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MULTIFACTORAL FORECAST OF ELECTRICAL ENGINEERING COMPLEXES OF COAL MINES CONSUMPTION FOR PLANNING THEIR ENERGY EFFICIENT MODES

The paper considers the solution of urgent scientific-applied problem of planning energy efficient modes of electrical engineering complexes of coal mines as a result of development and improvement of mathematical models and methods of multifactoral forecast of their energy consumption, taking into account technological characteristics.

Key words: *energy efficient modes planning, electric energy consumption, electrical engineering complex, coal mines, neural networks, multilayer perceptron.*

Introduction

Nowadays the state of Ukrainian economy is characterized by the deformed structure of production, considerable share in it occupy technologies of power-intensive and material consuming types of production [1], that is why the problems of increasing the efficiency of industrial complexes can be solved only by means of considerable reduction of energy expenses per unit of output. Energy consuming structure of industrial production, critical dependence of fuel-and energy complex on energy sources supply from Russia, high level of wear of basic production assets and low level of ecological security of enterprises stipulate urgent necessity of medium-term and long-term planning and forecast of energy consumption volumes [1, 2].

The important branch of fuel and energy complex (FEC) of Ukraine is coal industry. The importance of its functioning is stipulated by the fact that coal is the only energy source, produced in Ukraine, and it can provide energy security and meet the existing needs at the expense of own resources [3].

To provide profitability of coal industry it is necessary to introduce energy saving technologies and improve the efficiency of electric energy usage by electrical engineering complexes of coal mines that will reduce the cost of coal mining and increase its quality [4].

Due to structural reforms of Ukrainian economy the role of long term planning of production systems development i. e. scientifically substantiated forecasts will grow [5]. Main functions of the forecast are identification and analysis of regularities and tendencies of electric energy consumption; evaluation of the impact of these tendencies in future; assumption of situations, requiring solution; identification of possible alternatives of the development; accumulation of the information for substantiated choice of the direction of optimal planned solutions.

Without the forecast the efficient long-term planning of electric energy consumption is impossible, because the planning must be performed, taking into account rates and proportions of the development, determined for prospects.

During development of the forecasts and long-term plans of energy consumptions the uncertainty factor must be taken into account, stipulated by the fact that energy economic processes are influenced by many factors. That is why, there is no full coincidence of the set aim and final results.

Hence, the solution of the problem of coal industry of Ukraine profitability requires the development of new organization methodical support, further improvement of the system of planning and monitoring of energy consumption by electrical engineering complexes of coal mines, as a result the transition to efficient energy consumption will become possible. The paper considers the problem of improvement of mathematical models and methods of multifactoral forecast of coal mines energy consumption for the solution of the problem of their energy efficient modes planning.

Classification of electrical engineering complexes of coal mines by their energy usage efficiency

Energy efficiency of production – is one of main components of general efficiency (first of all, economic efficiency, that is stipulated by prices growth for energy sources).

The evaluation of the efficiency of the whole coal mining branch, of separate coal enterprise, of production processes is very important and necessary task as it enables to reveal reserves of efficiency increase of enterprises operation. The index, characterizing the efficiency of electric energy usage is its specific consumption. Operation efficiency of any production system in greater part of cases is determined by the state of its energy facilities, as energy resources occupy considerable share in the cost of any production of industrial enterprise [5].

Control values of specific consumption of electric energy are determined on the whole for separate coal association. Taking into account the fact that coal mines operate in different mining geological conditions, have different equipment, etc, it is expedient to identify homogeneous classes of objects, for which indices of the efficiency of electric energy consumption are determined.

In case of coal mines, mining-geological conditions, influencing mines operation, should be taken into account. The problem of classification of electric engineering complexes of coal mines by the degree of homogeneity can be solved applying Chekanovskiy methods [7] and cluster analysis [8].

Mathematical statement of the problem. Let the sample of preprocessed data vectors $\{x_p\}$ be set. Space of data vectors is denoted by E . Certain nucleus a will correspond to each class. The space of nuclei is denoted by A . For each $x \in E$ and $a \in A$ the degree of proximity $d(x, a)$ is determined. For each set of k nuclei a_1, \dots, a_k and any division $\{x_p\} = P_1 \cup P_2 \cup \dots \cup P_k$ into k classes quality criterion is determined [7]:

$$D = D(a_1, a_2, \dots, a_k, P_1, P_2, \dots, P_k) = \sum_{i=1}^k \sum_{x \in P_i} d(x, a_i). \quad (1)$$

We are to find the set a_1, \dots, a_k and division $\{x_p\}$, which minimize D .

At each step and stage of the algorithm quality criterion D decreases, the convergence of algorithm follows from here – after finite number of division steps $\{x_p\}$ it does not change.

As technological parameters, which considerably influence the level of energy efficiency of coal mining enterprises, the following ones were chosen: X_1 – annual volume of mineral resources mining, t; X_2 – annual level of development workings realization, m; X_3 – average dynamic thickness of mineral resources seam, m; X_4 – average annual water inflow in the mine, m³/h; X_5 – average number of production staff, men; X_6 – depth of seam occurrence, m; X_7 – number of mined coal seams, p-es; X_8 – gas saturation of seams, m³/t; X_9 – installed power of main mine equipment (MME), kW.

Method provides the realization of the following stages:

Stage 1. Formation of observations matrix.

Having the set of m elements, which are described by n signs, each unit can be interpreted as a point of m – dimensional space, with coordinates, equal to values of n signs of the considered object. Observation matrix has the following form:

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1k} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2k} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_{i1} & x_{i2} & \dots & x_{ik} & \dots & x_{in} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mk} & \dots & x_{mn} \end{bmatrix}, \quad (2)$$

where m – number of mines; n – number of technological parameters; x_{ik} – value of k sign for unit i .

Table 1

Example of the aggregate of annual technological parameters for coal mines

Serial number of the mine	Electric energy consumption, kWh.	Technological parameters								
		Annual volume of mineral resources mining, t	Execution of development workings, m	Average dynamic thickness of a seam, m	Average annual water inflow, m ³ /h	Average number of employees, men	Depth of mineral resources occurrence, m	Number of coal seams, pieces	Gas saturation of seams, m ³ /t	Installed power of main mine equipment, kW
1	2	3	4	5	6	7	8	9	10	11
1	14201712	47022	537	1.28	142	728	370	2	11.4	492
2	9434076	121105	1891	1.14	243	828	380	1	4.7	382
...										
13	16730100	452800	2601	1.18	31.98	1145	495	2	4.6	550

Stage 2. For values, included in observation matrix, it is necessary to perform the normalization of signs, as they are non uniform. Standardization of signs is performed by the expressions:

$$z_{ik} = \frac{x_{ik} - \bar{x}_k}{s_k}, \quad (3)$$

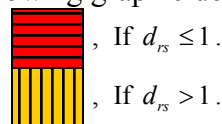
$$\text{and } \bar{x}_k = \frac{1}{m} \sum_{i=1}^m x_{ik}; s_k = \sqrt{\left[\frac{1}{m} \sum_{i=1}^m (x_{ik} - \bar{x}_k)^2 \right]},$$

where $k = 1, 2, \dots, n$; x_{ik} – value of sign k for unit i ; \bar{x}_k – arithmetic mean of sign k values; s_k – standard deviation of k sign for unit i .

Stage 3. Calculation of elements of distances matrix with the account of all elements of observation matrix by the expression:

$$d_{rs} = \frac{1}{n} \sum_{k=1}^n |z_{rk} - z_{sk}| \quad (r, s = 1, 2, \dots, m). \quad (4)$$

Stage 4. The next stage is presentation of distances matrix in graphical form. Two classes of objects are allocated, they have the following graphic designations:



Introduction of corresponding graphic symbols into distances matrix enables to obtain non-ordered diagram of Checranovskiy. To reveal the groups of uniform objects it is necessary to perform permutation of columns and rows. The process of rows and corresponding columns transport is realized to the moment of obtaining ordered diagram (Table 2), where concentration of signs, corresponding to the least distances, are located along main diagonal.

Table 2

Ordered Chekanovskiy diagram

Number of the mine	Number of the mine												
	1	3	10	4	11	2	9	12	5	6	7	8	13
1													
3													
10													
...													
5													
6													
7													
8													
13													

Proceeding from the results of the analysis (Table 2) four classes of coal mines can be distinguished: first class – 1, 3, 10; second – 4, 11; third – 2, 9, 12; fourth – 5, 6, 7, 8, 13. It should be noted, that the application of this method does not require complex mathematical procedures. Objects, in case of small volumes of information can be easily classified, that enables to apply the method for prior classification of energy objects.

Neural networking modeling of electrical engineering complexes of coal mines electric energy consumption on the basis of non ordered set of initial data

For efficient forecast of energy consumption by large electrical engineering complexes obligatory condition is registration of relations between consumption of electric energy and basic technological factors [5]. Hence, the construction of artificial neural network (ANN) must be realized, taking into consideration the set of information technological parameters.

Let technological parameters of coal mine and annual output of mineral resources be set by the vector of parameters $x^s \in X$, that has N_l components. Components are designated by the low index: $x^s = (x_1^s, \dots, x_{N_l}^s)^T$. The solution of the problem will be the set of vectors $\{y^1 \dots y^S\}$ of energy consumption. Each vector y^s has N_0 components; $y^s = f(x^s)$, where $s = 1 \dots S$ – number of the image. Neural network forms representation $X \rightarrow Y$ for $\forall x \in X$, that is representation of random number of points:

$$\begin{bmatrix} x^1 \rightarrow y^1 \\ \dots \\ x^S \rightarrow y^S \end{bmatrix}, \quad (5)$$

where the set of vectors $x^1 \dots x^S$ – formal condition of the problem, and set $y^1 \dots y^S$ – formalized solution.

Neural networking modeling was carried out, using data of energy consumption of 13 mines of State Enterprise «Volynvugilla» and State Enterprise «Lvivvugilla» during the period of 6 years (2009 – 2013). Technological parameters, influencing the energy consumption of the mines were sent to the input (Table 1), values of these parameters are registered for the same period of time.

Before the beginning of the forecast the procedure of data scaling, using the package *STATISTICA Neural Networks* [9] of minimax function was performed: it finds minimal and maximal

values of variable by trained set and performs linear transformation (using coefficients of scale and shift), in such a way that values were within the range $[-1,1]$. Recalculation of signs values x for i^{th} for example in the interval $[a, b]$ was realized according to the expression [9]:

$$\tilde{x}_i = \frac{(x_i - x_{\min}) \cdot (b - a)}{(x_{\max} - x_{\min})} + a, \quad (6)$$

where x_{\min}, x_{\max} – minimal and maximal optional value of the sign.

As forecast model multilayer perceptron was chosen, it has the following architecture: $N_i - N_j - N_k$, where $N_i = 9$ – number of neurons in the input layer; $N_j = 10$ – number of neurons in the hidden layer; $N_k = 1$ – number of neurons in the output layer (Fig. 1).

Functioning of neuron for output layer is determined by the relation [10]:

$$y_k^{(2)}(t) = \varphi \left(\sum_{l=1}^j w_{lk}^{(2)}(t) y_l^{(1)}(t) + b_k^{(2)} \right), \quad (7)$$

where $w_{lk}^{(2)}$ – bond weight of the l^{th} output of hidden layer neuron with k^{th} neuron of the output layer; $b_k^{(2)}$ – threshold of k^{th} neuron of the output layer; $\varphi(\bullet)$ – function of neuron activation.

As activation function for all the layers sigma function was chosen:

$$\varphi(y^{(L)}(t)) = \frac{1}{1 + \exp(-ay^{(L)}(t))}, \quad (8)$$

where a – parameter of sigma function slope.

Training of neural network is reduced to minimization of root-mean-square error. Adjustment of weights $w_{ij}^{(1)}$ and $w_{jk}^{(2)}$ is performed after sending on the neuron each example (serial mode of teaching). Adjustment of the weights of L layer is realized in accordance with the expression [10]:

$$w_{ij}^{(L)}(t+1) = \alpha w_{ij}^{(L)}(t) + \eta \delta_j^{(L)}(t) y_j^{(L)}(t), \quad (9)$$

where η – parameter, responsible of training rate; α – constant of the moment ($\alpha = 1$); $\delta_j^{(L)}$ – local gradient of j^{th} neuron of L layer.

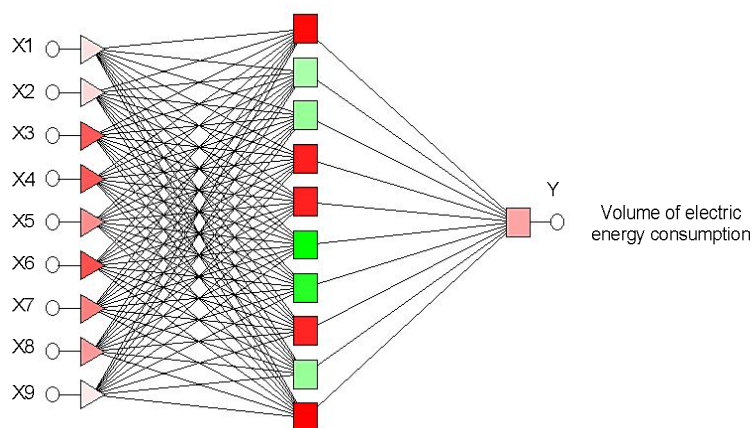


Fig. 1. Architecture of neural network

Local gradient for output layer:

$$\delta_k^{(2)}(t) = e_k(t), \quad (10)$$

where $e_k(t)$ – error of k^{th} neuron of the output layer, and for hidden layer:

$$\delta_j^{(1)}(t) = \sum_{l=1}^k \delta_l^{(2)}(t) w_{jl}^{(2)}(t) y_j^{(1)}(t). \quad (11)$$

Training of neural network was realized in two stages: the first stage – by the algorithm of back propagation of the error (100 iterations), the second stage – by the method of conjugate gradients (360 iterations). Control error was 3.06%, and training error – 3.89%.

The results of the forecast of electrical engineering complexes of coal mines energy consumption by neural network are shown in Table 3.

Analyzing data of the Table 3 it can be stated, that the chosen neural network provides sufficient adequacy of electric energy can consumption at the mine (average relative forecast error in 2013 was 3.5%).

Table 3

Results of the forecast for 2013

Number of the mine	Name of the mine	AEC, kWh	FEC, kWh	Relative error, %
1	Mine №1 N.V.	14201712	14732066	3,6
2	«BVUZHANSKA»	9434076	9522435	1,6
3	Mine №5 N.V.	4907198	5038191	2,6
4	Mine №9 N.V.	10298560	11133578	7,5
5	«VELYKOMOSTVSKA»	11750028	12447064	5,6
6	«BENDYUZKA»	11689227	11807300	1,0
7	«MEZHYRYCHANSKA»	17094030	18360934	6,9
8	«Vidrodzhenia»	17176641	17350142	1,0
9	«LYSOVA»	22264800	23535729	5,4
10	«ZARICHNA»	16099488	16683407	3,5
11	«VYZEISKA»	17729496	18821121	5,8
12	«STEPOVA»	42022410	42220848	0,47
13	«Chervonogradska»	16730100	16933300	1,2

Note: AEC – actual energy consumption; FEC – forecast energy consumption.

On condition of available plan of coal mining and other technological parameters, multifactoral model of electric energy consumption, obtained on the base of ANN is adequate and acceptable for annual planning of electric energy consumption for each coal mine and coal enterprise. But for improvement of the forecast model quality prior classification of coal mines by means of cluster analysis method, taking into account technological parameters, influencing the level of their energy efficiency should be done.

Neural networking modeling of electrical engineering complexes of coal mines energy consumption on the basis of ordered set of initial data

Neural networks can be adapted to changing environment. Improvement of system adaptability, provides its stability in non-stationary environment. To take use of the advantages of adaptability, main parameters of the system must be rather stable, not take into account external noise, and rather flexible, to provide the reaction on important changes of the environment.

To provide adaptability of the suggested forecast model, exhaustive search of neural networking configuration list and choice of the best by the criteria of error minimum at the output of the network and maximum of its performance was carried out.

At each step of training algorithm the error for the whole set of observations from the control set was calculated and compared with the error at training set. As a rule, the error at the control set exceeds the error at training set, but not the fact of difference is important, but the trend of error change.

Test set was used after completion of training for calculation of the performance of the obtained network and its error on new data. Quality network has the same low error on all three subsets.

For each of four classes of coal mines, allocated on the basis of prior classification, the best models of neural networks were constructed and chosen by means of *STATISTICA Neural Networks*.

The choice of the best architecture of neural network for the forecast of annual electric energy consumption of electrical engineering complexes of Lviv-Volyn coal field coal mines for each of the classes, is shown in Fig. 2 – 5.

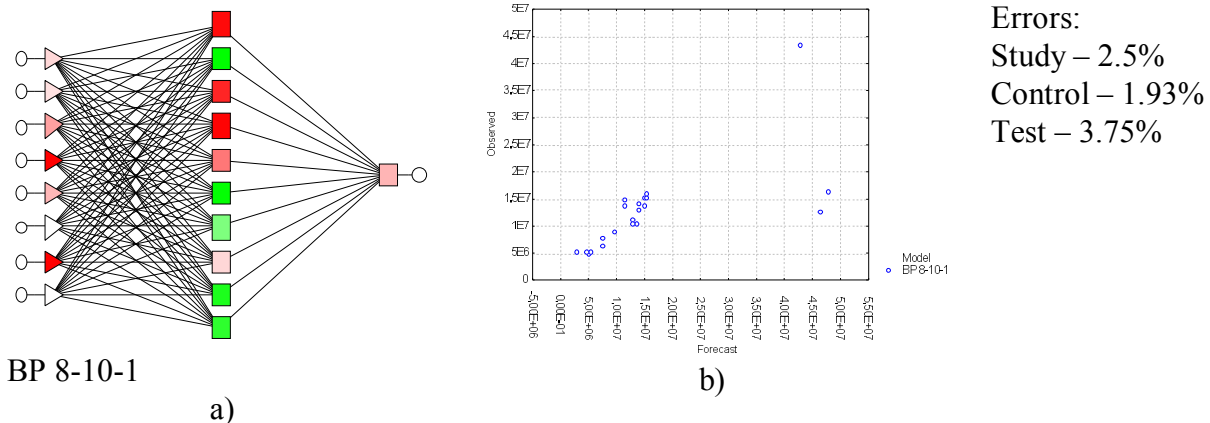


Fig. 2. Architecture of neural network for the forecast of electric energy consumption at coal mines of the 1st class
a) structure and type of ANN; b) graph of the forecast values dependence on real values

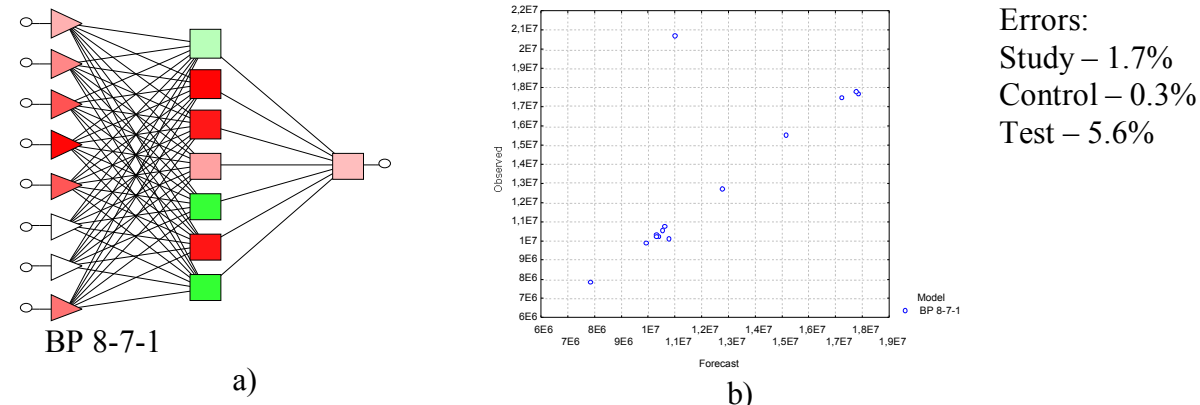


Fig. 3. Architecture of neural network for the forecast of electric energy consumption at coal mines of the 2nd class
a) structure and type of ANN; b) graph of the forecast values dependence on real values

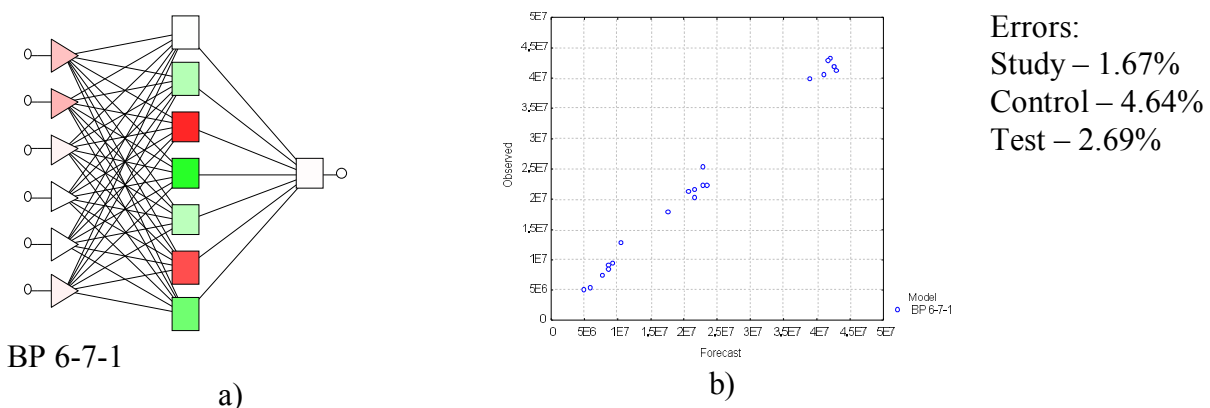


Fig. 4. Architecture of neural network for the forecast of electric energy consumption at coal mines of the 3rd class
a) structure and type of ANN; b) graph of the forecast values dependence on real values

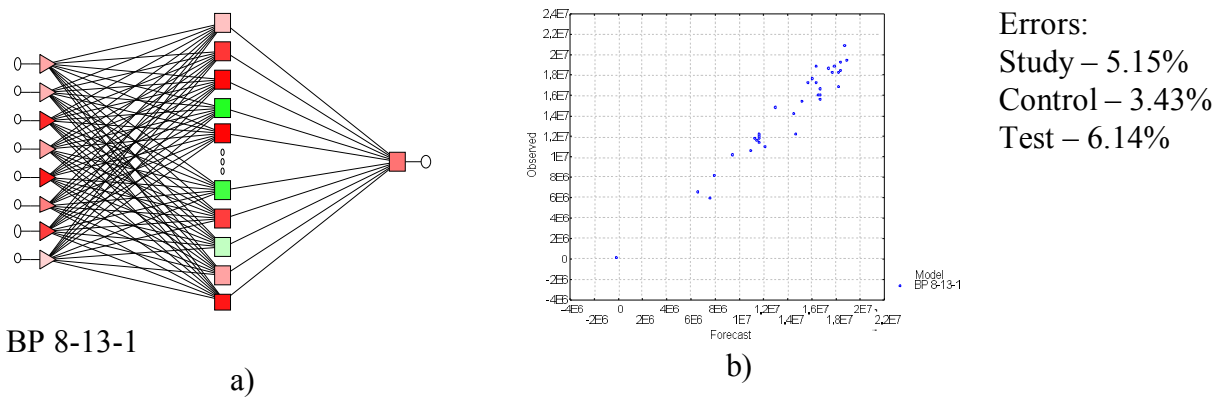


Fig. 5. Architecture of neural network for the forecast of electric energy consumption at coal mines of the 4st class
 a) structure and type of ANN; b) graph of the forecast values dependence on real values

As it is seen from Fig. 2 – 5, the forecast quality of coal mines electric energy consumption improved due to division of coal mines into uniform classes and choice of corresponding configurations of neural networks for separate classes of electrical engineering complexes.

Conclusions

1. The efficiency of energy consumption by electrical engineering complexes of coal mines depends on the number of factors, among these factors we can distinguish economical, technical and technological groups of factors. It is shown that the evaluation of the degree of influence of these factors on the efficiency of energy consumption must be done by means of expert-statistical classification procedure.

2. Forecast of annual energy consumption of coal mines on the basis of non-ordered set of initial data by means of artificial neural networks showed that to provide the necessary accuracy it is necessary to perform prior division of electrical engineering complexes of coal mines into uniform classes, according to energy efficiency and technological parameters. To improve the quality of the forecast model it is necessary to select its architecture separately for each class.

3. Modeling of annual energy consumption of coal mines on the base of ordered system of objects and sets of initial data by means of artificial neural networks to allowed to obtain the forecast error on the level of 3 – 4 %.

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