Development of Indirect Determination Model Based on Neural Networks for the Process of Iron Ore Beneficiation

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Abstract

The object of research is the processes of beneficiation of iron ore in the conditions of a mining and processing plant. The technology of operative forecasting of data of monitoring of production processes provides integration in the SCADA-systems of the specialized means of computer modeling operating at the industrial enterprises for the purpose of operative forecasting of technological indicators of production process. One of the main tasks of technology is to determine the formal connections between the components of the process input space. The large amount of process monitoring data provided by SCADA systems suggests that positive results can be obtained by using Data Mining methods, which allow not only to identify implicit relationships in the data, but also significantly reduce the dimensionality of the problem. The application of fuzzy logic and neural network methods for the construction of models of rapid analysis and forecasting of production process parameters based on current monitoring data can also be promising within the framework of the considered technology. This assumption is confirmed by the fact that the fuzzy logic device is already included in the libraries of the following SCADA-systems: DELTAV, TRACE MODE, SIMATIC WINCC, LABVIEW DSC and others. In the study of common intelligent computing architectures, it was found that the greatest prospects have counter-spread neural networks. Networks of this type have less learning time than reverse distribution networks. Therefore, such a network will respond quickly to changes in the conditions of the benefication process associated with fluctuations in the characteristics of raw materials. The following algorithms are combined in the counter-propagation neural network: the Kohonen self-organizing map and the Grossberg star.

Keywords 1

Classification Model, Computer Support System For Solutions, Neural Network, Ore Beneficiation

1. Introduction

The task of reducing the cost of the concentrate (final product of ore beneficiation) and improving its quality is particular importance. The average quality of the products of processing plants and mining (64-66%), is lower among potential competitors (Brazil, Sweden, Russia) – 70% [1]. At the same time, the share of harmful impurities in final product of Ukrainian processing plants and the cost, as a rule, are higher.

Grinding of ore using a complex of ball mills at the Mining and Processing Plant is one of the initial stages of production of ferrous metals. The process is characterized by high resource consumption and significantly affects the quality of further processing. During operation try to adhere to the modes of the maximum productivity, but at the same time not to allow an overload of mills and an emergency stop. One hour of idle mill means a loss of 290-310 tons of finished class for subsequent stages of benefication and entails additional costs for restart.

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According to the energy balance of mining and processing plant, the most energy-intensive technological processes are benefication and processing [2]. The ore beneficiation department accounts for 19.07% of the plant's energy resources and 44.08% of the total electricity consumption (Fig. 1), of which up to 30% is accounted for by ore grinding.

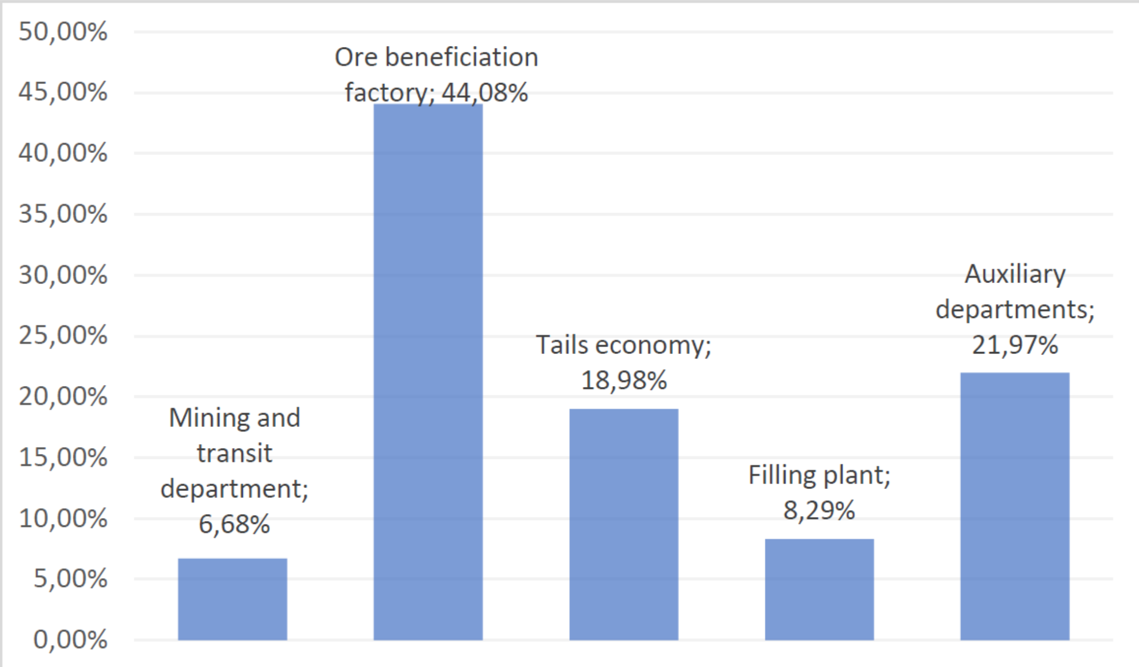

Figure 1: The structure of electricity consumption at the mining and processing plant

Studies [3] show that the use of the latest information technologies (IT) to automate decision-making at the stages of repair and operational management can increase the utilization rate of equipment from 0.759 to 0.949, and the total economic effect of such technologies is about 28 million UAH.

Existing ways to support decision-making in the regulation, and even more so the manual control of the grinding complex (mill-classifier, mill-hydrocyclone), do not provide a stable and optimal process parameters. The situation is characterized by the inability to directly measure the load of the mill, the difficulty of obtaining relevant information about the hardness, benefication of ore, the percentage of iron in it, the density and particle size distribution of the original product from the drain of the classifier.

The published studies show and characterize the relationships between individual parameters of the technological process, but there are no comprehensive recommendations for building effective systems. Therefore, it is now advisable to use intelligent technologies, models and methods for forecasting and automated decision-making to improve the operational management of the main complex of the concentrator.

2. The aim and objectives of research

The aim of research is in development of a classifying model for indirectly determining the ore strength on input of the beneficiation section using technological process model based on the classifying neural network. The efficiency of the iron ore beneficiation process will be improved.

Necessary objectives for the aim`s achieving:

1. To formulate the general goal of constructing a classifying model of indirect determination of the input parameters of the beneficiation section;
2. To determine the type and structure of the neural network;
3. To check the adequacy and functionality of the model.

3. Research of existing solutions of the problem

The mineral processing manufacturing process is a typical complex industrial process. It consists of several processes connected in series, where the outputs of each individual process are inputs for the subsequent [4].

The functioning of each unit contains a system of operational optimization of the highest level, keeps performance indicators within the target ranges [5, 6].

Nowadays, modern mining and processing plants has direct and indirect models and methods for determining the input, output and mode parameters of the technological process.

Direct measurements include direct measurement of strength, iron content, magnetic iron, particle size distribution, etc [2,9-12].

On the scale of Protodyaconov, the strength coefficient is equal to the fraction of the division of the value of the yield strength during uniaxial compression σ_{st} (in MPa) by 10.

Mohs scale - a set of reference minerals for determining the relative hardness by scratching. As standards, 10 minerals are adopted, arranged in ascending order of hardness.

The advantage of direct measurement is high accuracy in the classification of ore. But the use of these methods to obtain parameters on the pipeline in real time is not possible (only laboratory testing of technological samples).

An alternative is indirect measurement, in which the values of one or more measurands are found after transforming the genus of the quantity or calculating them according to known dependences on several quantities of arguments that are measured directly.

Shupov`s a model of a stage scheme of magnetite quartzite enrichment was proposed, which is based on the equations of tail yield and metal extraction in them from the food size class.

Its equations are quite simple, fairly accurately describe the change in performance at the stages of the scheme depending on the change in product size. However, they do not take into account the impact of the performance of the device, the content of one class inaccurately characterizes the particle size distribution of the product.

Mathematical models that describe the physical processes and phenomena that lead to the separation of mineral components in grinding machines are widely used to study the processes of mineral beneficiation. For example, the differential equations obtained by J. Watson describing the kinetics of separation of weakly magnetic minerals.

J. Watson's calculations do not take into account an important quantity - the mass of the particle, because he considers the particle as a point without mass. The need to calculate the parameters of all particles leads to an increase in the number of computational operations and makes it impossible to model the separation process in real time.

Fundamentally new possibilities of rejecting empirical information about baggage processes are displayed in the production facilities of automated systems of operational dispatch control and collection of data (Supervisory Control And Data Acquisition). The main aspect of the novelty of the described technology of the field in the integration of the authors of the models and the integration of the computer model of the engineering tasks with the SCADA-systems running on industrial enterprises with the addition of the expanded functional forecasts for the possibilities.

4. Research results

The presence of large data set from the operation of SCADA systems provides the creation and using of models based on Data Mining methods in combination with neural network methods. Prediction based on previous "experience" can provides information about raw materials in the intervals between direct measurements.

The most rational for forecasting multi-stage benefication schemes is the option of combined solutions, which involves the joint use of models of different types for different states of the benefication process or different components (devices) of the benefication scheme [15]. Given the multidimensionality of problems, heterogeneity of parameters and the presence of significant uncertainty in the relationships between the parameters of real production processes, it is proposed to use Data Mining methods to build the model. The created models will allow to receive the results adequate to tasks of operative management of technological process.

The capabilities of the counterpropagating network are superior to those of single-layer networks. The training time, in comparison with back propagation, can be reduced by a factor of one hundred. Counterpropagation is not as general as backpropagation, but it can provide a solution in applications where a lengthy training procedure is not possible. It will be shown that in addition to overcoming the limitations of other networks, counterpropagation has its own interesting and useful properties. In counterpropagation, two well-known algorithms are combined: a self-organizing Kohonen map and a Grossberg star (Fig. 2). Their combination leads to properties that none of them individually has. Techniques that, like counterpropagation, combine different networking paradigms as building blocks, can lead to networks that are closer to the brain in architecture than any other homogeneous structure. It seems that in the brain, it is the cascading connections of modules of different specializations that make it possible to perform the required computations. The counter-distribution network functions like a generalizable help desk. During training, input vectors are associated with corresponding output vectors. These vectors can be binary, consisting of zeros and ones, or continuous. When the network is trained, application of the input vector results in the required output vector. The generalizing ability of the network allows the correct output to be obtained even when an input vector is applied that is incomplete or slightly incorrect. This allows this network to be used for pattern recognition, pattern restoration and signal amplification [14].

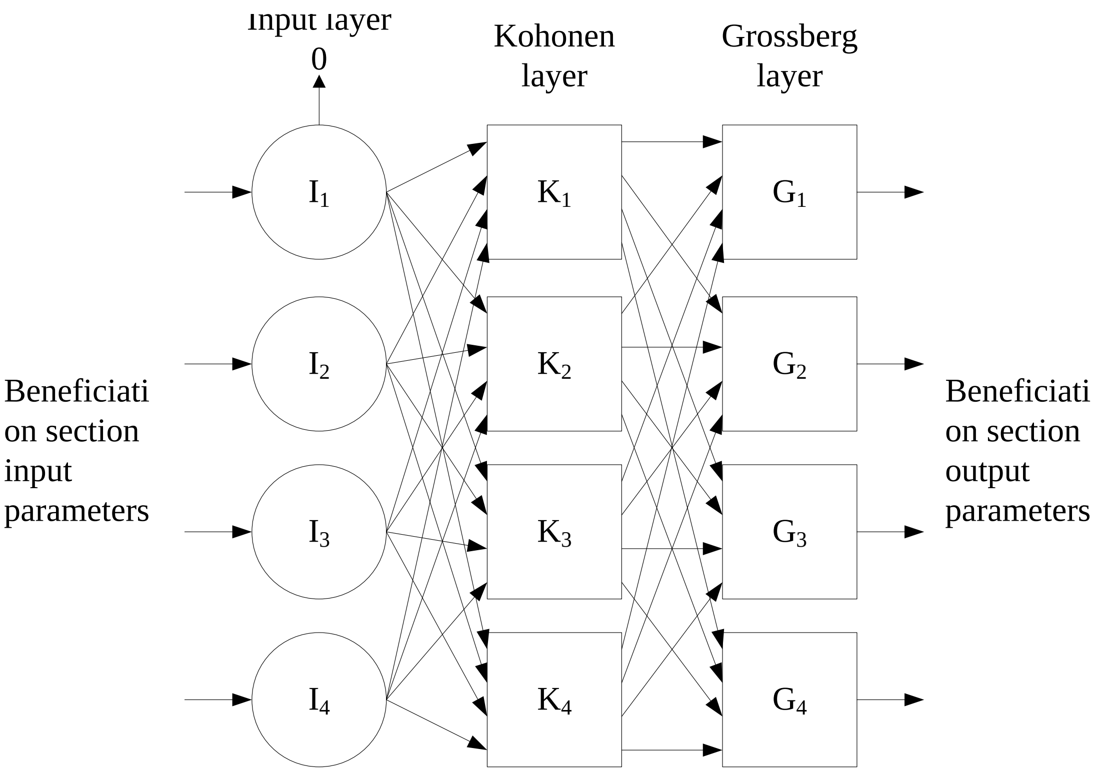

Figure 2: Network with counter recognition without feedback

Like other neural networks, the counter-propagation network operates in two modes: learning and use. In the first case, the inputs are fed simultaneously to the vector *X* and the vector *Y*, resulting in the correction of the weights. In the second mode, you can input either *X* or *Y*, and the output is the value of both *X* and *Y*.

An input neuron has n inputs that correspond to weighting factors *W*= (*w1*, *w2*, ..., *wn*), one output Y is the weighted sum of these inputs. Thus, the star is a detector of the state of the inputs and only responds to its input vector.

Adjustment of the scales is carried out according to the formula:

$$Wi(t+1) = Wi(t) + \mu(Xi - Wi(t)) \quad (1)$$

where *Wi*(*t*) – the weight vector of the i-th input star at the t-th learning cycle;

μ – learning speed (selected at the beginning of 0.1-0.2 and then gradually decreases)

Xi – the input vector.

Grossberg output star performs the opposite function – when a signal arrives at the input, a certain vector is issued. A neuron of this type has one input and m outputs with weights *W* = (*w1, w2, ..., wn*), which are adjusted according to the formula:

$$Wi(t+1) = Wi(t) + \alpha'(Yi - Wi(t)) \quad (2)$$

where *Wi(t)* – the weight vector of the i-th source star on the t-th learning cycle;

Yi – the output vector;

α'– learning speed. It is recommended to start learning with and gradually decrease to 0.

In the neural network operation mode, an input signal is provided $\vec{x}$ and the output signal vector is formed $\vec{y}$

$$y_j^{K1} = W_{1j}^1 x_1 + W_{2j}^1 x_2 + \cdots + W_{Nj}^1 x_N = \sum_{l=1}^{n} W_{lj}^1 x_l \quad (3)$$

y_j^{K1} – the output of the j-th neuron Kohonen before the activation;

$\overrightarrow{W_j}$ – vector of synoptic weights of the j-th neuron Kohonen.

The Grossberg layer works in conjunction with the single output unit (Cohonen layer in the accreditation mode).

The Grossberg shaw input is the weighted sum of the outputs of the Kohonen layer, ie it is a layer of neurons with linear activation functions.

$$y_j^G = W_{1j}^2 y_1^K + W_{2j}^2 y_2^K + \cdots + W_{mj}^2 y_n^K = \sum_{l=1}^{m} W_{lj}^2 y_1^K \quad (4)$$

When the Kohonen layer functions so that only one output is 1 and all other levels are 0:

$$y_j^K = \begin{cases} 1, if\ y_j^{K1} = \max\limits_j y_j^{K1} \\ 0\ if\ else \end{cases} . \quad (5)$$

then each neuron of the Grossberg layer gives the value of the synoptic weight that connects this neuron with a single Kohonen neuron, the output of which is different from 0

$$y_j^G = W_{ij}^2 \quad (6)$$

When predicting the criterion of the strength of the weight of the Grossberg layer will determine the strength of the ore on the Protodiakonov scale (from 4 to 10)

As input parameters $\vec{x}$ granulometry of class 0-10mm, granulometry of class 10-20mm, iron content, content of magnetic iron, tails, productivity, ore supply, water supply, loading by spheres, energy consumption are used. As a result of training on the scales of the layers of Grossberg and Kohonen will gain value:

$$y_1^{K1} = 0{,}080937x_1 + 0{,}122394x_2 + 0{,}049581x_3 + 0{,}020384x_4 + 0{,}119412x_5 + 0{,}078495x_6 + 0{,}094954x_7 + 0{,}181324x_8 + 0{,}181324x_9 + 0{,}049573x_{10} \quad (7)$$

$$y_2^{K1} = 0{,}091485x_1 + 0{,}130043x_2 + 0{,}05834x_3 + 0{,}028495x_4 + 0{,}18461x_5 + 0{,}080595x_6 + 0{,}075305x_7 + 0{,}178491x_8 + 0{,}029506x_9 + 0{,}059602x_{10} \quad (8)$$

$$y_3^{K1} = 0{,}11127x_1 + 0{,}142284x_2 + 0{,}047487x_3 + 0{,}043648x_4 + 0{,}122469x_5 + 0{,}078495x_6 + 0{,}072638x_7 + 0{,}166825x_8 + 0{,}036645x_9 + 0{,}047718x_{10} \quad (9)$$

$$y_4^{K1} = 0{,}074950x_1 + 0{,}11193x_2 + 0{,}0877493x_3 + 0{,}040049x_4 + 0{,}118495x_5 + 0{,}083749x_6 + 0{,}075531x_7 + 0{,}127711x_8 + 0{,}044402x_9 + 0{,}054183x_{10} \quad (10)$$

$$y_5^{K1} = 0{,}068493x_1 + 0{,}128459x_2 + 0{,}077493x_3 + 0{,}0644442x_4 + 0{,}127482x_5 + 0{,}081928x_6 + 0{,}093739x_7 + 0{,}117729x_8 + 0{,}049273x_9 + 0{,}032639x_{10} \quad (11)$$

$$y_6^{K1} = 0{,}083648x_1 + 0{,}117492x_2 + 0{,}02374x_3 + 0{,}027497x_4 + 0{,}0784902x_5 + 0{,}1137395x_6 + 0{,}097493x_7 + 0{,}187394x_8 + 0{,}028526x_9 + 0{,}030078x_{10} \quad (12)$$

$$y_7^{K1} = 0{,}073842x_1 + 0{,}118004x_2 + 0{,}053475x_3 + 0{,}068492x_4 + 0{,}118501x_5 + 0{,}086384x_6 + 0{,}13945x_7 + 0{,}29561x_8 + 0{,}042648x_9 + 0{,}023885x_{10} \quad (13)$$

$$y_j^{G\_1} = 4y_1^K + 5y_2^K + 6y_3^K + 7y_4^K + 8y_5^K + 9y_6^K + 10y_7^K \quad (14)$$

The neural network was trained using the NeuroSolution environment. The training sample contained 1000 records.

As alternative activation functions are proposed $f(x) = tg^{-1}(x)$ та $f(x) = \frac{x}{\sqrt{1+ax^2}}$. When changing the activation function and re-learning, the results shown in the Table 1 were obtained.

Table 1
Influence of activation functions on learning outcomes

Activation function	Correlation between actual and predicted parameters	RMS error
Single step	0,474	0,0271
Arctangent	0,397	0,0354
Reverse square root	0,281	0,0331

For the selected activation function, a study of the influence of the number of epochs on learning outcomes was conducted. With increasing training time, the following models were obtained:

$$y_1^{K1_2} = 0{,}074477x_1 + 0{,}120707x_2 + 0{,}04242x_3 + 0{,}016497x_4 + 0{,}121095x_5 + 0{,}079242x_6 + 0{,}076362x_7 + 0{,}173511x_8 + 0{,}173511x_9 + 0{,}044158x_{10} \quad (15)$$

$$y_2^{K1_2} = 0{,}091006x_1 + 0{,}130676x_2 + 0{,}048429x_3 + 0{,}020499_4 + 0{,}084595x_5 + 0{,}070039x_6 + 0{,}074301x_7 + 0{,}18758x_8 + 0{,}022009x_9 + 0{,}054591x_{10} \quad (16)$$

$$y_3^{K1_2} = 0{,}120411x_1 + 0{,}139402x_2 + 0{,}054014x_3 + 0{,}038888x_4 + 0{,}114091x_5 + 0{,}069369x_6 + 0{,}070266x_7 + 0{,}162143x_8 + 0{,}046316x_9 + 0{,}046065x_{10} \quad (17)$$

$$y_4^{K1_2} = 0{,}086925x_1 + 0{,}127056x_2 + 0{,}053908x_3 + 0{,}026574x_4 + 0{,}026574x_5 + 0{,}072854x_6 + 0{,}092304x_7 + 0{,}17893x_8 + 0{,}173365x_9 + 0{,}044096x_{10} \quad (18)$$

$$y_5^{K1_2} = 0{,}092013x_1 + 0{,}123866x_2 + 0{,}049315x_3 + 0{,}03067x_4 + 0{,}193594x_5 + 0{,}086372x_6 + 0{,}078594x_7 + 0{,}169733x_8 + 0{,}019969x_9 + 0{,}069007x_{10} \quad (19)$$

$$y_6^{K1_2} = 0{,}110872x_1 + 0{,}143763x_2 + 0{,}05353x_3 + 0{,}046177x_4 + 0{,}120062x_5 + 0{,}07329x_6 + 0{,}070977x_7 + 0{,}165954x_8 + 0{,}045886x_9 + 0{,}052772x_{10} \quad (20)$$

$$y_7^{K1_2} = 0{,}085318x_1 + 0{,}133782x_2 + 0{,}048385x_3 + 0{,}024344x_4 + 0{,}184612x_5 + 0{,}081892x_6 + 0{,}070414x_7 + 0{,}17815x_8 + 0{,}033063x_9 + 0{,}050298x_{10} \quad (21)$$

$$y_j^{G\_2} = 4y_1^K + 5y_2^K + 6y_3^K + 7y_4^K + 8y_5^K + 9y_6^K + 10y_7^K \quad (22)$$

$$y_1^{K1_3} = 0{,}080597x_1 + 0{,}123434x_2 + 0{,}041181x_3 + 0{,}020264x_4 + 0{,}119315x_5 + 0{,}072428x_6 + 0{,}094445x_7 + 0{,}181237x_8 + 0{,}024594x_9 + 0{,}042032x_{10} \quad (23)$$

$$y_2^{K1_3} = 0{,}091477x_1 + 0{,}131943x_2 + 0{,}058122x_3 + 0{,}028552x_4 + 0{,}18728x_5 + 0{,}080335x_6 + 0{,}075314x_7 + 0{,}178155x_8 + 0{,}029547x_9 + 0{,}059123x_{10} \quad (24)$$

$$y_3^{K1_3} = 0{,}11507x_1 + 0{,}142334x_2 + 0{,}047112x_3 + 0{,}043128x_4 + 0{,}122935x_5 + 0{,}073781x_6 + 0{,}072638x_7 + 0{,}166825x_8 + 0{,}036645x_9 + 0{,}047718x_{10} \quad (25)$$

$$y_4^{K1_3} = 0{,}074656x_1 + 0{,}12293x_2 + 0{,}081743x_3 + 0{,}040043x_4 + 0{,}118487x_5 + 0{,}083761x_6 + 0{,}075532x_7 + 0{,}121715x_8 + 0{,}044289x_9 + 0{,}058369x_{10} \quad (26)$$

$$y_5^{K1_3} = 0{,}068943x_1 + 0{,}126451x_2 + 0{,}073496x_3 + 0{,}0644241x_4 + 0{,}137442x_5 + 0{,}082922x_6 + 0{,}083559x_7 + 0{,}11294x_8 + 0{,}047362x_9 + 0{,}032394x_{10} \quad (27)$$

$$y_6^{K1_3} = 0{,}083743x_1 + 0{,}112494x_2 + 0{,}02373x_3 + 0{,}026491x_4 + 0{,}077492x_5 + 0{,}1147365x_6 + 0{,}097173x_7 + 0{,}187394x_8 + 0{,}027826x_9 + 0{,}030711x_{10} \quad (28)$$

$$y_7^{K1_3} = 0{,}073337x_1 + 0{,}110041x_2 + 0{,}053493x_3 + 0{,}068782x_4 + 0{,}118409x_5 + 0{,}086323x_6 + 0{,}13945x_7 + 0{,}29561x_8 + 0{,}042648x_9 + 0{,}023885x_{10} \quad (29)$$

$$y_j^{G\_3} = 4y_1^K + 5y_2^K + 6y_3^K + 7y_4^K + 8y_5^K + 9y_6^K + 10y_7^K \quad (30)$$

$$y_1^{K1_3} = 0{,}080915x_1 + 0{,}122229x_2 + 0{,}04174x_3 + 0{,}020651x_4 + 0{,}111244x_5 + 0{,}078958x_6 + 0{,}0949832x_7 + 0{,}182401x_8 + 0{,}025384x_9 + 0{,}049333x_{10} \quad (31)$$

$$y_2^{K1_3} = 0{,}091635x_1 + 0{,}130003x_2 + 0{,}05984x_3 + 0{,}028735x_4 + 0{,}184111x_5 + 0{,}080872x_6 + 0{,}075102x_7 + 0{,}178171x_8 + 0{,}028706x_9 + 0{,}059552x_{10} \quad (32)$$

$$y_3^{K1_3} = 0{,}11237x_1 + 0{,}143384x_2 + 0{,}047157x_3 + 0{,}043457x_4 + 0{,}1224569x_5 + 0{,}078567x_6 + 0{,}072295x_7 + 0{,}160905x_8 + 0{,}036135x_9 + 0{,}047458x_{10} \quad (33)$$

$$y_4^{K1_3} = 0{,}074994x_1 + 0{,}11127x_2 + 0{,}0877833x_3 + 0{,}040018x_4 + 0{,}118575x_5 + 0{,}083756x_6 + 0{,}076731x_7 + 0{,}127331x_8 + 0{,}044122x_9 + 0{,}0541293x_{10} \quad (34)$$

$$y_5^{K1_3} = 0{,}068383x_1 + 0{,}128449x_2 + 0{,}077993x_3 + 0{,}064424x_4 + 0{,}12782x_5 + 0{,}08298x_6 + 0{,}093596x_7 + 0{,}117293x_8 + 0{,}049188x_9 + 0{,}032929x_{10} \quad (35)$$

$$y_6^{K1_3} = 0{,}083614x_1 + 0{,}11342x_2 + 0{,}02164x_3 + 0{,}02715x_4 + 0{,}0784222x_5 + 0{,}113075x_6 + 0{,}097493x_7 + 0{,}187394x_8 + 0{,}028526x_9 + 0{,}030078x_{10} \quad (36)$$

$$y_7^{K1_3} = 0{,}073282x_1 + 0{,}118234x_2 + 0{,}05338x_3 + 0{,}068342x_4 + 0{,}118951x_5 + 0{,}086294x_6 + 0{,}13285x_7 + 0{,}29131x_8 + 0{,}042748x_9 + 0{,}02138x_{10} \quad (37)$$

$$y_j^{G\_4} = 4y_1^K + 5y_2^K + 6y_3^K + 7y_4^K + 8y_5^K + 9y_6^K + 10y_7^K \quad (38)$$

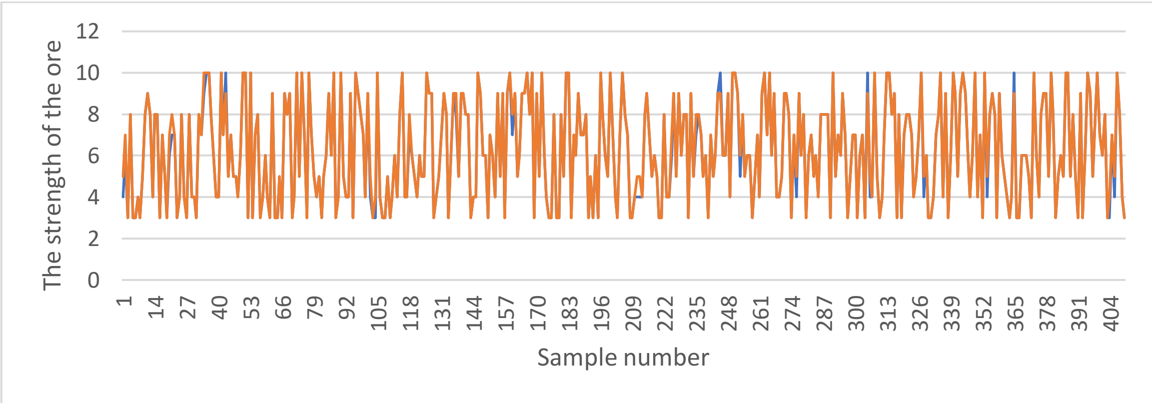

Figure 3: Forecasting results by model y^{G_1}

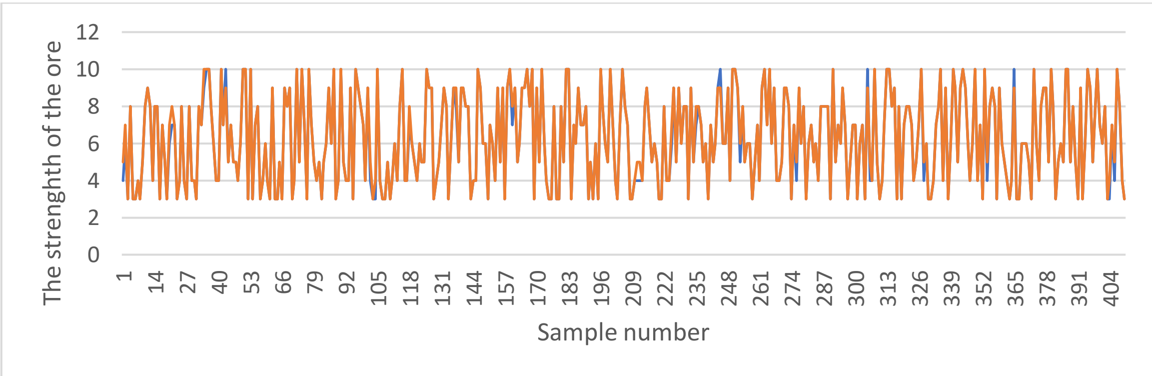

Figure 4: Forecasting results by model y^{G_2}

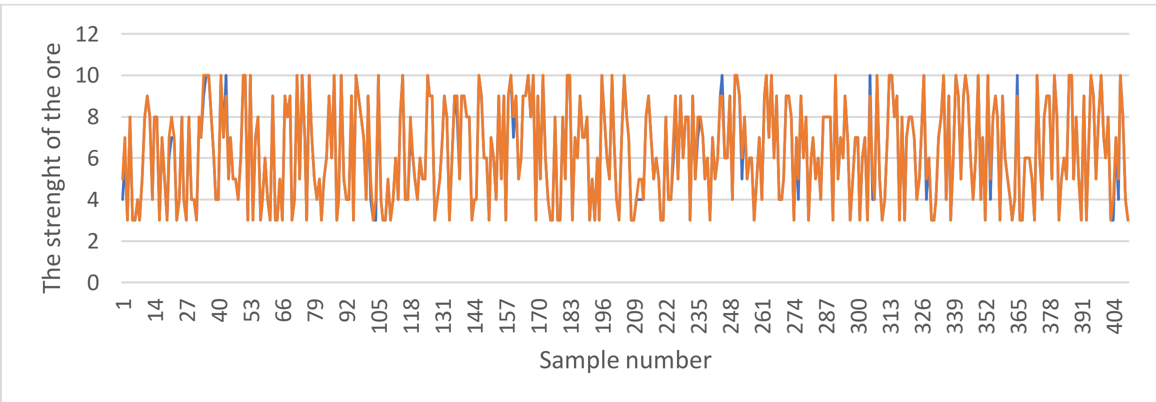

Figure 5: Forecasting results by model y^{G_3}

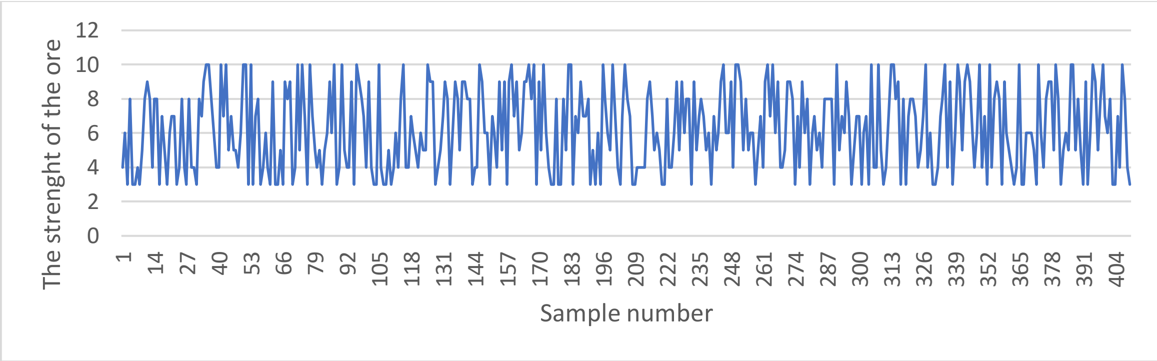

Figure 6: Forecasting results by model y^{G_4}

The generalized results of the analysis of the received models are given in the Table 2.

Table 2
Influence of the number of epochs on the qualitative indicators of the neural network

The output function of the trained network	Number of epochs	Study time, s	The standard deviation
$y_j^{G\_1}$	500	66	0,0271
$y_j^{G\_2}$	550	68	0,0248
$y_j^{G\_3}$	600	73	0,0225

Increasing the number of iterations maintains a positive trend (Fig. 7).

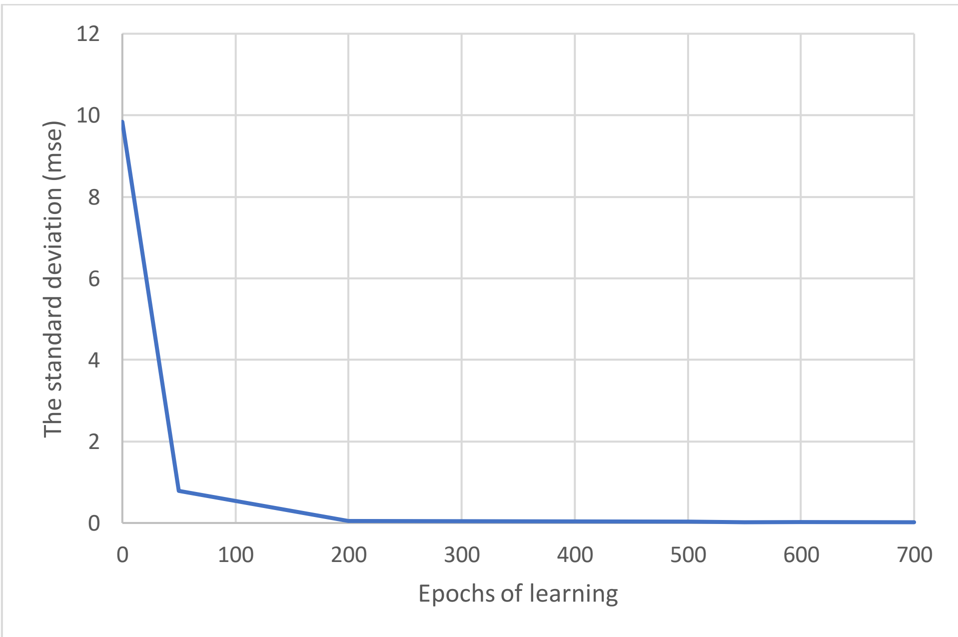

Figure 7: The process of learning a neural network of counter-propagation

To check the adequacy of the obtained model from the generated sample, control points were selected that did not participate in the training of the neural network.

In the model y^{G_4} as the number of learning epochs increases, the mean square error is observed in comparison with other models. Due to the higher number of calculations to obtain this model, its use is not considered appropriate.

In the model$y_j^{G_3}$ the standard deviation is the smallest relative to other models, but in some cases the model gave a predicted value that differed significantly from the standard (2-3 positions on the strength scale). The presence of such an absolute error calls into question the use of this model to predict the parameters of the technological process.

Models $y_j^{G\text{-}1}$ and $y_j^{G\_2}$ issue adequate forecasts and can be used in the framework of the developed information technology. Suggested use of $y_j^{G\_2}$ due to greater accuracy despite greater compared to $y_j^{G\_1}$ number of calculations.

In order to analyze the adequacy of neural network modeling, the results obtained by the predictive neural network and the prediction of actual data that were not included in the training sample were compared. The criterion of the average absolute error ($MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_i - \sum_{j=1}^{n} x_j\right|$) is 0,086.

To improve the adequacy of neural network modeling, it is proposed to pre-process the training sample. The forecasting process in this case can be considered as a complete sequence of diagnostic tests, the effectiveness of which depends on the strategy of finding a diagnosis for many possible reasons based on the analysis of time series.

According to the principles of fractal analysis, time series have a fractal dimension 1<D<2 i endowed with the properties of large-scale self-similarity and the memory of their initial conditions.

The straight line has a fractal dimension D=1. If D=1, then the distribution of the fractal time series is Gaussian. In practical calculations, the fractal dimension is sometimes replaced D by Hurst index H based on the implementation of the procedure of sequential R/S analysis, where R(t) – the scope of the sequences of accumulated deviations, S(k) – standard deviation. So, Hurst's figure H – is number Hϵ[0;1] which characterizes the component function of the trend to white noise and can be used as a measure of persistence - ie the propensity of processes to trends.

Trend characteristics of time series were studied Q(t), β_1(t), β_2(t), β_3(t), where Q(t) – mill productivity, β_1(t) – size class 0-10mm, β_2(t) – size class 10-20mm, β_3(t) – size class +20mm.

Based on the application of R/S- analysis Hurst it is possible to establish some additional properties concerning tendencies of changes of parameters of section of benefication. Namely: to obtain estimates regarding the preservation / change of time series properties. In addition, you can calculate the period of trend. Data processing was performed at 120 minute, four-hour and daily intervals.

To calculate the Hurst index, linear regression coefficients were found between the logarithm of the standard deviation of interval increments of different time series and the logarithm of the timeframe (Fig. 8).

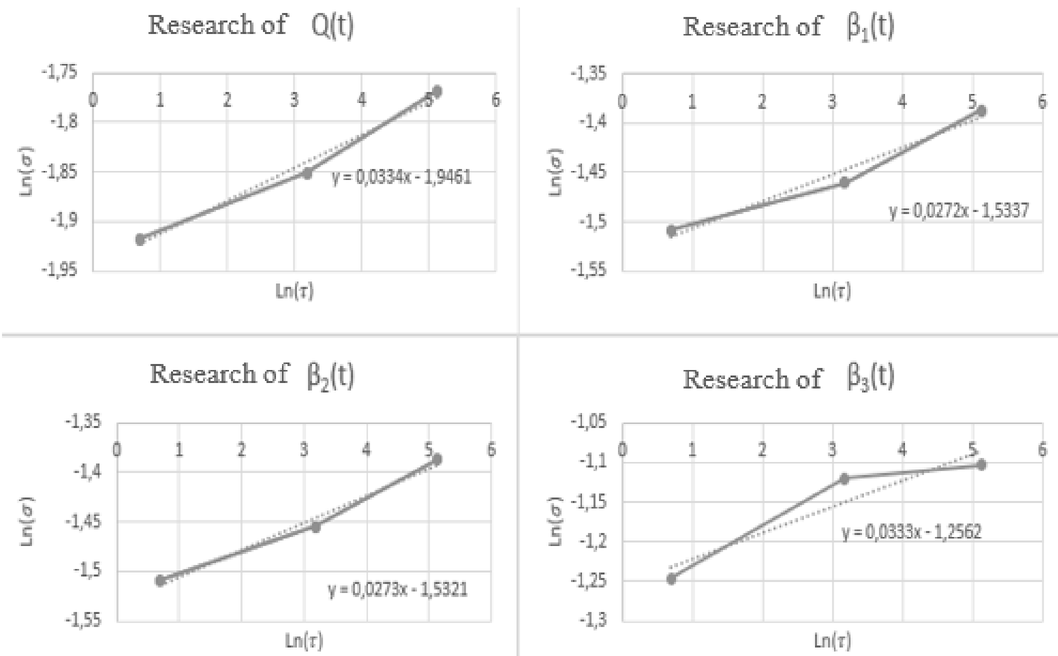

Figure 8: Obtaining linear regression coefficients

Hurst indices are obtained from the linear regression equations shown in Table 3.

Table 3
The results of calculations of chaotic indicators of time series

The studied time series	Hurst index H
Q(t)	0,0334
β_1(t)	0,0272
β_2(t)	0,0273
β_3(t)	0,0333

For all series, the value of the Hearst coefficient does not exceed 0.0334. That is, H <0.5 (series are antipersistent, the trend is expected to change).

In the case of anti-persistence processes, and hence the corresponding time series, forecasting can still be justified and performed using known techniques. For a reasonable interpretation of the results of R / S analysis can be done as follows.

Based on the original time series, a sequence of auxiliary derivative series is formed, the levels of which are the average values for the values of the original time series that are adjacent. This averaging procedure is performed until a new, derived, series is persistent according to the measurement of the Hearst coefficient. This requirement is met because within a range is replaced by an average value. For practice, this result is often satisfactory - the estimate of the forecast is the average value of the series over time. With anti-persistent properties of the processes, it is possible to provide a forecast only of the derived series obtained from the total values of indicators calculated over a period of time. The averaging interval depends on the properties of the time series. When selecting this interval as a criterion, you can use the minimum value of successive levels of the series, at which the derived series will be persistent or random.

The application of the proposed approach to the above time series made it possible to increase the Hearst index to values of H> 0,573. Based on this, you can make averaged predictions of the values of the series for extended periods of time.

But this approach does not allow us to talk about the trend of time series indicators for short periods of time, which calls into question the ability to predict changes in the parameters of the benefication section at short intervals.

To solve this problem, it was proposed to study the presented time series at separate intervals. As a criterion for selecting the interval, the time series parameters belong to one of the clusters.

5. Conclusions

Compared with similar developments, offered classification model allows to obtain the value of the ore strength parameter without placing additional sensors on the input section's conveyor.

The analysis of technological complexes of wet magnetic benefication of iron ores as objects of automated control, forecasting and decision making is carried out. The use of SCPR is proposed, in which the management strategy is based on the inclusion of a mathematical model in the decision-making circuit and forecast on it in real time the results of the process.

An abstract model is developed that implements a probabilistic neural network for inverse prediction of the ore strength parameter. The mean absolute error (MAE) criterion is 0.086.

The properties with respect to the tendencies of changes in the parameters of the benefication section based on the use of Hurst R / S-analysis are established. Namely: estimates were obtained regarding the preservation / change of time series properties. In addition, a period of trend persistence was calculated for further forecasting within the established intervals.

Efficiency of obtaining input parameters can be increased up to 24 times by using of a computer support system.

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