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INFORMATION-EXTREME MACHINE LEARNING OF THE CONTROL SYSTEM OVER THE POWER UNIT OF A THERMAL POWER MAIN LINE

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Розглядається інформаційно-екстремальний метод навчання системи підтримки прийняття рішень для керування генеруючим енергоблоком теплоелектроцентралі. В процесі машинного навчання оптимізація контейнерів класів розпізнавання, що відновлювалися в радіальному базисі простору ознак, здійснювалася за модифікованим критерієм Кульбака. При цьому показано, що застосування вкладених контейнерів класів розпізнавання підвищує функціональну ефективність машинного навчання у порівнянні з контейнерами класів розпізнавання, центри яких розподілено в просторі ознак

Ключові слова: інформаційно-екстремальна інтелектуальна технологія, машинне навчання, система підтримки прийняття рішень, інформаційний критерій, енергоблок

Рассматривается информационно-экстремальный метод обучения системы поддержки принячтия решений для управления энергоблоком теплоэлектроцентрали. В процессе машинного обучения оптимизация контейнеров классов распознавания, восстанавливаемых в радиальном базисе пространства признаков, осуществлялась по модифицированному критерию Кульбака. При этом показано, что использование вложенных контейнеров классов распознавания повышает функциональную эффективность машинного обучения в сравнении с контейнерами классов распознавания, центры которых распределены в пространстве признаков

Ключевые слова: информационно-экстремальная интеллектуальная технология, машинное обучение, система поддержки принятия решений, информационный критерий, энергоблок

1. Introduction

Application of intelligent information technology for data analysis makes it possible to increase a functional efficiency of systems of control by weakly formalized processes. Processes of control of power units of thermal power plants relate to such processes. A promising way to increase a functional efficiency of weakly formalized controlled processes is the use of ideas and methods of machine learning and pattern recognition. Data analysis methods within the so-called information-extreme intelligent technology (IEI-technology) provide a high accuracy of control in this case. The technology is based on maximization of informational capacity of a control system during a learning process. But problems of construction of decisive rules, which are error-free by a learning matrix, under conditions of substantial intersection of recognition classes in a space of attributes in a process of machine learning remain actual.

The study considers an information-extreme learning of a decision-making support system of control over a power unit of a thermal power plant with polymodal and unimodal decisive rules.

2. Literature review and problem statement

Most of the existing methods of control of generating units of TPP are based on traditional mathematical modeling of control objects and do not take into account real properties of a weakly formalized technological process due to scientific and methodological constraints [1, 2]. Another promising approach is the application of intelligent information technology of data analysis. It is based on ideas of machine learning and pattern recognition [3–5]. The reliability of the proposed methods of classification control by a weakly formalized object depends on a choice of a recognition method essentially. Authors consider methods of control of a boiler unit with a use of artificial neural networks in works [6, 7]. The disadvantage of a use of artificial neural networks is the sensitivity to multidimensionality of a space of attributes of recognition and alphabet of classes of recognition, which characterize possible functional states of a technological process. This significantly complicates creation of a centralized informational and analytical system of control of the technological process of a thermal power plant on a base of a decision-making support system (DMSS), which is able to analyze large volumes of data. Application of expert systems in the heat power engineering, as discussed in work [8], has the main disadvantage   it is inflexibility to a change in operating conditions of a control object. Monograph [9] considers methods of machine learning for decision making support systems of control of a unit of thermal power plant. The paper mentioned shows methods of machine learning in detail on a base of the application of distant measures of proximity of realization of recognition classes. But practice shows that optimization criteria, which are built on distant measurements, do not always give possibility to formulate decisive rules, which are error-free by a learning matrix, in the event of a significant intersection of recognition classes in a space of attributes. In literature, some works, for example [10, 11], widely discuss application of fuzzy controllers for control of power units. But creation of fuzzy regulators for control systems that use quantitative measurement scale of controlled parameters is not promising. Because an area of the application of fuzzy presentation and knowledge extraction methods are systems with qualitative measurement scales of functioning parameters.

The most suitable for informational synthesis of systems of control by weakly formalized technological processes are methods of machine learning and pattern recognition, their decisive rules arise in the framework of IEI-technology of data analysis [12]. A base of this technology is a maximization of information capability of a control system in a process of machine learning. In a paper [13], in the framework of IEI-technology, authors considered a problem of information synthesis of DMSS, which is able to learn, to control a power unit of a thermal power plant. But authors failed to achieve high reliability of recognition of functional states of a technological process through a priori non-optimal control tolerances to attributes of recognition.

Let us consider a formalized problem statement of information synthesis of DMSS, which is able to learn, to stabilize a pressure and temperature of a steam at a turbo unit's input in the framework of IEI-technology. Decisive rules of two types will be used to compare reliability in the framework of geometric approach in the process of information-extreme machine learning in this case. We will call decisive rules of the first type polymodal, they are built according to geometric parameters of containers of recognition classes with centers of dispersion of vectors-realizations distributed in a space of attributes. Decisive rules of the second type will be called unimodal, since in this case, recognition classes have a single center of variance of vectors-realizations, and containers of recognition classes have an enclosed structure.

Firstly, let us consider the problem statement of information synthesis of DMSS with polymodal decisive rules. Let us suppose we have an alphabet of recognition classes $\{X_m^o \mid m=\overline{1,M}\}$, they characterize possible functional states of a controlled technology process. An input multidimensional learning matrix is formed for the alphabet $\{X_m^o\}$. A line in it is the implementation of a pattern where N is a number of structured recognition attributes and a matrix column is a random learning sample $\{y_{m,i}^{(j)} \mid j=\overline{1,n}\}$, where n is a sample volume. In addition, there is a known structured vector of DMSS learning parameters to recognize realizations of a certain class X_m^o within a given alphabet

$$g_m = < x_m, d_m, \delta, \rho_m >, \quad (1)$$

where x_m is the statistically averaged binary vector-realization of X_m^o, class that defines a geometric center of a container of a class of recognition, which restores in a radial basis of a recognition attributes space; d_m is the radius of a container of X_m^o, class, its value is given by a code distance in the Hamming's binary space; δ is the parameter of a field of control tolerances to recognition attributes, it is equal to a half of a symmetrical field of control tolerances and it is determined relative to a base X_1^o, class, and this characterizes the most desired functional state of a technological process; ρ_m is the level of selection of coordinates of an averaged binary vector-realization of X_m^o recognition class.

Learning parameters have the following limitations:

$$d_m \in \left[0; d\left(x_m \oplus x_c\right) - 1\right],$$

where $d\left(x_m \oplus x_c\right)$ is a code distance from a center of container of X_m^o class to a center of a container of X_c; neighboring class; where $\delta_{H,i}$ is a standardized tolerance field, which defines a region of values of a parameter δ for the i-th attribute of recognition; $\rho_m \in [0; 1]$. A parameter δ is given in percentage of a nominal (averaged by sampling) value of an attribute at different measurement scales of attributes of recognition.

It is necessary to determine optimal values of coordinates of a parameters vector in the process of machine learning (1). They provide a maximum of the informational criterion averaged by an alphabet of recognition classes in a working (acceptable) area of its function definition:

$$\overline{E}^{*}=\frac{1}{M}\sum_{m=1}^{M}\max_{G_E\cap\{k\}}E_m^{(k)}, \qquad (2)$$

where $E_m^{(k)}$ is the informational criterion of optimization of parameters of DMSS learning, it is calculated on k-th step of learning; G_E is the working (acceptable) area of determination of a function of an information criterion; $\{k\}$ is the set of learning steps on which recognition class containers are restored in a radial basis of a space of attributes).

The problem statement of information synthesis of DMSS with unimodal decisive rules has the following differences in comparison with the above statement:

1) an alphabet $\{X_m^o\}$ is ordered, a magnitude of deviation of technological parameters from a standard characterize recognition classes in it;

2) there is no need to optimize averaged vectors-realizations of recognition classes, since all of them have a single center of dispersion;

3) there is no need to optimize a radius of an outer container.

Thus, within the framework of the IEI-technology, maximization of the information capability of DMSS in a process of machine learning is a solution of a problem of informational synthesis of DMSS, which is able to learn.

3. The aim and objectives of the study

The aim of present study was to develop an information-extreme algorithm for information-extreme machine learning of DMSS to stabilize a pressure and temperature at the input of a steam turbine power unit.

To achieve the objective, it was necessary:

– to develop a method of deep machine learning of a decision-making support system of control of a power unit of a thermal power plant in the framework of IEI-technology;

– to implement an algorithm of DMSS learning programmatically with a use of polymodal decisive rules obtained when using hyper-spherical containers of recognition classes, centers of which are distributed in a space of attributes;

– to implement an algorithm of DMSS learning programmatically with a use of unimodal decisive rules obtained when using enclosed classes of recognition classes.

4. Materials and methods of the study of a decision-making support system

We consider a categorical model of information-extreme learning of DMSS in the form of a generalized oriented graph since the controlled process is weakly formalized. An operator of a reflection of a corresponding set to another set characterizes an edge of a graph. The input mathematical description has the form of a set of structures

$$\Delta_B=<T,G,\Omega,Z,Y,X;\Phi_1,\Phi_2>,$$

where T is the set of moments of time of information retrieval; G is the set of input factors; Ω is the space of attributes of recognition; Z is the space of possible functional states of a technological process; Y is the sample set (input learning matrix); X is the binary learning matrix; $\Phi_1: G\times T\times\Omega\times Z\to Y$ is the operator of formation of a sample plural Y; $\Phi_2: Y\to X$ is the operator of a formation of a binary learning matrix X.

Fig. 1 shows a categorical model of DMSS with polymodal decisive rules and optimization of a system of control tolerances.

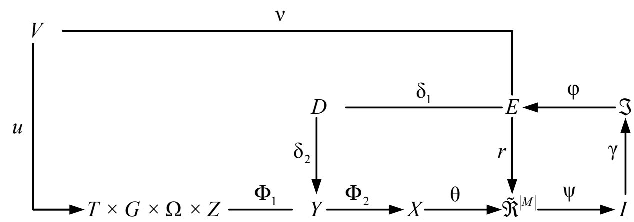


Fig. 1. Categorical model of learning of DMSS with polymodal decisive rules

Cartesian product $T\times G\times\Omega\times Z$ sets a universe of tests in Fig. 1. The operator θ reflects binary vectors-realizations of the learning matrix X on the partition $\Re^{|M|}$ of the attribute space into recognition classes, and the operator ψ verifies the basic statistical hypothesis about the belonging of realizations to the corresponding recognition class. A set of statistical hypotheses I is formed according to the results of the statistical hypothesis check, and the operator γ forms the set of precise characteristics $\Im$. The operator φ calculates the set of E values of the information criterion for optimization of learning parameters, and the operator r restores containers of recognition class, which are constructed in the radial basis of the space of attributes, at each step of the machine learning. Categorical model shown in Fig. 1 has an additional contour of optimization of control tolerances to recognition attributes. It is closed through the term-set D – a system of control tolerances. The operator v chooses from the plural V a type of a radial-basic decisive rule, and the operator u regulates the process of machine learning.

The categorical model (Fig. 1) presents an information-extreme algorithm for learning of DMSS with optimization of a system of control tolerances to recognition attributes in the form of an iterative procedure of a search for the global maximum of the information criterion (2).

$$\delta_K^{*}=\arg\max_{G_\delta}\left\{\max_{G_E\cap\{k\}}\overline{E}^{(k)}\right\}, \qquad (3)$$

where G_δ is the acceptable range of values of the parameter δ of the control tolerance field to recognition attributes.

Thus, the optimization of the system of control tolerances to recognition attributes consists in organization of a search of the global maximum of the information criterion (4) in a working (admissible) area of determination of its function in the process of machine learning. A paper [14] presents the main stages of implementation of the information-extreme algorithm (3) of DMSS learning with the parallel optimization of the system of control tolerances to recognition attributes.

We can use modified criteria of Shannon or the criteria of Kullback as an information criterion for optimization of machine learning parameters in methods of IEI-technology. They provide the same optimization results. We will use a modified Kullback measure to evaluate the functional efficiency of machine learning. For two alternative solutions with a priori probabilistic hypotheses it takes the form [12]

$$E_m^{(k)}(d)=[P_{t,m}^{(k)}(d)-P_{f,m}^{(k)}(d)]\log_2\frac{P_{t,m}^{(k)}(d)}{P_{f,m}^{(k)}(d)}=$$

$$=[D_{1,m}^{(k)}(d)-\beta_m^{(k)}(d)]\log_2\left[\frac{1+[D_{1,m}^{(k)}(d)+\beta_m^{(k)}(d)]+10^{-r}}{1-[D_{1,m}^{(k)}(d)+\beta_m^{(k)}(d)]+10^{-r}}\right], \quad (4)$$

where $P_{t,m}^{(k)}(d), P_{f,m}^{(k)}(d)$ are the full probabilities of correct and incorrect decision-making, respectively, they are calculated on the k-th step of the optimization of DMSS learning parameters; $D_{1,m}^{(k)}(d)$ is the first reliability, it characterizes the probability of a correct classification of a vector-realization of X_m^o; class; $\beta_m^{(k)}(d)$ is the mistake of a second type, it characterizes the mistaken assignment of a vector-realization of another class to X_m^o class; d is the distance measure, it determines a radius of a hyper-spherical container of X_m^o; recognition class; 10^{-r} is the sufficiently small number to be entered to avoid division into zero (r value is chosen in the interval $1<r\le 3$ in practice).

The standardized form of the criterion (4) has the form

$$E_m^{(k)}=\frac{E_m^{(k)}(d)}{E_{\max}}, \quad (5)$$

where E_{max} is the maximum value of the criterion (4) at

$$D_{1,m}^{(k)}(d)=1 \text{ and } \beta_m^{(k)}(d)=0.$$

Polymodal decisive rules constructed in a work [14] did not provide high functional efficiency of machine learning, since control tolerances changed at each learning step at the same time for all attributes of recognition. We should consider control tolerances obtained by reaching the information criterion (2) of their maximum value as quasi-optimal in this case. We can achieve improvement in the functional efficiency of machine learning through the implementation of parallel-sequential optimization of control tolerances to recognition attributes. In this case, quasi-optimal control tolerances obtained by results of parallel optimization are starting points for sequential optimization. This approach can increase both the reliability of decision making and the efficiency of the algorithm of sequential optimization, since the search for the global maximum of the information criterion takes place in a working area of its function definition only.

We will carry out a sequential optimization of control tolerances to recognition attributes in the process of machine learning in the iterative procedure of approaching of the global maximum of the information optimization criterion (4) to the limit value in the acceptable range of its function definition

$$\delta_i^*=\arg\bigotimes_{l=1}^{L}\left\{\max_{G_{\delta i}}\left[\frac{1}{M}\sum_{m=1}^{M}\max_{G_{Em}\cap\{k\}}E_m^{(l)}(d_m)\right]\right\},\quad i=\overline{1,N}, \quad (6)$$

where $G_{\delta i}$ is the area of acceptable values of the parameter δ_i of a control tolerance field for the i-th recognition attribute; L is the number of runs of the iterative procedure of sequential optimization of control tolerances to recognition attributes; $\otimes$ is the symbol of repetition of an operation.

In accordance with a Walter Ashby's principle of delayed decisions, the process of machine learning should continue until the time when decisive rules will be obtained without error in a learning matrix. For this purpose, we consider a level of selection $\rho_{m,i}, m=\overline{1,M}, i=\overline{1,N}$ of coordinates of averaged binary vector-realizations of recognition classes as one of parameters of study in frames of IEI-technology. By a level of selection in IEI-technology we mean a threshold value of frequency of finding of a recognition attribute in its field of control tolerances. A coding of coordinates of binary averaged vectors realizations of recognition is carried out in relation with a level of selection. The selection level is usually $\rho_{m,i}$=0.5 by default. The idea of optimization of such a parameter in the process of information-extreme machine learning relates to the need to implement the maximum-distance principle of pattern recognition theory. Its essence is to maximize an average center-to-center distance of recognition classes of the given alphabet $\{X_m^o\,|\,m=\overline{1,M}\}$.

Fig. 2 shows a categorical model of machine learning with polymodal decisive rules and optimization of control tolerances to recognition attributes and levels of selection of coordinates of binary averaged vectors realizations of recognition classes.

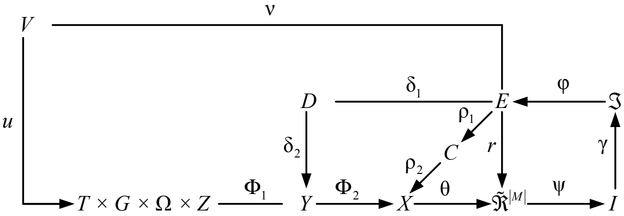


Fig. 2. Categorical model of training of DMSS with optimization of selection levels of coordinates of averaged binary vectors-realizations of recognition classes

The categorical model shown in Fig. 2 contains an additional optimization contour with a term-set C, whose elements are values of selection levels from the interval [0; 1] in comparison with the previous model (Fig. 1).

The structure of the iterative procedure of parallel optimization of a level of selection of coordinates of an averaged vector-realization of the base recognition class ρ_m, $m=\overline{1,M}$, in relation to which the system of control tolerances to recognition attributes is constructed, has the form [12]

$$\rho_m^*=<\arg\max_{G_\rho}\left\{\max_{G_\delta}\left\{\max_{G_E\cap(k)}\overline{E}^{(k)}\right\}\right\}>,\ m=\overline{1,M}, \quad (7)$$

where G_ρ is the acceptable range of values of ρ parameter.

The algorithm of sequentail optimization of the level of selection $\rho_{m,i}$ also consists of the approximation of the global maximum of the information optimization criterion to the maximum limit value in a working (acceptable) region of its function definition and has a structure

$$\{\rho_{m,i}^*\}=<\arg\bigotimes_{s=1}^{S}\left[\max_{G_{\rho_i}}\left\{\frac{1}{M}\sum_{m=1}^{M}\max_{G_E\cap(k)}E_m^{(l)}(d_m)\right\}\right]>,$$

$$i=\overline{1,N}, \quad (8)$$

where G_{ρ_i} is the range of acceptable values of $\rho_{m,i}$ parameter for the i-th recognition attribute; S is the number of runs of the iterative procedure of sequential optimization of the level of selection of coordinates of averaged binary vector-realizations of patterns; $\otimes$ is the symbol of repetition of an operation.

We structured the alphabet of recognition classes in order to improve the functional efficiency of machine learning. Recognition classes corresponded to the following functional states of the technological process: "Less than normal", "Normal" and "More than normal". Such a structuring of the alphabet of recognition classes gives possibility to switch from polymodal decisive rules to unimodal rules, which are built by parameters of enclosed containers of recognition classes with a single geometric center.

Fig. 3 shows a categorical model of machine learning with an enclosed structure of recognition class containers.

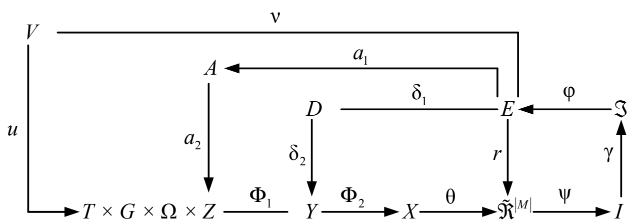


Fig. 3. A categorical model of DMSS learning with unimodal decisive rules

Categorical model shown in Fig. 3 has an additional contour. Its purpose is a sequential selection from the ordered alphabet *A* of the neighbor class for further determination of the optimal outer radius of its hyper-spherical container.

Categorical models are essentially generalized structural schemes of algorithms of information-extreme machine learning and they are widely used for resolution of problems of functional programming.

5. Results of machine learning of a decision-making support system

We carried out the implementation of the mentioned above DMSS learning algorithms for a power unit control according to the learning matrix formed on the archival data obtained at Shostkinskaya TPP (Shostka, Ukraine). The total number of recognition attributes periodically measured was 64. In this case, the ordered alphabet consisted of three classes, the classes characterized a functional state of the technological process at the input of the steam turbine. The X_1^o class "Standard" characterized a functional state, when the temperature and steam pressure corresponded to the technological regime. Accordingly, we defined X_2^o class as "Less than standard" and X_2^o class X_2^o as "More than standard".

Fig. 4 shows the graph of the dependence of the information criterion averaged by recognition classes alphabet (5) on the parameter δ of the field of control tolerances to recognition attributes. The graph was obtained during the parallel optimization process with polymodal decisive rules. A dark color shows the working (acceptable) area of the definition of the function of the criterion (4). In this area, the criterion is calculated under condition that the first authenticity assumes a value greater than 0.5, and the error of the second type is less.

An analysis of Fig. 4 shows that the maximum value of an average standardized criterion (5) in the working area is equal $\overline{E}=0{,}35.$ An optimal value of the parameter δ was selected by the lowest averaged coefficient of fuzzy compactness of realizations of recognition classes [12] since the maximum values of the criterion belong to the area of a plateau type:

$$\eta=\frac{1}{M}\sum_{m=1}^{M}\frac{d_m^*}{d(x_m\oplus x_{c,m})}, \quad (9)$$

where d_m^* is the optimal radius of a container of X_m^o; class; $d(x_m^*\oplus x_{m,c})$ is the code distance between the optimal vector x_m^* and the averaged vector-realization of the recognition class X_c^o, closest to X_m^o class.

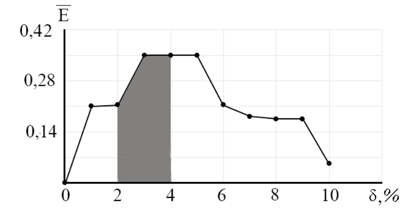


Fig. 4. Graph of dependence of the information criterion on the parameter of the field of control tolerances to attributes of recognition

In the process of machine learning, we obtained a minimum value of expression (9) at the quasi-optimal parameter of a field of control tolerances $\delta=\pm 3\,\%$ from a nominal value of recognition attributes.

We implemented an algorithm (6) for sequential optimization of control tolerances to recognition attributes to improve the functional efficiency of machine learning. We took the quasi-optimal value of the field parameter of tolerance obtained from the results of parallel optimization as a starting point for the sequential optimization algorithm.

Fig. 5 shows a chart of the change of the standardized criterion (5) from the number of learning steps with sequent optimization of control tolerances to recognition attributes.

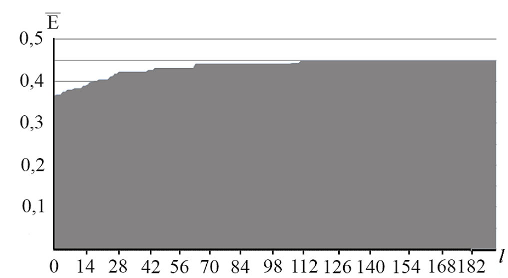


Fig. 5. Chart of information criterion change in case of consistent optimization of control tolerances to recognition attributes

An analysis of Fig. 5 shows that we obtain the maximum value of the average information optimization criterion, which exceeds the value obtained during the implementation of the parallel optimization algorithm at the second run of the sequential optimization algorithm. At the same time, each run consisted of 64 learning steps, in which an iterative search for an optimal field of control tolerances to all recognition attributes was carried out.

Fig. 6 shows charts of dependence of the information criterion (4) on the radii of recognition class containers, obtained during the process of sequent optimization of the control tolerances to recognition attributes.

An analysis of Fig. 6 shows that the optimal value of the radius of the container of the recognition class X_1^o is $d_1^*=24$

(here and below in code units) and accordingly for the class – X_2^o – $d_2^* = 34$ and the class – X_3^o – $d_3^* = 26$.

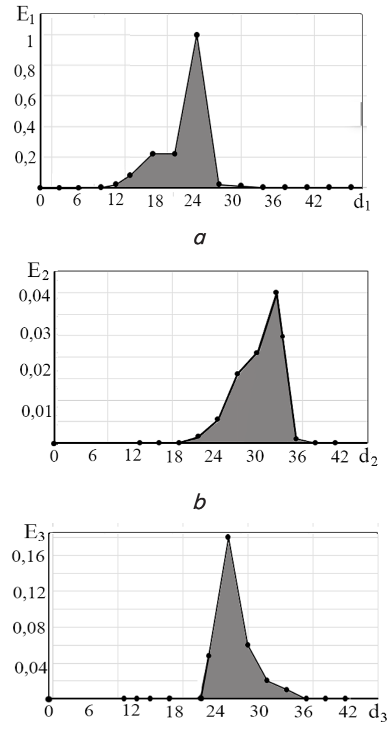


Fig. 6. Charts of dependence of the information criterion on the radii of containers of recognition classes: *a* – class X_1^o; *b* – class X_2^o; c – class X_3^o

It was not possible to construct decisive rules based on error free learning matrix with the use of the results of parallel-sequential optimization of control tolerances to recognition signs. Therefore, according to the principle of delayed solutions, we additionally implemented the algorithm of parallel optimization of a level of selection of coordinates of average binary vector-realizations of recognition classes according to the procedure (7).

Fig. 7 shows a fragment of the chart of dependence of the averaged standardized information criterion (5) on ρ level of selection of coordinates of averaged binary vector-realizations of recognition classes.

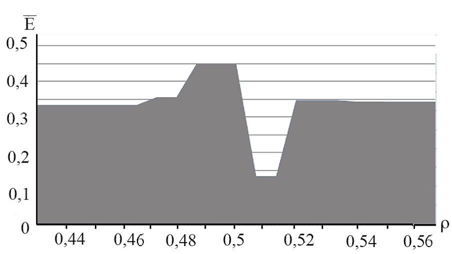
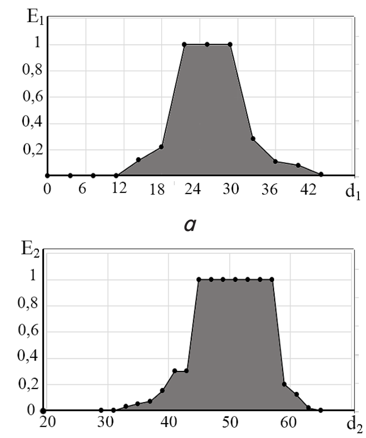


Fig. 7. Chart of dependence of the information criterion on ρ parameter

A chart analysis in Fig. 7 shows that the value of the parameter $\rho = 0{,}5$ taken during the formation of an input of learning matrix belongs to sets of its optimal values, and therefore the maximum value of the information criterion in the process of its optimization remains unchanged.

Thus, the machine learning of DMSS of the control of a power unit of a thermal and power plant did not give possibility to achieve its high functional efficiency due to a substantial intersection in a space of attributes of recognition classes. According to the principle of delayed solutions, increase in the functional efficiency of machine learning is achieved by increasing the depth of machine learning, including the optimization of parameters of the formation of an input mathematical description of DMSS. But in practice this way does not always makes possible to construct decisive rules, which are error-free by a learning matrix. Therefore, we carried out a transition from the polymodal classifier to the unimodal class with enclosed structure of containers of recognition classes.

Fig. 8 shows charts of dependence of the information criterion (4) on the radii of enclosed containers of recognition classes obtained by machine learning with the parallel optimization of control tolerances.



b

Fig. 8. Charts of dependence of the information criteria on radii of containers of recognition classes: *a* – class X_1^o; *b* – class X_2^o

An analysis of Fig. 8 shows that the optimal external radii of the enclosed containers of recognition classes, taking into account the expression (9), are: for the class – X_1^o – $d_1^* = 22$ and for the class – X_2^o – $d_2^* = 44$. And it is possible to construct decisive rules, which are by error-free by a learning matrix, since the average information optimization criterion reaches its maximum limit value $\overline{E} = 1$.

6. Discussion of results of studying machine learning of a decision-making support system

The proposed method of information synthesis of a decision-making support system, which is able to learn, for the control of a power unit of a heat power plant is realized in the framework of IEI-technology of data analysis. Such an approach takes precedence over other methods of data analysis, since it gives opportunity to construct decisive rules, which are error-free by a learning matrix, under condition of substantial intersection of recognition classes in a space of attributes. A use for optimization of learning parameters of the modified Kullbak information criterion contributes to this significantly. The peculiarity of mentioned criterion is the fact that it is a functional of precise characteristics. Precise characteristics, in turn, depend on geometric parameters of containers of recognition classes. Thus, we can state that the information criterion of the optimization of machine learning parameters is a generalized measure of similarity of patterns.

In addition, we transformed an input learning matrix into a binary learning matrix in the proposed method. And this made possible to adapt the incoming mathematical description of DMSS to the maximum functional efficiency of machine learning. We applied a deep machine learning with optimization of the system of control tolerances to recognition attributes and levels of selection of coordinates of binary averaged vectors realizations, since recognition classes substantially intersected in a space of attributes. At the same time, we implemented the information-extreme algorithm of machine learning with polymodal decisive rules. Analysis of the obtained graphs of the dependence of the information criterion of optimization on parameters of machine learning (Fig. 4–7) showed that the constructed polymodal decisive rules have low functional efficiency. We implemented an information-extreme algorithm of machine learning with unimodal decisive rules after the ordering of the alphabet of recognition classes by a magnitude of deviation of a functional state of the technological process from the standard regime. Analysis of the graphs of the dependence of the information criterion (4) on a magnitude of external radii of enclosed containers of recognition classes showed that it is possible to construct decisive rules, which are error-free by a learning matrix, in this case. In addition, the use of the unimodal classifier increases the efficiency of machine learning, since it is no longer necessary to determine the closest neighbor for a recognition class and it is not necessary to determine a radius of an outer class recognition container.

Thus, the use of unimodal decisive rules in the framework of IEI-technology can increase the functional efficiency and reduce the calculating work content of machine learning if to compare with the use of polymodal decisive rules. The scope of application of unimodal decisive rules is controlled technological processes with a magnitude of deviation from the standard mode by functional states.

For the sake of clearness we considered an example of the implementation of the proposed method of machine learning for three recognition classes in the study. In practice, it is advisable to structure an alphabet of recognition classes of greater power. This will increase the accuracy of control and thus reduce energy costs. At the same time, the expansion of an alphabet will reduce areas of recognition classes in a space of attributes. The consequence of this will be a decrease in the reliability of decisive rules. Therefore, further study should be directed to the introduction of redundancy of a binary learning matrix by methods of maladaptive encoding, which will expand a space of attributes and increase radii of enclosed classes of recognition classes.

7. Conclusions

1. We proposed a method of deep machine learning of DMSS to control a power unit of a thermal power plant in the framework of IEI-technology of data analysis. At the same time, we carried out the optimization of the system of control tolerances to recognition attributes and levels of selection of coordinates of averaged vectors-realizations of recognition classes in the process of machine learning. It made possible to construct decisive rules, which are error-free by a learning matrix.

2. Machine learning of DMSS with polymodal decisive rules did not make possible to obtain high functional efficiency due to a priori high degree of intersection in a space of attributes of recognition classes.

3. Machine learning of DMSS with unimodal decisive rules makes possible to build decisive rules, which are error-free by a learning matrix, and to reduce the calculation complexity of the learning algorithm in comparison with polymodal decisive rules.

4. Analysis of the obtained results showed that the area of application of unimodal decisive rules is controlled technology processes with a magnitude of deviation from the standard mode by functional states.

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Роботу присвячено дослідженню ефективності класифікатора на основі імовірнісної нейронної мережі для багатокласової діагностики об'єкта за наявності багатоосередкового пошкодження. Використано багатовимірний вектор діагностичних ознак, що містить 5 елементів. Сформовано множини навчальних та тестових вхідних векторів, виконано навчання та тестування класифікатора. Проаналізовано ефективність багатокласового розпізнавання в залежності від характеристик класифікатора та множини навчальних векторів

Ключові слова: багатокласове розпізнавання, нейромережевий класифікатор, вектор діагностичних ознак, імовірність правильної класифікації

Работа посвящена исследованию эффективности классификатора на основе вероятностной нейронной сети для многоклассовой диагностики объекта при наличии многоочагового повреждения. Использован многомерный вектор диагностических признаков, содержащий 5 элементов. Сформированы множества учебных и тестовых входных векторов, выполнено обучение и тестирование классификатора. Проанализирована эффективность многоклассового распознавания в зависимости от характеристик классификатора и множества обучающих векторов

Ключевые слова: многоклассовое распознавание, нейросетевой классификатор, вектор диагностических признаков, вероятность правильной классификации

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MULTI-CLASS RECOGNITION OF OBJECTS TECHNICAL CONDITION BY CLASSIFIER BASED ON PROBABILISTIC NEURAL NETWORK

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1. Introduction

Ensuring the reliability and efficiency of operation of complex spatial objects is a topical issue in the aviation, power, oil and gas indries, as well as for special-purpose engineering structures. In general, such objects are characterized by large dimensions, non-stationarity of processes, distribution of parameters, nonlinearity, incomparteness of control of external factors, conditions and modes of functioning. Design of structural elements of such objects is based on the principle of safe damage, which allows for a microdefect, but such that does not lead to efficiency loss and object destruction [1–3]. However, the presence of welded or rivet joints of structural elements of complex spatial objects poses a threat of the emergence and development of multi-site damages. This may lead to destruction characterized by a sudden and rapid propagation due to combining among themselves and absorbing small-size cracks. Such a nature of damage development, difficult operating conditions, limited information about the actual technical condition lead to the multi-classing of objects in both time and space. In order to ensure safe and effective operation of such objects, it is necessary to provide multi-class diagnostics for timely detection of damage, assessment of its extent, monitoring of its development and interaction on large-sized surfaces of complex spatial objects. This will contribute to ensuring the reliability and efficiency of operation, preventing the destruction of complex spatial objects and averting catastrophic consequences.

2. Literature review and problem statement

Continuous monitoring of the technical condition (TC) of structures in operation, development control of damage, operational loads can be implemented in monitoring systems based on the concept of Structural Health Monitoring