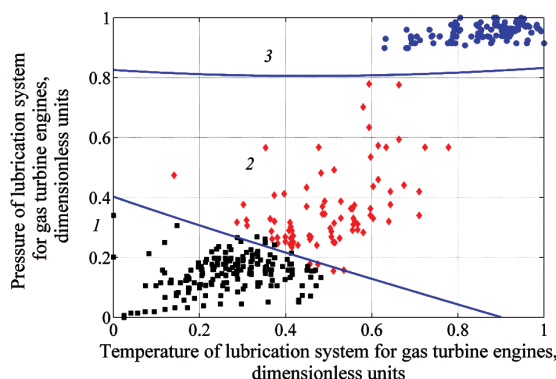*Fig. 6. Division of the feature plane of the lubrication system of GTE*

Fig. 7. Division of the feature plane by dividing lines

outlet should be selected as lubrication system technical condition signs.

For the effective recognition of the lubrication system states, the coordinates of the images x_1 and x_2 are reduced to dimensionless units using the following formula

$$x_i = \frac{X_i - X_{i,\min}}{X_{i,\max} - X_{i,\min}}, \quad i = 1,2,$$

where X_i is dimensional units (temperature); $X_{i,\max}$, $X_{i,\min}$ are maximum and minimum values of the unit size X_i.

The plane of the GTE lubrication system characteristics was divided into three classes with the help of the LVQ-network (Fig. 6).

The first class will be attributed as a normal mode of operation; the second as a satisfactory, and the third as before the emergency.

Separate classes among themselves will use separate lines, which are built on the developed algorithm. It was chosen as a second-degree polynomial. Other parameters of the algorithm remained unchanged. Separate lines that are marked on the feature plane are shown in Fig. 7.

The following dividing lines equations were obtained.

The equation of a dividing line separating the first class from the second is

$$a_1 + a_2 x_1 + a_3 x_2 + a_4 x_1 x_2 + a_5 x_2^2 = 0, \tag{15}$$

where $a_1 = -2.6077$; $a_2 = 2.8800$; $a_3 = 9.5001$; $a_4 = -2.9105$; $a_5 = -7.5131$.

The equation of the dividing line dividing the second class from the third is

$$a_1 x_2 + a_2 x_1^2 + a_3 x_1 x_2 + a_4 x_2^2 = 0, \tag{16}$$

where $a_1 = -5.2764$; $a_2 = -0.5093$; $a_3 = 0.567432$; $a_4 = 6.3922$.

As a result of the genetic operators' action, equations (15, 16), whose structure does not contain part of the members of the complete polynomial of degree 2, were obtained. The obtained "shortened" polynomials (15, 16) do not contradict the work's statement [6] that "there is no need always to use all the members of a polynomial when choosing the degree of a polynomial".

To construct the graph of the dividing line, it was necessary to solve equations (15, 16) relative to the variable x_2. As a result, dividing lines that are shown in Fig. 7 were obtained.

The results analysis shows that the error-free division of classes occurs in the case when classes *2* and *3* are separated from each other. Classes *1* and *2* are partially mixed, which led to an error of class separation. Three objects of the first class fell into the second class, and vice versa, two objects from the second class fell into the first class (Fig. 7).

Thus, the method evaluating aggregate technical state based on the artificial intelligence has been developed to divide the space of attributes into a certain number of classes, each of which defines a certain state of the working unit.

Conclusions. The developed method for evaluating the technical condition of working units using artificial neural networks and genetic algorithms allows dividing the space of signs into a certain number of classes. Each class is associated with the appropriate technical state as "normal", "satisfactory", and "passive". Classes are separated by dividing lines, the equations of which are synthesized using genetic algorithms that allow determining both the structure of the polynomial and its parameters. The efficiency and convergence of the developed algorithm are confirmed using the test example. As an application example of the evaluation method for technical units, the lubrication system of the gas turbine engine, that is the drive of the natural gas centrifugal supercharger, is considered. With the help of the developed algorithm, the plane of the features — the temperature, and the GTE lubrication system pressure, is divided into three classes and dividing lines between classes are constructed, which confirms the effectiveness of the method for estimating the technical state of a unit with the help of artificial intelligence.

References.
1. Bulatov, A. I. (2015). Concept of quality of drilled oil and gas wells. *Drilling and oil*, (12), 15-19.
2. Dobrotvor, I. G., Chykhira, I. V., & Yarema, I. T. (2017). Conditions of oscillation of kinetics characteristics of microstructures of composites. *Bulletin of the Khmelnytskyi National University. Technical Sciences*, (4), 52-55.
3. Gorbiychuk, M. I., & Pashkovskyi, B. V. (2016). Method of determining the generalized coefficient of technical state of a gas pumping unit on the basis of fuzzy logic and genetic algorithms. *Methods and devices of quality control, 2*(37), 102-107.
4. Zhao, Z., Chu, L., Tao, D., & Pei, J. (2018). Classification with label noise: a Markov chain sampling framework. *Data Mining and Knowledge Discovery*, 1-37.
5. Gershilov, A. A. (2014). *Mathematical methods for decision making*. Moscow: Publishing house of Moscow State Technical University. N. E. Bauman.
6. Marchenko, O. O. (2016). Machine-learning methods for recognizing named entities of text. *Programming problems*, (2-3) (Special issue), 150-157.
7. Walkman, Yu. R., & Stepashko, P. V. (2015). Towards building an ontology of intellectual modeling. *Inductive modeling of complex systems: Collection of research papers*, (7), 101-115.
8. Zygmunt Lech Warsza, & Zabolotnii, S. W. (2018). Polynomial estimation of measurand parameters for samples from non-Gaussian distributions based on higher order statistics. *Advanced Mathematical and Computational Tools in Metrology and Testing XI*, 383-400.
9. Zabolotnyi, S. V., Chepinoga, A. V., Bondarenko, Yu. Y., & Rud, M. P. (2018). Polynomial parameter estimates for exponentially distributed data. *Visnyk NTUU "KPI". Seriia Radiotekhnika Radioaparatobuduvannia*, 75, 40-47.
10. Huang, Huajuan, Wei, Xiuxi, & Zhou, Yong-Quan (2018). Twin Support Vector Machines: A Survey. *Neurocomputing*.
11. Norkin, V. I. (2017). B&B solution technique for multicriteria stochastic optimization problems. *Optimization Methods and Applications*.
12. Bodyanskiy, Ye., Vynokurova, O., Savvo, V., Tatiana Tverdokhlib, T., & Mulesa, P. (2016). Hybrid Clustering-Classification Neural Network in Medical Diagnostics of Reactive Arthritis. *International Journal of Intelligent Systems Technologies and Applications, 8*(8), 1-9. https://doi.org/10.5815/ijisa.2016.08.01.
13. Nikolenko, S., Kadurin, A., & Arkhangelskaya, E. (2017). *Deep learning*. "Peter" Publishing House.
14. Horbiichuk, M. I., Kohutiak, M. I., & Zaiachuk, Y. I. (2008). Inductive method for constructing mathematical models of natural gas pumping units. *Oil and gas industry*, (5), 32-35.
15. Glybovets, M. M., Gulaeva, N. M., & Pasichnyk, M. M. (2015). A Parallel Genetic Algorithm for Creating a Work Schedule. *Programming Problems*, (2), 76-85.
16. Horbiichuk, M. I., & Shchupak, I. V. (2010). Diagnostic model of natural gas supercharger lubrication system. *Scientific Bulletin of the Ivano-Frankivsk National Technical University of Oil and Gas, 3*(25), 130-137.

Метод оцінки технічного стану агрегатів на засадах штучного інтелекту

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Мета. Підвищення ефективності експлуатації газоперекачувальних агрегатів природного газу шляхом застосування методів штучного інтелекту для оцінки їх технічного стану.

Методика. Для розпізнавання станів агрегатів використана теорія штучних нейронних мереж, зокрема, мережа зустрічного поширення із двома шарами Кохонена та Гросберга. Вибір структури та обчислення коефіцієнтів роздільної лінії здійснено з використанням генетичних алгоритмів.

Результати. Задача оцінки технічного стану агрегатів сформована як задача розпізнавання образів. Аналіз літературних джерел показав, що задача розпізнавання образів відноситься до важко формалізованих задач, і їх розв'язання вимагає застосування нових підходів, які ґрунтуються на методах штучного інтелекту. Для розпізнавання технічного стану агрегатів запропоновано використовувати штучні нейронні мережі зустрічного поширення. Показано, що для такої оцінки доцільно використовувати мережі типу LVQ-network, що мають у своєму складі два шари Кохонена та Гросберга. Ефективність роботи мережі підтверджена тестовим прикладом. Для побудови роздільної лінії, що відділяє один клас ознак від іншого, використано генетичний алгоритм, який дає змогу вибрати як структуру поліному, так і його параметри. Як приклад застосування розробленої методики оцінено технічний стан системи змащування газоперекачувального агрегату природного газу.

Наукова новизна. Знайшов подальший розвиток метод оцінки технічного стану газоперекачувальних агрегатів на засадах штучного інтелекту, що дало змогу в режимі експлуатації оцінювати їх стан і на цій основі розробити ефективні алгоритми оптимального завантаження парельно працюючих агрегатів.

Практична значимість. На основі запропонованого методу оцінки технічного стану агрегатів розроблено алгоритмічне та програмне забезпечення, що апробоване на тестовому прикладі. На прикладі оцінки технічного стану системи змащування газотурбінного двигуна показано, що запропонований метод ефективно вирішує задачу розбиття площин ознак на класи, кожний з яких характеризує певний його стан.

Ключові слова: *розпізнавання образів, технічний стан, нейронна мережа, генетичний алгоритм, газоперекачувальний агрегат*

Метод оценки технического состояния агрегатов на основе искусственного интеллекта

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Цель. Повышение эффективности эксплуатации газоперекачивающих агрегатов природного газа путем применения методов искусственного интеллекта для оценки их технического состояния.

Методика. Для распознавания состояний агрегатов использована теория искусственных нейронных сетей, в частности, сеть встречного распространения с двумя слоями Кохонена и Гроссберга. Выбор структуры и вычисления коэффициентов разделительной линии осуществлен с использованием генетических алгоритмов.

Результаты. Задача оценки технического состояния агрегатов сформирована как задача распознавания образов. Анализ литературных источников показал, что задача распознавания образов относится к трудно формулированным задачам, и их решение требует применения новых подходов, основанных на методах искусственного интеллекта. Для распознавания технического состояния агрегатов предложено использовать искусственные нейронные сети встречного распространения. Показано, что для такой оценки целесообразно использовать сети типа LVQ-network, имеющие в своем составе два слоя Кохонена и Гроссберга. Эффективность работы сети подтверждена тестовым примером. Для построения разделительной линии, отделяющей один класс признаков от другого, использован генетический алгоритм, который позволяет выбрать как структуру полинома, так и его параметры. В качестве примера применения разработанной методики оценено техническое состояние системы смазки газоперекачивающего агрегата природного газа.

Научная новизна. Нашел дальнейшее развитие метод оценки технического состояния газоперекачивающих агрегатов на основе искусственного интеллекта, что позволило в режиме эксплуатации оценивать их состояние и на этой основе разработать эффективные алгоритмы оптимальной загрузки параллельно работающих агрегатов.

Практическая значимость. На основе предложенного метода оценки технического состояния агрегатов разработано алгоритмическое и программное обеспечение, которое апробировано на тестовом примере. На примере оценки технического состояния системы смазки газотурбинного двигателя показано, что предложенный метод эффективно решает задачу разбиения плоскости признаков на классы, каждый из которых характеризует определенное его состояние.

Ключевые слова: *распознавания образов, техническое состояние, нейронная сеть, генетический алгоритм, газоперекачивающий агрегат*