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Comparison of Intelligent Control Methods for the Ore Jigging Process

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***Abstract*—Efficient control of the process of jigging ore of small and fine grain allows avoiding the loss of valuable material in production residual. Due to the multi-dimensionality and multi-connectivity of this enrichment process, classical control methods do not allow achieving the maximum technological indicators of enrichment. This paper proposes investigating intelligent algorithms for controlling the jigging process, which determine the key variables - the level of the natural «bed» and the ripple frequency of the jigging machine. Algorithms are developed using fuzzy logic, neural and hybrid networks. The adequacy of intelligent algorithms was evaluated using the following criteria: correlation of expert and model values (R); Root Mean Square Error (RMSE); Mean absolute percentage error (MAPE). To assess the adequacy of the obtained algorithms, a test sample of input variables, different from the training one, was compiled. As a consequence, we determined an algorithm that gives a minimal discrepancy between the calculated and experimental data.**

***Keywords*—Neural network, Ore jiggling, Control algorithm, fuzzy logic, correlation**

I. Introduction

THE search for new ways of controlling the process of jigging grade 5–10 mm ore allows increasing the percentage of extracting useful component without changing the technology and using new processing equipment [1]. It is important to note that these processes have a high level of automation, but the systems used, which certainly facilitate the work of a technologist, provide average, but not maximal, technological indicators of processing.

The vulnerability of classical control methods is associated with the multidimensional nature of the jigging process. For example, the processing technological parameters of jigging machines are simultaneously influenced by about 20 factors determined by the characteristics and power supply mode of jigging machines, technological and hydrodynamic parameters of the process [2]. Many of them are in complex interaction with each other and show themselves ambiguously under various conditions. Therefore, the disadvantage of the existing systems for controlling the processes of gravitational preparation is that the key variables in the equipment are not continuously regulated depending on the perturbing factors; they have a fixed value and are changed by a technologist only 2-3 times per shift. And the technologist makes a decision on the optimal value of these variables, based on his competence, that is, the human factor is of great importance.

The analysis of background literature [3,4] and long-term communication with technology experts working directly on gravitational preparation equipment carries the inference that the best option for determining the optimal values of the essential variables of the process of gravitational ore processing is using intelligent algorithms that formalize the knowledge of experienced technologists.

The paper proposes a method for determining the key process variables using three intelligent algorithms. In order to select an algorithm that provides a minimal calculation error, they were tested on an independent sample according to several criteria for the goodness of fit. The selected algorithm may become the core of an intelligent control system for the process of jigging ore of fine and small grades.

The mathematical description and construction of a determined model of the jigging process is complicated by the fact that jigging is a mass process (all available models consider a single particle in the gravitational field), the ore composition and the distribution of particles in the jigging machine is of stochastic nature. Consequently, the developed models have a number of limitations and do not describe the process of particle separation in the jigging process sufficiently fully and sufficiently [5].

That is why it is proposed to use intelligent methods in the development of methods for controlling the jigging process. As a result, to determine the key variables of the process, we built:

- algorithm using fuzzy logic;
- neural network;
- hybrid (neuro-fuzzy) network.

The development of algorithms based on fuzzy logic and neural networks is described in detail in [6]. In this paper, we propose to consider the development of a fuzzy neural production network and compare the obtained models according to the goodness of fit criteria.

II. Literature Review

The jigging process is a fairly common method of gravitational preparation of ore and coals of fine and small grades. Therefore, the search for effective ways to control it is a burning task [7]. In the course of this study, an analysis of background literature sources concerning the intelligent control of gravitational preparation processes was carried out.

Paper [8] considers predicting the performance of a gravity concentrator using artificial neural networks. The study demonstrates the development of an artificial neural network

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(ANN) to predict the performance of a gravity concentrator depending on the input process variables, such as water flow per table (l/min), tilt angle (degree), and slurry feed rate (l/h). The predicted value obtained with the help of the neural network agrees with the experimental values with satisfactory accuracy. The obtained algorithms were not tested under industrial conditions.

In [9], neural networks are considered as a tool for working with small sets of experimental data. Artificial neural networks (ANNs) are commonly seen as tools that can help analyse cause-effect relations in complex systems within big data. But neural network tools capable of processing small data sets of experimental or observational data are equally important; they can help identify the underlying causal factors that lead to changes in some variable that determines the behaviour of a complex system. The paper describes the possibility of using ANN in the control of gravity preparation processes.

The paper [10] describes the application of a neural network to analyse the efficiency of processing small-grade iron ore using a gravity separator. A three-layer neural network with backpropagation of error was developed, taking into account three significant parameters: the drum angular displacement, the drum speed and the ripple amplitude (input variables); and the processing and separation indicators (output variables) were evaluated. The predicted value obtained by ANN agrees well with the experimental values.

The paper [11] considers the use of an artificial neural network (ANN) to optimize the process of jigging small-grade coke coal. The developed model of a three-layer artificial neural network (ANN) is used to determine the flammability and concentration of ash in the concentrate. The results showed that the predicted values of the ANN model are in good agreement with the experimental results.

In [12], the process of jigging brown coals is considered. The fluidization air velocity and pulsation frequency were selected as the main parameters for determining the optimal separation efficiency. This paper considers the optimization of the gravity enrichment process itself by various methods, including intelligent ones.

Thus, the analysis of the research literature allows drawing the following conclusions:

- research that is conducted in the field of gravity preparation technologies is mainly focused on the processing of coal, and not the extracted ore;
- almost all research is carried out in laboratories, where disturbances and uncertainty in the technological process are excluded;
- artificial neural networks are used for the development of control algorithms, there are no comparisons with other methods of artificial intelligence (fuzzy logic and hybrid networks);
- the use of intelligent methods is limited to the local prediction of the key processing variable;
- no systematic intelligent approach to the control of gravity ore dressing processes has been found.

III. MODEL AND METHODS

Based on the analysis of literature sources and the opinion of expert technologists working directly on gravity enrichment devices, it was concluded that the best option for determining the optimal values of significant variables of the gravitational ore enrichment process is intelligent algorithms that formalize the knowledge of experienced technologists.

In general, the creation of intelligent algorithms is carried out in several stages:

- development of a training sample (knowledge base) for intelligent algorithms;
- development of management models using intelligent technologies;
- comparison of the adequacy of the obtained models;
- testing in real industrial conditions.

The main task in the synthesis of intelligent models is to compile a planning matrix for a complete factorial experiment (PFE). This matrix is used to create a model for managing an object or process [13, 14]. The planning method, which is a procedure for selecting the conditions for conducting all experiments, is a method of a complete factor experiment. All possible combinations of factor levels are implemented in the PFE. The number of combinations (experiments) is calculated by the formula:

$$m = k^n \tag{2}$$

where n is the number of factors (controlled variables) and k is the number of levels.

A training sample (knowledge base) is an important component of an intelligent system. Only on the basis of a reliable knowledge base can a high-quality management system be built. When forming the PFE matrix, the main source of information is an expert, and to increase the objectivity and quality of the decision–making procedure, it is advisable to take into account the opinions of several experts. This leads to special requirements for the selection of experts, in particular to the level of their professional competence, since an insufficient level of expert competence can lead to gross errors in data and the need to use complex computational methods for processing expert information.

The entire set of tasks for obtaining reliable PFE matrices, a knowledge base, a training sample, etc. can be divided into two large classes: with sufficient and insufficient information potential of specialists.

When solving problems of the first class, specialists are high-quality and accurate sources of information. Based on this, the generalized opinion of a group of experts is determined by averaging their individual judgments and is close to the true one.

In relation to the problems of the second class, experts cannot be considered as sufficiently accurate meters. The use of an averaging method acceptable to competent experts may lead to errors, since the opinion of one expert, which differs significantly from the opinion of others, may be correct. In this regard, in this case, it is necessary to use high-quality, resource-intensive processing of the results of expert evaluation [15].

Therefore, to create databases for intelligent algorithms for controlling the process of gravitational enrichment, in order to increase the reliability of expert information, the competence of experts was evaluated and the most competent ones were selected.

It is proposed to use a combined method for assessing the competence of experts. In order to assess the competence of specialists, the following factors are taken into account: the level of education of a specialist, work experience in the mining and processing industry, experience working on a processing apparatus, passing advanced training courses.

The essence and stages of implementing the combined method are as follows:

- selection of experts *n* from a set of N, through intermediate levels, factors for comparison;
- when assessing the competence of experts, it is necessary to take into account the factors that determine their competence in numerical terms [16].

The development of models for controlling the process of gravitational enrichment using fuzzy logic and neural networks was discussed in detail in [17]. In this paper, it is proposed to consider the development of a neuro-fuzzy (hybrid) network for managing the enrichment process and a comparison of all three control models (fuzzy, neural network and hybrid).

Fuzzy neural networks are endowed with all the advantages of conventional neural networks, as well as a fuzzy inference system and fuzzy logic [18]. They allow you to develop and present models of systems using fuzzy rules that have clarity and simplicity of presentation. The advantage of fuzzy neural networks is the parallelization of information processing and the ability to self-learn, creating generalizations that are able to obtain a reasonable result based on data that did not participate and did not occur in the learning process of the network. Hybrid networks are able to solve complex, and sometimes large-scale task. Such tasks include the development of algorithms for controlling the processes of gravitational enrichment, since they are multidimensional processes with a stochastic nature of the input variables.

The main advantages of fuzzy neural networks:

- the possibility of solving the problem with unknown data and patterns;
- the stability of a fuzzy neural network to noise in the input information;
- adaptation to the environment and its changes;
- fuzzy neural networks are characterized by high performance. The use of mass parallelism of information data processing allows fuzzy neural networks to have high performance;
- fault tolerance of a fuzzy neural network. In the case of adverse effects on fuzzy neural networks, the performance of which decreases slightly, and are fault-tolerant. In this study, the ANFIS editor of MATLAB was used to analyze, develop, and model a system based on the Takagi-Sugeno fuzzy inference system. Fuzzy neural networks make it possible to solve unformalized problems by feeding various data to the network input and evaluating the output result [18].

The output signal in the Takagi-Sugeno fuzzy production network is performed using the formula:

$$y(X) = \frac{\sum_{i=1}^{M} w_i \cdot y_i(X)}{\sum_{i=1}^{M} w_i} \qquad (2)$$

where $y(X) = p_{i0} + \sum_{j=1}^{N} p_{ij} \cdot x_j$ is the *i*-th polynomial of the approximation component.

The weight coefficients of the w_i components of the network can be calculated using the following formula (in this case, the rational form of the Gaussian function is used, but other functions can also be used):

$$w_i = \prod_{j=1}^{N} w_{ij}\left(x_j\right) = \prod_{j=1}^{N} \frac{1}{1+\left(\frac{\left|x_j - c_{ij}\right|}{\sigma_{ij}}\right)^{2b_{ij}}} \qquad (3)$$

These expressions correspond to a five-layer fuzzy neural network, which is used to determine the ripple frequency (Figure 3).

It is proposed to tune Sugeno-type fuzzy inference system using training data in order to determine the crucial variables of the ore jigging process.

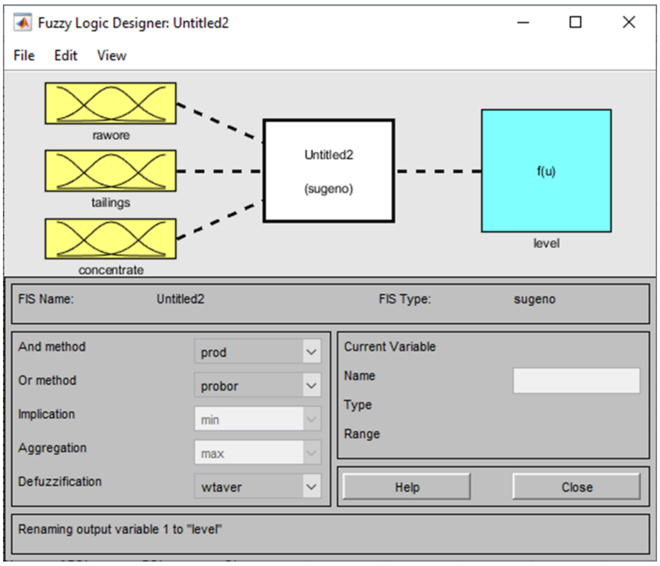

Fig. 1. Fuzzy logic designer for fuzzy neural network

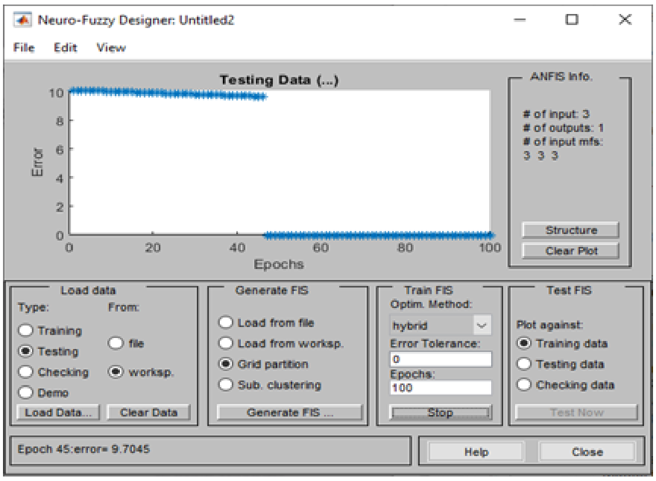

Fig. 2. The learning procedure a neuro-fuzzy network

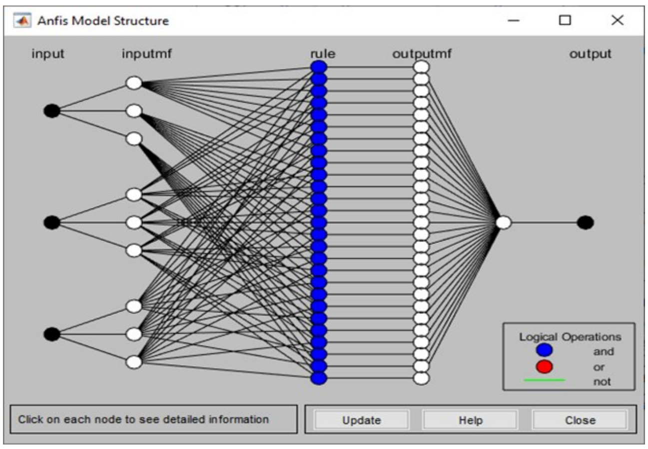

Fig. 3. Block diagram of the fuzzy production network of the Takagi-Sugeno-Kang network

It is worth noting that here is an example of only one output variable-the level of the "natural" bed, for the calculation of the other output variables, similar procedures are performed [20,21]. The assignment of each input and output variable as a fuzzy set and the learning process of the neuro-fuzzy network are shown in Figures 1 and 2, respectively.

The next step in creating a hybrid network is to generate the structure of the fuzzy inference system. At this stage, the network architecture can be viewed (Figure 3).

After the network training is complete, there is an opportunity to test it, load the verification data, or view and set any valid values in the FIS Rule Viewer editor that is presented in Figure 4.

Fig. 4. "RuleViewer" Editor after leaning procedure

The estimation of the accuracy of the calculation of the variables of the jigging process using the obtained algorithms is carried out using the following statistical criteria [22]:

- correlations of expert and model values (R);
- root mean square error (RMSE);
- mean absolute error (MAPE).

The correlation coefficient between the expert values and the values obtained by the model (algorithm) is performed using the formula:

$$R_{Y^E Y^M} = \frac{\sum_{i=1}^{m}(Y_i^E - \overline{Y^E})(Y_i^M - \overline{Y^M})}{\sqrt{\sum_{i=1}^{m}\left(Y_i^E - \overline{Y^E}\right)^2 \sum_{i=1}^{m}(Y_i^M - \overline{Y^M})^2}} \quad (4)$$

where Y_i^E is the i-th value of expert data;
$\overline{Y^E}$ is the average value of expert data;
Y_i^M is the i-th value of the data obtained from the model;
$\overline{Y^M}$ is the average value of the data obtained from the model.

The root mean square error is calculated by the formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_i^E - Y_i^M\right)^2}{n}} \quad (5)$$

where Y_i^E is the *i*-th value of expert data;
Y_i^M is the *i*-th value of the data obtained from the model;
n is the number of values.

And the next criterion is the average absolute error, which is performed by the formula:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i^E - Y_i^M\right| \quad (6)$$

where Y_i^E is the *i*-th value of expert data;
Y_i^M is the *i*-th value of the data obtained from the model;
n is the number of values.

To assess the adequacy of the obtained algorithms, a test sample of input variables other than the training sample was compiled. The output variables were obtained as a result of a survey of experts (Y^E) and testing of the resulting algorithms (Y^M).

The graphical interface shown in Figure 5 presents a fuzzy model (algorithm) for obtaining optimal values of output variables. In this case, the level of the "natural" bed (level), the ripple frequency (speed) and the violation of the enrichment technology (alarm). Thus, it is possible to determine the optimal output values when setting the input variables from the test sample using a fuzzy algorithm.

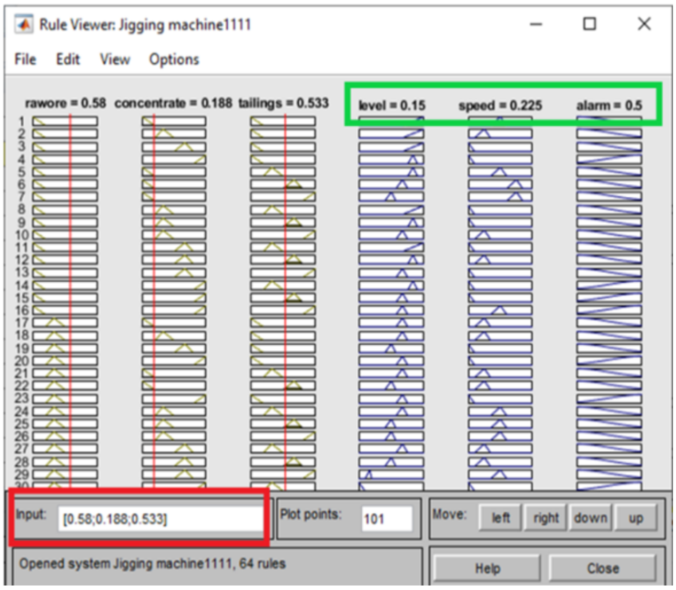

Fig. 5. Graphical interface of the rules viewer

Figure 6 shows testing a neural network using the command sim.

Fig. 6. Testing the neural network

The command is used to test the hybrid network. This command allows us to generate a matrix of output variables based on the test sample.

Thus, all three algorithms were tested on a sample other than the training one. Then the adequacy was evaluated for each type of models using criteria such as the correlation between the model values and expert one, the root mean square error and the average absolute error.

IV. RESULTS AND DISCUSSION

The developed algorithms for determining the variables of the jigging process using artificial intelligence formalize the knowledge, experience and intuition of people-experts who are well acquainted with the subject area. It is obvious that over many years of work, the technology staff develops experience in optimal equipment management. The formalization of the" ready-made" knowledge of experienced experts allows us to create a flexible control system, with the exception of the human factor (greater or lesser competence of the staff, fatigue, inattention, slowness, etc.).

The main purpose of this paper is to compare three algorithms for calculating the variables of the jigging process using statistical adequacy criteria.

Thus, using formulas 3-5 and the data obtained during testing of the algorithms, the adequacy of the developed intelligent algorithms for controlling the process of gravity enrichment will be evaluated.

The results of the assessment of the adequacy of the intelligent algorithms of the gravity ore dressing process in the jigging machine are listed in tables I, II and III.

TABLE I
THE ADEQUACY OF THE FUZZY ALGORITHM

Criterion	*L*	*n*	*A*
R	0,98	0,986	0,974
RMSE	0,06	0,059	0,101
MAPE, %	4,76	4,203	7,85

TABLE II
THE ADEQUACY OF THE NEURAL NETWORK

Criterion	*L*	*n*	*A*
R	0,96	0,98	0,954
RMSE	0,082	0,063	0,221
MAPE, %	7,4	6,1	8,55

TABLE III
THE ADEQUACY OF THE NEURO-FUZZY NETWORK

Criterion	*L*	*n*	*A*
R	0,987	0,9951	0,962
RMSE	0,0563	0,0345	0,204
MAPE, %	3,903	2,711	6,79

The analysis of the data presented in the above tables allows us to conclude that the values of the statistical criteria for the adequacy of all three experimental algorithms do not exceed 5%. The exception is the "alarm" variable. This is due to the complex relations of this variable and the need for further work on the training sample for this variable.

The algorithm based on the neuro-fuzzy (hybrid) model has the best indicators of adequacy. MAPE for three variables is the natural "bed" level (3.903%), the ripple frequency of the jigging compartment (2.71%) and alarm (6.79%). In addition, the correlation coefficient between expert and received values is 0.987 and 0.995, respectively.

The correlation between the values of the natural bed level indicated by the experts for the test sample and the data calculated by the hybrid network is shown in Figure 7.

The correlation of the ripple frequency values specified by the experts for the test sample and the data calculated by the hybrid network is shown in Figure 8.

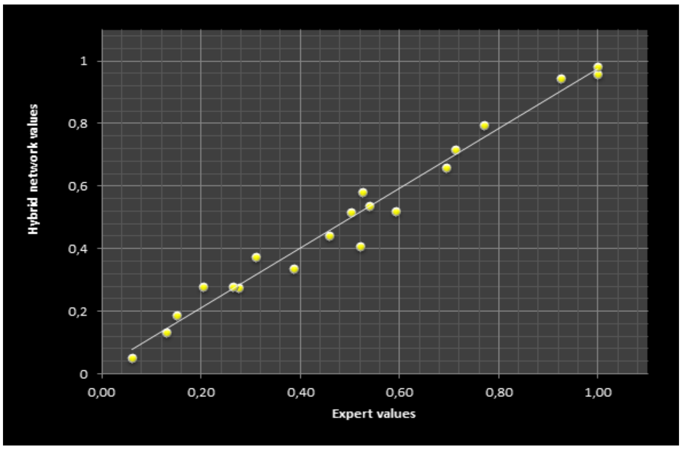

Fig. 7. Correlation of expert values of the natural bed level obtained using a neuro-fuzzy network R=0.987

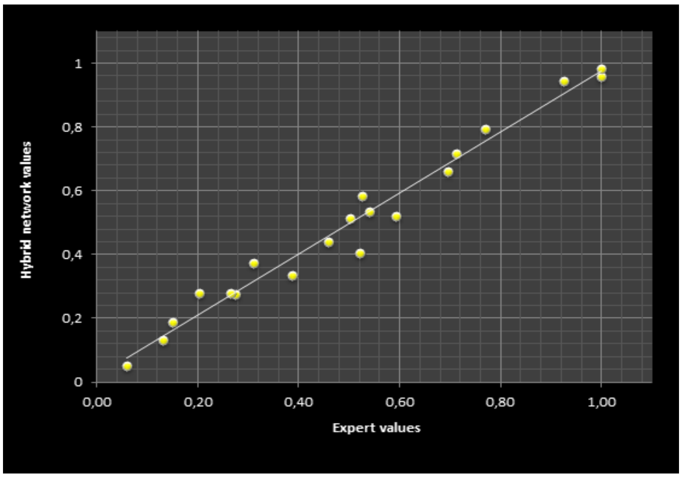

Fig. 8. Correlation of expert values of the ripple frequency and the values obtained using the neuro-fuzzy network R=0.9951

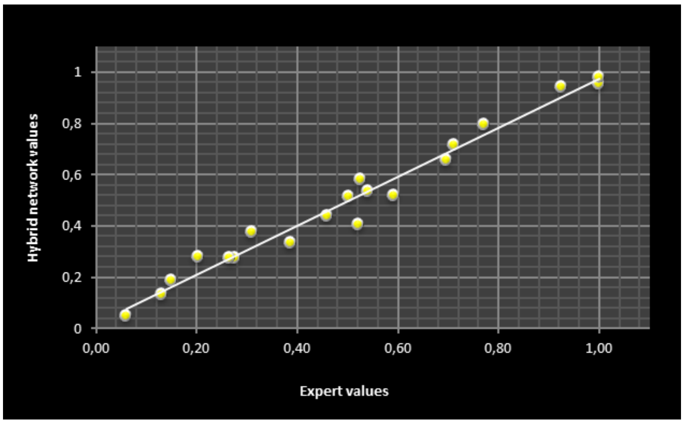

Fig. 9. Correlation of expert values of the alarm signal and the values obtained using the neuro-fuzzy network R=0.962

The correlation of the alarm signal values specified by the experts for the test sample and the data calculated by the hybrid network is shown in Figure 9.

Based on the conducted research and calculations, it was determined that a hybrid algorithm will be used to develop an intelligent control system for the jigging process.

V. CONCLUSIONS

This paper describes the comparison of the intelligent algorithms for determining the key variables of the ore jigging process. The use of intelligent control systems for ore deposition processes will eliminate the influence of the human factor on the production technology, improve the quality and yield of valuable components. In this regard, three intelligent algorithms were developed to determine the key variables, their adequacy was evaluated according to statistical criteria, and the best one was determined.

The minimum discrepancy between expert data and model data is inherent in a neuro-fuzzy algorithm. The RMSE (Root Mean Square Error) value for the test sample of expert and model data was 0,0563, 0,0345 and 0,204 respectively. For comparison, the RMSE values for the neural network made 0,064, 0,059 and 0,101. This study helped to determine the algorithm that ensures the exact operation of the intelligent control system of the jigging process.

The methods of testing and the results of the obtained models (algorithms) in real industrial conditions will be presented in the subsequent works of the authors.

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