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DEVELOPMENT OF NEURAL NETWORK MODEL OF THE MULTIPARAMETRIC TECHNOLOGICAL OBJECT

Y. I. Eremenko*, D. A. Poleshchenko, Y. A. Tsygankov

Starooskolsky Technological Institute named after A.A. Ugarov (branch) FSAEI of Higher Education "National University of Science and Technology "MISiS", Stary Oskol

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ABSTRACT

At present, there are a large number of methods for identifying the technological objects on the basis of data of their industrial operation [1-3]. The most promising direction is the construction of a model, which will allow to take into account the multifactorial nature of the object, and the nonlinearity of interrelation between variables. This will make it possible to control the object, taking into account the change in its states, and based on the current data,to predict the change in the output value with different input characteristics[4-6]. All this will provide the opportunity to create an operating system, based on the currently measured technological indicators. In order to implement this approach, a comparative study of the regression analysis models, using polynomials of various types and neural network algorithms, for the synthesis of a complex technological unit model, was carried out in the work. In the regression analysis, the following models were investigated: polynomials, linear, fractional and exponential functions, Kolmogorov-Gabor polynomial. In the process of the research of neural networks to solve this problem, their structure was varied, with subsequent learning according to the Levenberg-Marcardt algorithm. In the process of simulation of the object models in the Matlab package, the degree of similarity of the outputs for each of the obtained models and the actual output of the object were estimated. Quadratic criterion and the coefficient of correlation were calculated, that made it possible to judge the accuracy of the constructed models. The best structure of the model was established for identifying a complex multiparameter object, using the example of statistics for the operation of a ball mill.

Author Correspondence, e-mail: author@gmail.com

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It was a network with three hidden layers and 50, 35 and 25 neurons in them, with activation functions, respectively by layers - hyperbolic tangent, sigmoid function in 2 layers, and a linear activation function in the output layer. The vector, including 15 parameters, was supplied to the network input: the volume of ore supply to the mill, the volume of water supply to the mill and the mill'strommel, the signals with the first-, the second-, and the third-order lags, and the signal of current with the first-, the second-, and the third-order lags. This approach to identification has increased the accuracy of the object model, that ultimately will affect the quality of the developed control system of the unit as a whole, allowing to improve the quality of the ball millcontrol.

Description of the problem

At present, in view of the prevailing economic situation and increasing market competition, the issue of improving the efficiency of equipment raises increasingly at the enterprises, in order to reduce production costs and to increase profits. However, in most industries, automation solutions of the control area of certain technological process parameters, as a rule, have been already implemented on the basis of PI- and PID- regulators. And serious technological changes, which can increase the profitability of the process, have high cost requirements and, often, the need for a significant change in the technological process, entailing the requirements for retraining of personnel [7].

In view of this, the aspect of the operation of automation systems, which can be modified with the aim to improve economic indicators, is their algorithmic support. There are many approaches to improving the quality of managed processes, when changing the program side of control systems [8]. The APC-systems (Advanced Process Control) have been actively introduced at enterprises in recent years. The idea is to predict the future course of technological process and to select such management actions, which will ensure better value of the given quality criterion for the object functioning, while satisfaction of technical and economic constraints [7,9]. This idea is not new and, in fact, is a kind of MPC (Model Predictive Control–forecasting control, based on the model). The founders of this direction are domestic scientists, and the first works were published in the 1970s and 1980s [10]. The world leaders in the field of automation, such as Honeywell, Schneider Electric and others, have evaluated the advantages of systems, based on this functionality and created proprietary software products, which were actively implemented around the world [11,12].

The bases of these systems are models, built on the regression analysis, which cannot fully approximate the real nonlinear properties of the object. In the presence of qualitative model, the system successfully acts as a multiparameter controller, or a structure is created from several lower-level controllers for each particular process or unit, functioning according to the abovementioned principles, and one "main" controller. The system can manage the process either directly, or through affecting the existing PID loops, in case of their appropriate adjustment [9,11,12]. This circumstance is a serious advantage, since it allows avoiding serious technical modernization, and, accordingly, expenses. However, this requirement introduces additional conditions for the quality of operation of the initial regulators and the field level of the automatic process control system.

The aspect of scientific novelty in the systems of this type is the introduction of virtual analyzers. Virtual analyzer – is a "sensor", modeled on the basis of retrospective statistical data, which, in essence, is a model, based on regression analysis methods with the help of linear and nonlinear dependencies or neural networks (NN), and allows real-time evaluation of the future change in selected parameter [7,9]. This approach is applied to such technological parameters, the measurement of which is difficult, impossible, or done only on the basis of laboratory analysis, but they represent important indicators of the facility's quality. The presence of such functionality allows the operator in real time to track the change in important process parameters, in case of changes in operation, even if the actual change occurs after a long period of time or is not available to the operator at all.

In this paper, the possibility of identifying a complex process unit, based on neural network algorithms was investigated. Neural network algorithms, having the ability to detect hidden and approximate nonlinear dependencies, due to the nonlinear activation functions in layers, should improve the quality of modeling, in comparison with regression models. In this paper, a ball mill is used as an object of the research. The model of the mill is developed with a view to the subsequent solution of the problem of creation of the effective control system.

Description of the research object

The rotator ball mill is a hollow cylindrical drum, closed with end bells, filled with a certain number of tumbling bodies, and rotating around a horizontal axis. When the drum rotates, the tumbling bodies are dragged by the inner surface of the drum, due to the friction, and are raised to a certain height. Then they fall freely or roll down.

In a continuously operating mill, the mill charge is fed through a central hole in one of the end bells inside the drum and, due to the water supply into the same hole, moving along it, it is subjected to the action of tumbling bodies. In this case, the milling of the material is performed by the impact of the falling tumbling bodies, abrasion and crushing between the bodies. In ball mills, the tumbling medium is made up of steel or cast iron balls,having the same size or different. Discharging of the milled material occurs in the double-helix classifier, by free rundown through the hollow discharge spout, therefore the pulp level in the mill is slightly higher, than the lower surface generator of the discharge spout hole, since its diameter is much smaller than the diameter of the drum.Spiral classifier 2KCH-30 with non-immersed spiral is designed for wet separation of solid material onto granular residues, with particle sizes not more than 25 mm, and overflow, containing fine suspended particles. The classification process in the spiral classifiers is carried out in a moving flow of water. The pulp is fed into the precipitation compartment of the classifier, located in its lower part, through the branch pipe. Slowly rotating spirals perform the necessary mixing of pulp. The fine particles of the product in the form of overflow are discharged through the lower end of the classifier. The larger material (granular residues) settles on the bottom of the body, are picked up by the spirals and discharged at the top of the classifier. Further, the granular residues are passed to the mill. The mill processes the entire flow of the material, while more than 50% of energy, consumed by the concentrator, is used for the mill process. And due to the wide use of mills in various industries, about 3-4% of the world's electric energy is consumed at the milling stages. [1] The problem is that the ball mill is a multiparameter object, whose output is affected by several input influences. Taking into account this fact, the input channels with the greatest impact on the output parameter of the object were selected. The output parameter was the current in the classifier spiral. In the study, various data samples were analyzed, for which regression analysis was performed to select the coefficients of polynomials of various kinds. Taking into account the above-mentioned reasons, it can be said, that the task of developing a system, which will allow to manage a ball mill in the most energy efficient mode, while preservation of quality of the output product, is quite relevant for enterprises.

Identification, using regression analysis

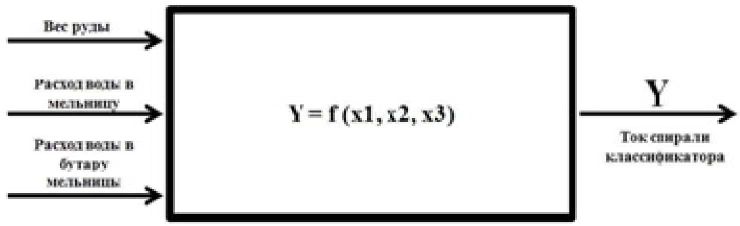
The work was carried out on the identification of a ball mill, based on the regression analysis (RA), in order to simulate the process of the operation of this object in the Matlab package. Indications, obtained from a real object, during its operation in the technological cycle of grinding, were used as basic data for the analysis. The sample consisted of data for a period of more than a month, with a discreteness of readings - 1 minute. This allows to speak about changes of different nature, reflected in the model. An example of data array is shown in Figure 1.

	A	B	C	D	E	F	G	H
1	Дата Время	Вес руды в 21-ой м-це	Мощность 21-ой м-цы	Расход воды в 21-ой м-це	Вода в бутару 21 м-цы	классификатор 21 м-цы	21 М-ца 1-я спираль	21 М-ца 2-я спираль
2	2014.05.10 00:00:00	490.6125031	3978.854248	103.4250031	132.8799998	1953	81.62999725	96.30000305
3	2014.05.10 00:01:00	494.9933319	3987.694824	101.0708313	130.9000015	1993.033366	81.27000427	94.83000183
4	2014.05.10 00:02:00	493.780014	3822.576416	100.2999954	129.7485722	1974.374969	83.54999542	91.02000427
5	2014.05.10 00:03:00	490.5600077	3857.197998	101.0583293	131.2400055	1959.900024	83.43000793	93.99000549
6	2014.05.10 00:04:00	494.1299845	3978.545654	100.2999954	131.5866597	1937.299927	84.15000153	95.49000549
7	2014.05.10 00:05:00	492.975001	3875.544434	105.0250015	130.055006	1966.524994	83.1000061	94.31999969
8	2014.05.10 00:06:00	492.4149984	3881.299316	107.2999954	131.4199982	1959.099976	82.73999786	92.42999268
9	2014.05.10 00:07:00	492.1155531	3870.033691	106.3000005	130.8400065	1987.900024	82.52999878	90.69000244
10	2014.05.10 00:08:00	490.8633321	3882.860352	106.9749985	131.3599955	1967.900024	83.61000061	93.75
11	2014.05.10 00:09:00	495.827507	3820.55127	104.9000015	129.4080017	1958	81.81000519	94.08000183
12	2014.05.10 00:10:00	489.4866587	3899.111572	106.9499969	132.1599986	1942.099976	84.29999542	97.61999512
13	2014.05.10 00:11:00	494.2599923	4104.625488	106.0749995	133.1999969	1979.866699	85.76999664	96.18000031
14	2014.05.10 00:12:00	491.4400068	3956.425781	106.875	133.5333252	1943.200033	86.04000092	94.01999664
15	2014.05.10 00:13:00	491.1277805	3926.675293	105.2749996	130.5599976	1922.966634	87	97.01999664
16	2014.05.10 00:14:00	497.0233307	3911.283936	103.8833364	131.9733327	1947.466634	86.79000092	99.48000336
17	2014.05.10 00:15:00	490.5833486	3905.34375	104.6750031	131.0600014	1932.933309	87.41999817	97.44000244
18	2014.05.10 00:16:00	492.8466695	4155.654297	104.6750031	131.5466614	1917.5	89.43000031	97.59000397
19	2014.05.10 00:17:00	492.0475006	3888.160889	104.6750031	130.5599976	1917.5	90.56999969	100.0200043
20	2014.05.10 00:18:00	493.1733297	3992.632324	104.6750031	131.9466705	1890.5	91.56000519	103.0200043

Дата, время	Date, time
Вес руды в 21-ой м-це	Ore weight in the 21st mill
Мощность 21-ой м-цы	Capacity of the 21st mill
Расход воды в 21-ой м-це	Water consumption in the 21st mill
Вода в бутару 21 м-цы	Water in the trommelof the 21st mill
Классификатор 21 м-цы	Classifier of the 21st mill
21 М-ца 1-я спираль	The 21st mill, the 1st spiral
21 М-ца 2-я спираль	The 21st mill, the 2nd spiral

Fig.1. The example of chunks of data

To develop the models, we took the following channels as the input actions: "ore weight", "water consumption for the mill", "water consumption for the mill'strommel", as the main parameters of the unit control. The current of the classifier spiral, as the main parameter of the mill, was chosen as a dependent (output) parameter, which reflects the efficiency of mill's functioning. The model under development corresponded to the scheme, shown in Figure 2.



Вес руды	Ore weight
Расход воды в мельницу	Water consumption for the mill
Расход воды в бутару мельницы	Water consumption for the mill'strommel
Ток спирали классификатора	Current of the classifier spiral

Fig.2. Functional diagram of the ball mill model (x1 - is the weight of the ore, x2 - is the water consumption for the mill, x3 - is the water consumption for the mill's trommel, and Y- is the current of the classifier spiral)

For the approximation, we used such functions as: linear (1), fractional (2), polynomials (up to and including the fifth order) (3), exponential function (4) and Kolmogorov-Gabor polynomial (5), also known as the Wiener series, used for description of nonlinear objects in the method of group accounting of the arguments of Ivakhnenko A.G.General form of the functions is presented below.

$$Y_1(x_1 ... x_n) = b_0 + \sum_{i=1}^{n} b_i x_i \quad (1)$$

$$Y_2(x_1 ... x_n) = b_0 + \sum_{i=1}^{n} \frac{1}{b_i x_i} \quad (2)$$

$$Y_3(x_1 ... x_n) = b_0 + \sum_{j=1}^{m} \sum_{i=1}^{n} b_{ij} x_i^j \quad (3)$$

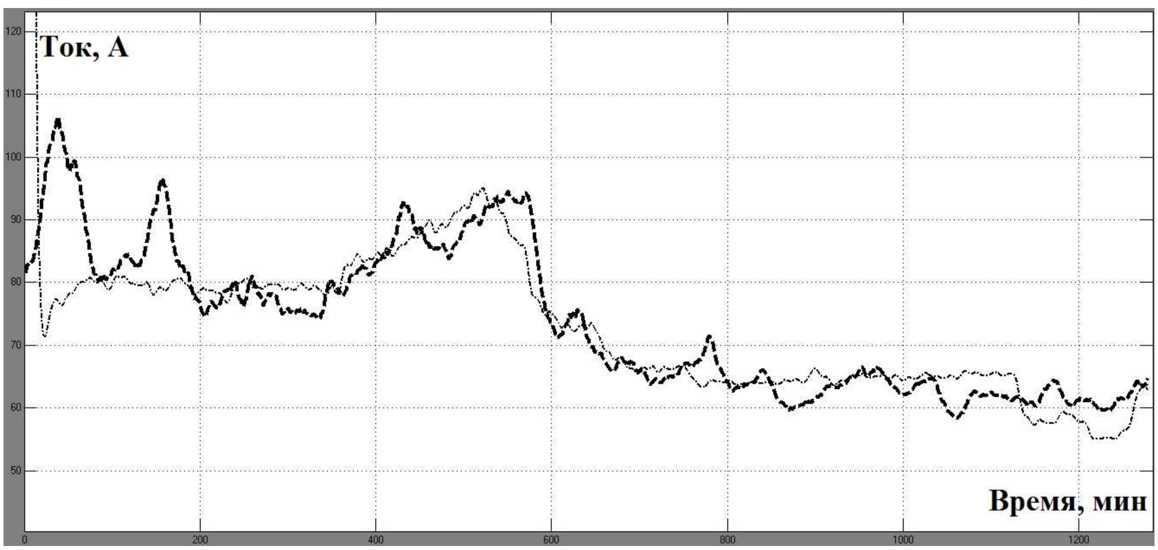
$$Y_4(x_1 ... x_n) = b_0 + \sum_{i=1}^{n} \exp^{x_i} \quad (4)$$

$$Y_5(x_1 ... x_n) = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} \sum_{j=1}^{n} b_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} b_{ijk} x_i x_j x_k \quad (5)$$

Initially, for the regression analysis, a sample of data was selected, which corresponded to the whole day of unit's operation. As a result of the analysis, the coefficients of the above polynomials were obtained. However, the correlation between the obtained curves and the graph of the classifier spiral current was relatively low; the overall accuracy of the models was below the recommended 80%. Then it was suggested, that such a low accuracy was obtained due to the noisiness of data, which was a consequence of errors in the measurement system. To prevent such a negative impact, the data was filtered out. As a filter of high-frequency oscillations, a "moving average" filter was used with averaging for 7 points. Obtained data were subjected to regression analysis again. This time, the descriptive functions were much more accurate.

Next, the mill was simulated with various approximating functions. The best results are shown in Figures 3 and 4, where the heavy dashed line - is the current graph, and the thin dash-dot line - is the simulated output of the object.

As can be seen from the graphs in the figures, the models, based on the functions, obtained by regression analysis, fairly closely repeat the graph of the current, to some extent averaging the changes in the output of the object. However, there was no exact match, both for the separate peak values,and for the overall level of the mean value of signal.



Ток, А	Current, A
Время, мин	Time, min

Fig.3. Results of modeling of unit’s operation, using a quadratic polynomial

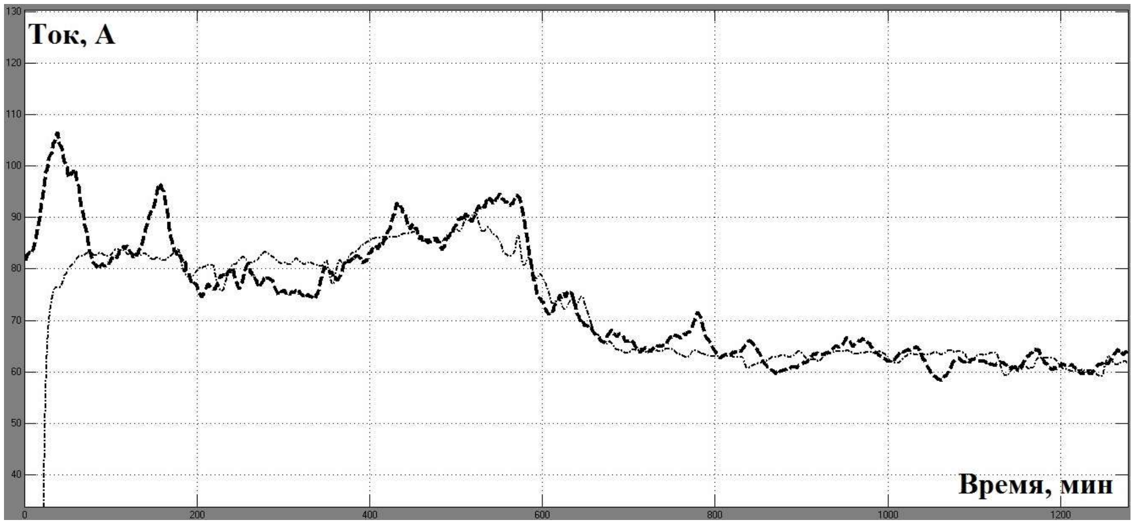


Fig.4. Results of modeling of unit's operation, using Kolmogorov-Gabor polynomial

For all models, the calculations of quadratic criterion (10) and the correlation coefficient (11) were performed. This made it possible to quantify the quality of models. The results of the criteria values are presented in Table 1.

$$F = \sum_{i=1}^{n} (Y\text{мод}_i - Y\text{эксп}_i)^2 , \tag{10}$$

whereYмод$_i$–are the values of the real graph of current, Yэксп$_i$–are the simulated values of the model output.

$$r = \frac{\sum_{i=1}^{n} (Y\text{мод}_i - \overline{Y}\text{мод})(Y\text{эксп}_i - \overline{Y}\text{эксп})}{\sqrt{\sum_{i=1}^{n} (Y\text{мод}_i - \overline{Y}\text{мод})^2 \sum_{j=1}^{n} (Y\text{эксп}_i - \overline{Y}\text{эксп})^2}} , \tag{11}$$

where $\overline{Y}\text{мод} = \frac{1}{n}\sum_{i=1}^{n} \overline{Y}\text{мод}_i , \overline{Y}\text{эксп} = \frac{1}{n}\sum_{i=1}^{n} \overline{Y}\text{эксп}_i$

The operation schedules of the models are shown in the pointed figures and in the table. They showed the greatest accuracy and the best values of the criterion and the correlation coefficient. The models, based on the remaining polynomials, were eliminated.

Table 1. Numerical values of the modeling quality criteria

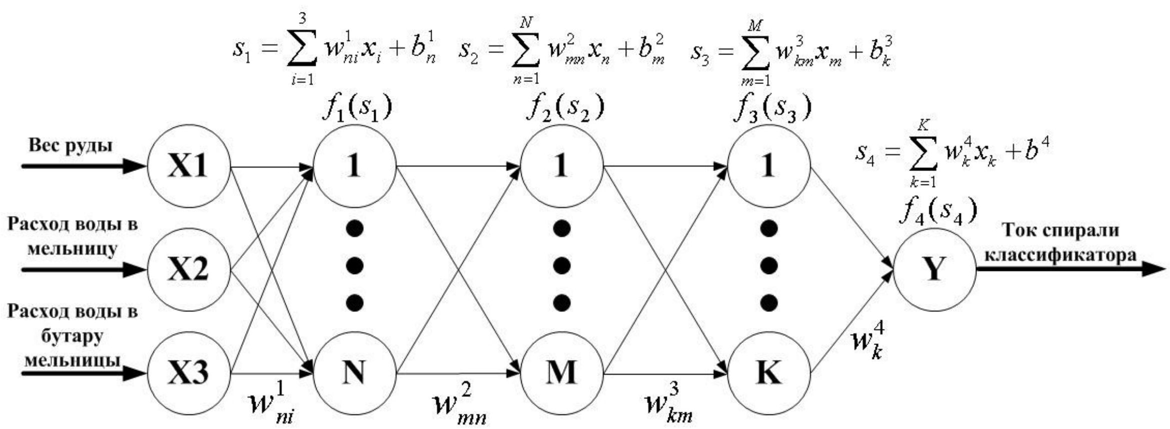
Type of function	**F**	**r**
Linear function	4.5*10^5	0.6683
Quadratic polynomial	6.9*10^6	0.6725
Kolmogorov-Gabor polynomial	3.6*10^5	0.753

Identification, using the artificial neural networks

Mathematical models of the ball mill were developed with the use of a neural network (NN),in order to improve the accuracy of the model.

For further experiments, we used a sample, consisting of 4500 points. In order to test the model, a sample of data with a volume of 500 points was supplied at its input.

For modeling we used the multi-layer feedforward neural networks. A typical structure, adapted for solving this problem, is shown in Figure 5.



Вес руды	Ore weight
Расход воды в мельницу	Water consumption for the mill
Расход воды в бутару мельницы	Water consumption for the mill’s trommel
Ток спирали классификатора	Current of the classifier spiral

Fig.5. Typical architecture of a multi-layer feedforwardneural network, adapted for solving the problem of ball mill identification

In the above figure, X1, X2, X3 - are the neurons of the input layer of the network, Y – is the neuron of the output layer of the network, $s_1 = \sum_{i=1}^{3} w_{ni}^1 x_i + b_n^1, s_2 = \sum_{n=1}^{N} w_{mn}^2 x_n + b_m^2, s_3 = \sum_{m=1}^{M} w_{km}^3 x_m + b_k^3, s_4 = \sum_{k=1}^{K} w_k^4 x_k + b^4$ - are the formulas for calculation the values of the weighted sums in the layers, $f_1(s_1), f_2(s_2), f_3(s_3), f_4(s_4)$-are the functions of activation in the layers, $w_{ni}^1, w_{mn}^2, w_{km}^3, w_k^4$-are the values of weight coefficients in the layers, respectively.

To smooth the interference of the measurement system, a moving average filter was used:

$$x_{\phi j} = \frac{\sum_{i=1}^{N} x_i}{N}, \tag{12}$$

whereN- is the number of data points, processed by the filter, x_i–are the values of the input signals, $x_{\phi j}$–are the values of the filter output.

Then, in order to give the values of the real signal the corresponding values from the domain of the activation functions, their normalization was performed:

$$x_{нj} = \frac{x_{\phi j} - \min}{\max - \min}, \tag{13}$$

where $i = \overline{1,N}$– is the number of data points of the vector, min, maxare the minimum and maximum values of the vector, $x_{\phi j}$ - are the values of the input signals, and $x_{нj}$ - are the normalized values of the vector.

In order to identify the architecture of the neural network, allowingto obtain the most qualitative result, the experiments were carried out with a change in the number of neurons in the layers, various activation functions were used. Initially, positive result was obtained when using NN with 2 hidden layers, with 60 and 30 neurons, respectively. The functioning of this network is carried out according to the model:

$$Y_6(t) = f_3(b^3 + \sum_{k=1}^{M} w_{km}^3 f_2(b_m^2 + \sum_{n=1}^{N} w_{mn}^2 f_1(\sum_{i=1}^{3} w_{ni}^1 x_{нj}(t) + b_n^1))), \tag{14}$$

whereN=60, M=30 –are the numbers of neurons in the corresponding layers, b_n^1, b_m^2, b^3 -are the displacements of neurons, $w_{ni}^1, w_{mn}^2, w_{km}^3$- are the weight coefficients in the corresponding layers.

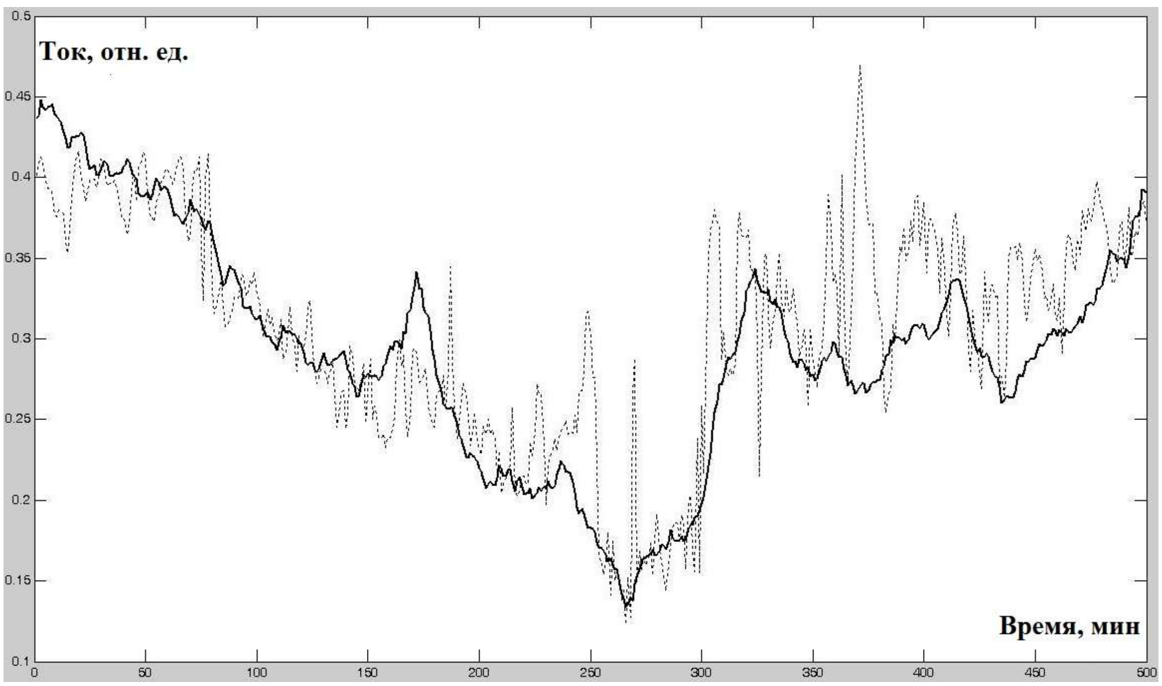
After achieving high quality indicators during training, a test sample was supplied to the input of the neural network. As a result, the output of the model repeated the current signal, but there were fluctuations, reducing the quality of the simulation.

Therefore, it was decided to complicate the structure of the neural network. Experiments with NN, having 3 hidden layers, showed that the most qualitative result was obtained by using a structure with 55, 50, and 45 neurons, respectively, and the functions of activation -hyperbolic tangent, sigmoid function in the 2nd and the 3rd hidden layer, as well as linear function of activation in the output layer. The functioning of this network is described by the model:

$$Y_7(t) = f_4(b^4 + \sum_{k=1}^{K} w_k^4 f_3(b_k^3 + \sum_{k=1}^{M} w_{km}^3 f_2(b_m^2 + \sum_{n=1}^{N} w_{mn}^2 f_1(\sum_{i=1}^{3} w_{ni}^1 x_i(t) + b_n^1)))), \qquad (15)$$

whereN = 55, M = 50, K = 45 –are the numbers of neurons in the corresponding layers, b_n^1, b_m^2, b_k^3, b^4 - are the displacements of neurons, $w_{ni}^1, w_{mn}^2, w_{km}^3, w_k^4$ - are the weight coefficients in the corresponding layers.

The result of operation of this NN, using the test sample, is shown in Figure 6. Hereinafter, the real graph of current is shown by the heavy line, and the output signal of the model is shown by the dotted line.



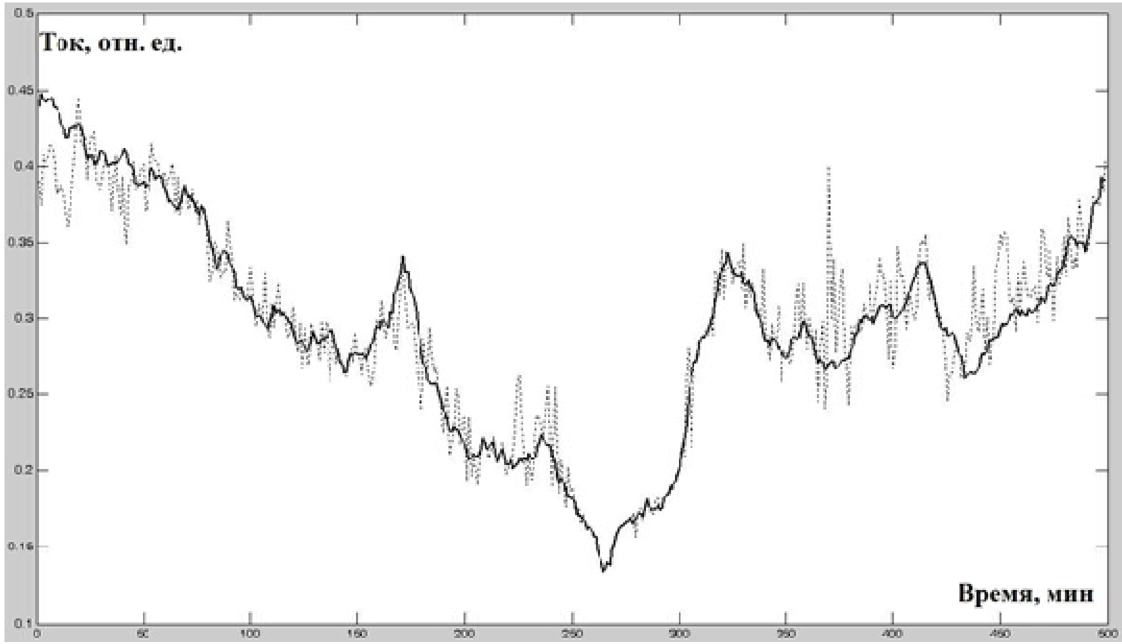
Ток, отн.ед.	Current, relative units
Время, мин.	Time, min

Fig.6. The schedule of the neural network operation with 3 hidden layers

Further complication of the neural network structure did not lead to a significant improvement in the quality of the simulation. But it is should be noted, that at some points of time significant fluctuations in amplitude are noticeableat the output of the model, which can affect the operation of the system, during its industrial operation.

Therefore, further in the work, with the aim of improving the quality of modeling, by taking into account the dynamics of the object, it was decided to change the structure of NN by adding additional neurons to the input layer. Additional neurons are designed for the processing of information, which is represented by the same input signals, but with a discrete lags (first-order and more). The introduction of thefirst-order lag along the supply channels of ore and water to the mill allowed to obtain a much less noisy output signal of the model. And it was noticed, that it was achieved when using the NN with a smaller number of neurons. It is a positive moment, since it allows using a smaller amount of computing resources of the system. The result of NN operation with the first-order lagged signals and 3 hidden layers of 50, 35 and 25 neurons, respectively, is shown in Figure 7.

The gradual increase in the number of discrete lags to the third order consistently led to improvement in the quality of simulation.

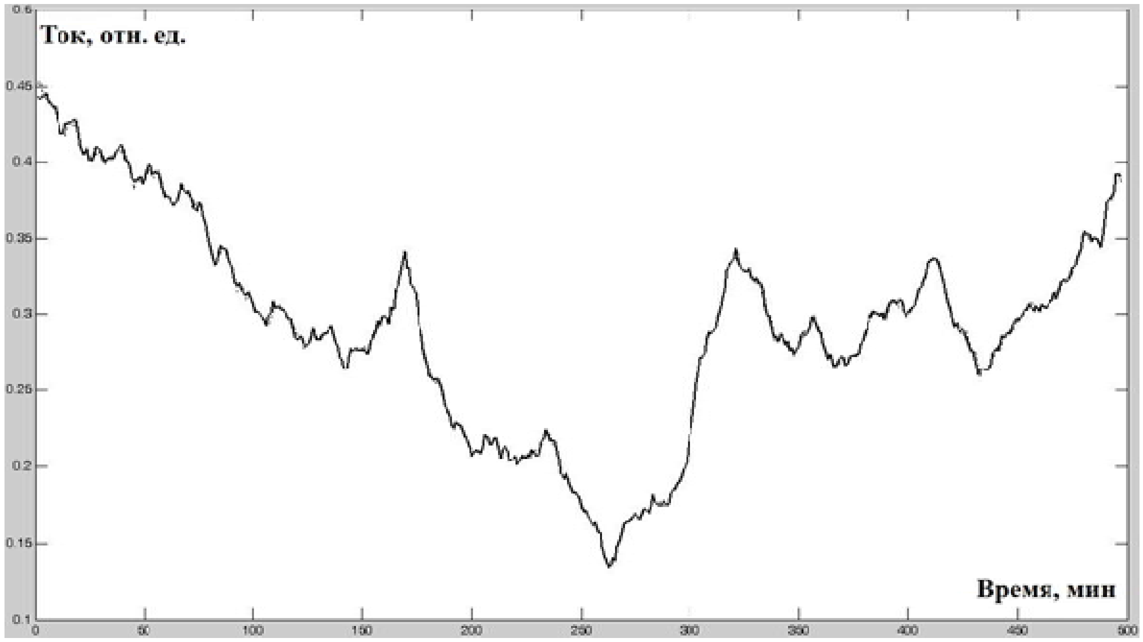


Ток, отн.ед.	Current, relative units
Время, мин.	Time, min

Fig.7. The schedule of the neural network operation with 3 hidden layers and the first-order discrete lag of the input signals

Then, the experiments with addition of neurons were subsequently carried out.Neurons processed the signal of current with the first-, the second-, and the third-order lags. Due to this, the results were obtained,shown in Figure 8. This figure presents the simulation of the ball mill operation, with the help of NN with 3 hidden layers, and 50, 35 and 25 neurons in them, with the functions of activation - hyperbolic tangent, sigmoid function in the 2nd and the 3rd hidden layer, as well as linear activation function in the output layer. In the input layer, 15 neurons are used - the volume of ore, feeding into the mill, the volume of water, supplied to the mill and to the mill's trammel, signals with the first-, the second-, and the third-order lags, and the signal of current with the first-, the second-, and the third-order lags.

It can be seen from the graph, that the output signal of the model almost completely repeats the signal of the real value of the current on the test sample. The high quality of the model is also reflected in the numerical values of the quality indicators.



Ток, отн.ед.	Current, relative units
Время, мин.	Time, min

Fig.8. The schedule of the neural network operation with 3 hidden layers and the first-, the second-, and the third-order discrete lags of the input signals

Numerical values of quality indicators, obtained using the models of different types, are presented in Table 2.

Table 2. Numerical indicators of simulation quality, using the neural network

The method of model development	Training sample		Test sample	
	F	r	F	r
Regression analysis based on polynomial (5)	49.9588	0.5821	8.3704	0.1011
Neural network with 2 hidden layers	9.2839	0.9361	0.8752	0.8364
Neural network with 3 hidden layers	12.0503	0.9161	0.7714	0.8585
Neural network with the first-order discrete lag of the input signals	1.44	0.9903	0.209	0.9569
Neural network with the first-, the second-, and the third-order discrete lags of the input signals	0.0253	0.9998	0.0028	0.9994

CONCLUSION

The mathematical model of a ball mill was developed in the research. It was based on a neural network, with high quality indicatorsof operation on a test sample, which was the data for a different time interval, than the training one. This allows to talk about the ability of a model, based on a neural network, to approximate previously unknown signals, that makes it possible to develop a control system, using this apparatus.

The shortcomings include a sufficiently long learning time for neural networks of this type. Therefore, the further direction of the work is an attempt to apply neural networks with radial-basis activation function, which due to the change in the learning mechanism, have a substantially shorter learning time.

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