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Development and Research of Intelligent Algorithms for Controlling the Process of Ore Jigging

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ABSTRACT

The search for methods for control the beneficiation of chromite ore, eliminating the loss of chromite in the form of tailings, has both economic and environmental importance. Jigging machines are used to enrich such ore. Optimal control of these units allows achieving maximum technological enrichment indices. So, in this study, a fuzzy logic approach was attempted for develop an intelligent algorithm to determine the optimal value of the key process variables: the level of the natural «bed» (mm), the pulsation rate of the jigging compartment (s-1) depending on the grade Cr2O3 of the raw ore (%), the grade Cr2O3 of the tailings (%) and the grade Cr2O3 of the concentrate fraction (%). The algorithm is based on the knowledge of competent expert, the knowledge base consisting of 64 operating modes. The values obtained by the fuzzy model and experimental values have a minimum divergence.

Key words : Chromite, Fuzzy Logic, Intelligent Algorithm, Jigging Machine, Knowledge Base.

1. INTRODUCTION

In the modern world, in the context of economic and emerging environmental crises, environmental and economic aspects of mining and processing of minerals come to the fore. Therefore, it is important to use technologies that minimize the negative impact of industrial production on the environment and workers' safety [1] in order to avoid losses of raw materials and energy resources at all stages of technological processing of minerals and organic matter [2]. Some of the recent examples are the technologies developed in India: the use of burned agricultural wasteas an effective method for strengthening concrete [3] and the use of crushed clam shellsin pervious concrete for low traffic areas [4].

Kazakhstan ranks first in the world in terms of explored reserves, and second in terms of potential reserves of chromium, and provides 15% of its world production [5]. Of particular interest to the concentration of chrome ore are thin and small grades (with the size of 2-10 mm), which fall into the dumps without the use of special processing technologies, which is absolutely economically impractical.

The demand for chromite ore is growing every day. Therefore, it is necessary to look for new approaches to concentration that will ensure maximum extraction of the useful component from the extracted ore and can be used to process existing tailings.

Gravity dressing methods are used to process small and fine grades of mined ore. The modern concept of gravitational methods includes the separation of mineral particles under the influence of gravity force and resistivity, as well as the separation of particles by size and shape. The variety of particles with their individual properties complicates reliable quantitative description of gravitational processes. Therefore, the development of this method of dressing, despite its long history and wide range of application, is used mainly through experiments.

One of the most common methods of gravity dressing of chromite ore is the jigging process. Jigging is a method of gravitational dressing of minerals based on the separation of the mineral mixture into layers that differ in density; it takes place as a result of periodic exposure to ascending and descending flows of the isolation medium.

The final products of the jigging process are concentrate with a high content of the useful component and waste.

This paper proposes defining the key variables of the jigging process using artificial intelligence technologies. The result will be 2 algorithms using fuzzy logic and artificial neural networks. The algorithms will be tested on an independent sample (that is, on data that was not used for the neural network adaptation and the fuzzy algorithm knowledge acquisition). This procedure will allow us to evaluate the adequacy of the developed algorithms. Therefore, the algorithm used to obtain data with minimal discrepancies with the ideal experimental sample will be integrated into the jigging machine control system.

2. LITERATURE REVIEW

Upon the face of the jigging process it is quite simple and, accordingly, controlling it to achieve high dressing rates is not of particular difficulty and interest. But a thorough analysis of literary sources [5]–[9] considering this method of dressing shows that this is not the case. The complexity of the jigging process and, as a consequence, its control, is connected with two peculiarities of this process. Firstly, there is no unified view on the mechanism of separation of the material in the jigging machine. Secondly, a quality jigging process depends on many internal factors related to the physical properties of dressing materials and the external ones, for example, process variables such as the level (thickness) of natural bed, pulsation frequency, underscreen water flow, etc.

Due to the complexity of the mathematical description of the jigging process, the authors considered the possibilities of using intelligent models for controlling it. The subject of [10], [11] are some algorithms for determining key variables in the process of jigging coal and chromium based on ANN. But unfortunately, these studies use the data obtained from laboratory installations and not from real technological units.
The authors [12], [13] deal with the key variables of the jigging process and their influence on the dressing indicators, but do not propose the formalization of dependence and control methods.

In connection with the fact that the number of chromium deposits in the world is relatively small, studies on controlling the process of dressing chromite ore are presented in the scientific literature a few.
Based on the analysis of modern research on the use of intelligent algorithms for controlling the jigging process, the following conclusions can be drawn:

- all the papers deal with one type of algorithms, there isnocomparativeanalysis;
- the input data for building algorithms are experimental data obtained at a specific laboratory installation;
- no studies of intelligent control algorithms for jigging machines have been found;
- when evaluating the adequacy of the algorithms, some “ideal” data are used, that is, obtained at a laboratory; therefore, the influence of natural external factors encountered directly at a dressing plant is not taken into account. This leads to the need for additional verification of the received algorithms intheplantconditions.

Thus, in order to build an adequate model (algorithm) for controlling the jigging process, it is necessary to use the data obtained from the analysis of the theoretical foundations of the process and the survey of competent technological personnel who know all the nuances of equipment operation.

3. MODELS AND METHODS

The vulnerability of classical control methods is related to the multidimensional nature of gravitational dressing processes. For example, the technological parameters of dressing of jigging machines are simultaneously affected by about 20 factors determined by the power characteristics and mode, technological and hydrodynamic parameters of the process. Many of them are in complex interaction with each other and show out ambiguously in different conditions.

Therefore, it is proposed to develop intelligent algorithms for calculating the main parameters of the jigging process. The algorithms were developed based on fuzzy logic and neural networks using the Matlab package.

The main task of synthesizing intelligent models is to develop a planning matrix for a complete factor experiment (FPE). Using this matrix, an object or process control model is set up [13]. As a result of a survey of experienced operators who have worked with the jigging machine for a long time, the basic rules (knowledge base) were obtained. The resulting FPE matrix became the basis for developing an intelligent algorithm using fuzzy logic, which is explained in the next section.

4. FUZZY LOGIC

Currently, fuzzy logic is widely used in control and simulation tasks using MIMO systems, expert systems, analytical technologies, and many other applications. Fuzzy logic is an approach to computing based on “degrees of truth” rather than the usual “true or false” Boolean logic (1 or 0) on which a modern computer is based. The idea of fuzzy logic was first put forward by Dr. LotfiZadeh of the University of California, Berkeley in the 1960s [14].

In this study, the fuzzy Logic Toolbox ™ software tool from MATLAB® was used to analyze, develop, and model systems based on fuzzy logic.

Fuzzy logic is a modelling tool that can be successfully applied to complex nonlinear systems where it is difficult to establish correlations between input and output variables.

The stages of algorithm development [15],[16]:

- determininginputandoutput variables of the dressing process in the jigging machine;
- normalizingvariables;
- creating a planningmatrix for a complete factor experiment (PFE);
- designingalllinguisticvariables and their membership functions;
- selecting a basicset of terms for the linguistic variable or a set of its values (terms), each of which is the name of a separate fuzzy variable;
- formingproductfuzzyrules;
- getting a fuzzyalgorithm for determining the key variables of the jigging process;
- analyzingtheadequacyofthereceivedcontrolalgorithm.

Sincethetechnologicaldataobtainedfromexperiencedtechnologistsisbusinessinformation, therefore, normalizationinthiscaseservesas a protectivefunction.

In this situation, normalization in the range from 0 to 1 of the input and output variables is performed using the formula:

$$\bar{x} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Where $\bar{x}$ – normalized value of the input or output variable, x - running value of the variable, $x_{min} x_{max}$– minimum and maximum value of the variable.

The PFE planning matrix implements all possible combinations of factor levels. With the number of levels equal to four for each factor, the PFE matrix consists of m = 4n rows, where n is the number of factors (controlled variables), and m is the number of experiments [13]. In this case, m = 43 = 64.

The linguistic variables are listed in Table 1.

Table 1: Linguistic variables of the jigging process

Input variable	Output variable
Cr_2O_3 content in the run-of-mine ore (%)	Pulsation frequency, s^{-1}
Cr_2O_3 content in the tailings (%)	Level of natural “bed”, mm
Cr_2O_3 content in the concentrate fraction (%)	Alarm

Figure 1 presents a fuzzy logic designer for developing an algorithm of calculating key variables in the jigging process.

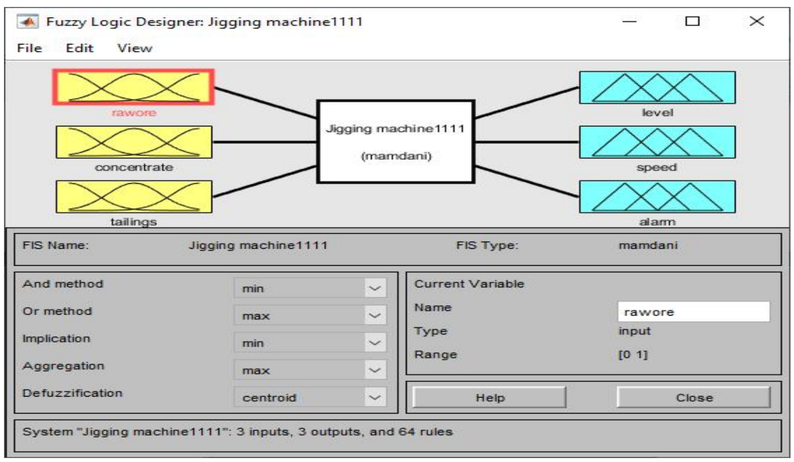

Figure 1: Fuzzy logic designer

The functions of linguistic variables membership are defined, and the type of terms – trigonal – is selected. The choice of trigonal terms is justified by the studies [17], [20].

After defining the membership functions, fuzzy rules are formed for each linguistic variable, that is, each experiment has a rule in the form:

Rule 1: if raw ore = 0 and tailings = 0 and concentrate = 0, then level = 1, speed = 0.5, alarm = 0.

An alarm is a variable that indicates violations of the dressing technology. It should be noted that a certain combination of input variables indicates a situation in which dressing either does not take place at all, or proceeds improperly.

The rules are prescribed in the Rule Editor of the Fuzzy Logic Matlab program. Their total number is 64 (Fig. 2).

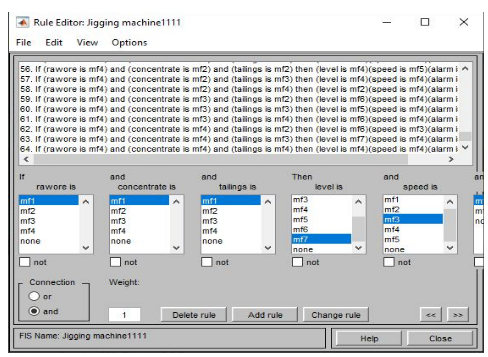

Figure 2: Fuzzy logic rule editor

As a result, we received an algorithm for determining the key variables of the jigging process in the Alljig-G / F jigging machine: the level of the natural “bed”, mm and the pulsation frequency, c-1. In addition, the third output variable allows the operator to get information about the state of the process.

5. ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) are computing systems vaguely inspired by the biological neural networks that constitute animal brains. Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules. The most widespread type of neural network is multilayer perception (MLP) feed forward neural network [18]. A multilayer perception is a class of artificial neural networks of direct distribution, consisting of at least three layers: input, hidden and output. With the exception of input, all neurons use a nonlinear activation function. One of the most commonly used activation functions is a binary sigmoid function with a range of values in (0, 1) and defined as:

$$f_1(x) = \frac{1}{1+e^x} \qquad (2.1)$$

$$f_1'(x) = f_1(x) * [1 - f_1(x)] \qquad (2.2)$$

where f is the output and x the input value.

When designing a neural network, the first step would be to solve the problem of the number of layers and the number of elements (neurons) in each layer. There is a trade-off between accuracy and the generalizing ability of the network, which can be optimized by choosing the number of hidden elements for the network. The number of hidden elements on the one hand must be sufficient to solve the task, and on the other hand, must not be too large to increase the learning time of the network.

One of the methods for calculating the upper bound on the number of neurons in a hidden layer is Kolmogorov's theorem. According to this theorem, any function of n variables can be represented as a superposition of 2n +1 one-dimensional functions. This boundary h is equal to twice the number of input elements i plus one [19]:

$$h \leq 2i + 1 \qquad (3)$$

where i is the number of input variables.

In present study a three layer feed forward ANN architecture (3:3–7–2:2) has been proposed for determining the key variables of the jigging process: the level of the natural “bed”, mm and the pulsation frequency, c-1. According to formula 3, the number of neurons in the hidden layer is seven ($\boldsymbol{h \leq 2 * 3 + 1 = 7}$). The ANN architecture is illustrated in Fig. 3. The details about the learning method could be read from literature [12], [18], [19]. The considered neural network has the following characteristics: architecture (3:3–25–2:2) back propagation algorithm, learning algorithm - Levenberg–Marquardt algorithm, the activation function – sigmoid function.

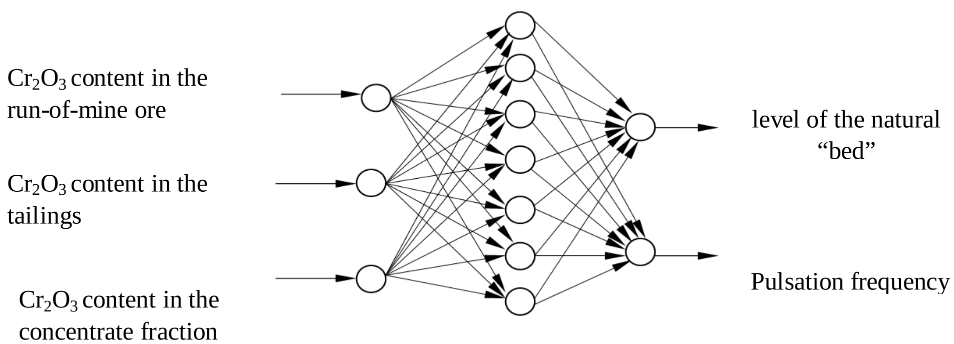

Figure 3: MLP architecture for level of the natural “bed” and pulsation frequency

6. RESULTS AND DISCUSSION

Input and output variables in the algorithm development were selected based on the analysis of the theoretical foundations of the jigging process [6], [8] and a survey of technology experts. All data for the fuzzy algorithm rule base acquisition and neural network adaptation are obtained from a survey of several technology experts, and represent a generalized assessment for the entire group of experts. This enhances the reliability of adaptation information.

The ultimate goal of the work is to choose an algorithm that formalizes the knowledge of experienced technologists with minimal discrepancy. This will free the personnel from decision-making, eliminate the human factor in the control process (inattention, lack of competence, fatigue) and, as a result, maximize the concentration of chrome ore during the jigging process. It is important to note that the “alarm” variable is an auxiliary variable. The main function of this variable is to provide the technologist with information about the state of the jigging process in the jigging machine in real time mode. The future studies will consider this variable in more detail. The main task of the obtained algorithms is to calculate the key variables: the pulsation frequency, c-1 and the level of natural “bed”, mm. It is basing on these data that the adequacy of the algorithms will be evaluated.

To test the obtained algorithms, another survey of experts was conducted, and 15 modes of operation of the jigging machine were obtained (different from those specified in the PFE matrix). In other words, the experts were offered 15 combinations of input variables. After that, all combinations were used to test the resulting algorithm. This procedure is shown in Fig. 4. The input variables are in the area marked in red, and the output variables are in the area marked in green. This procedure was performed with all the 15 combinations in turn.

Figure 4: Algorithm testing

As a result, 15 values of the natural “bed” level and 15 values of the pulsation frequency of the jigging compartment were obtained.

Table 2 shows the data for testing fuzzy and neural network algorithms, and the data specified by experts. Fig.5 and Fig.6 illustrate the correlation between the data obtained as a result of testing algorithms and expert data for two output variables (the level of the natural “bed” and the pulsation rate of the jigging compartment).

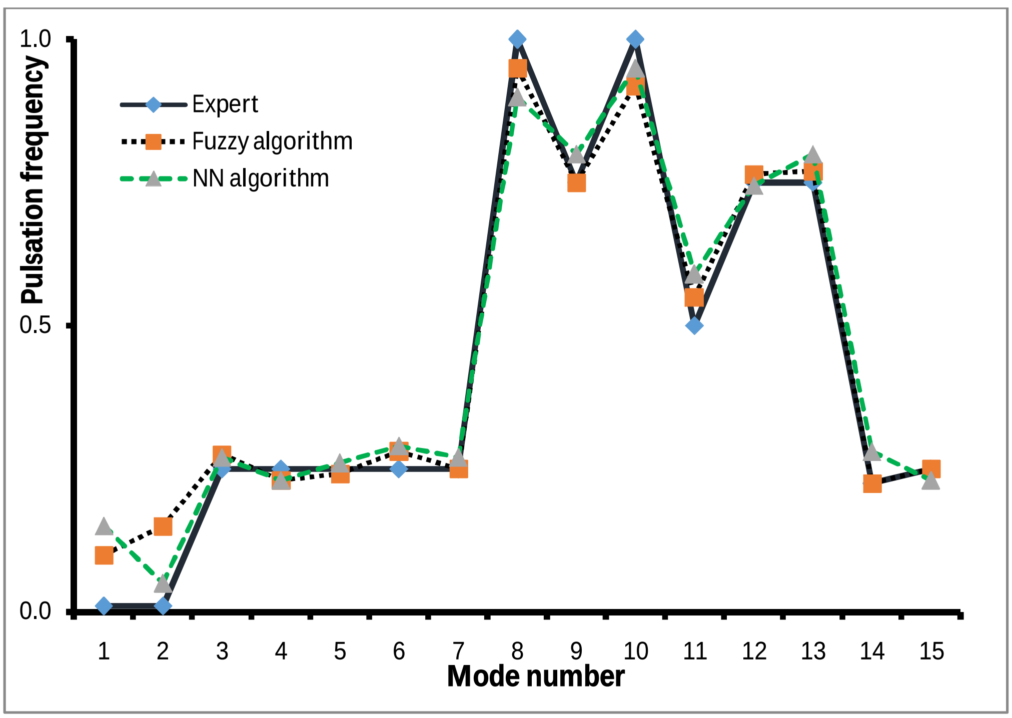

Figure 5: Comparison between obtained and expert values fortesting data set (pulsation frequency)

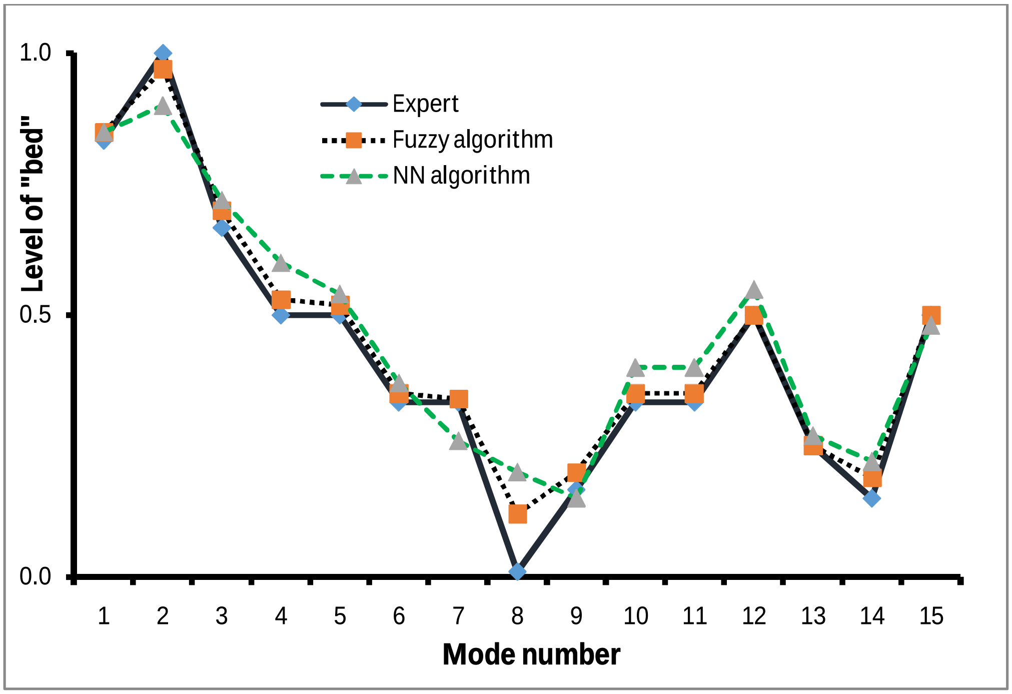

Figure 6: Comparison between obtained and expert values for testing data set (the level of the natural “bed”)

The adequacy of the obtained algorithms was evaluated by the following criteria: the correlation coefficient (R), mean absolute percentage error (MAPE), Root Mean Square Error (RMSE). The values are listed in Table 2.

Table 2: The adequacy of the algorithms

Algorithm	**Fuzzy**		**ANN**	
Criteria	natural “bed” level	pulsation frequency	natural “bed” level	pulsation frequency
R	0,995	0,991	0,96	0,98
RMSE	0,036	0,055	0,082	0,063
MAPE, %	4,64	5,02	7,4	6,1

It was found that the obtained values according to the fuzzy algorithm are consistent with the expert values with the mean absolute percentage error for both the natural “bed” level (4.64%) and the pulsation frequency of the jigging compartment (5,02%). In addition, the correlation coefficient between expert and received values is 0.995 and 0.991, respectively. The values of the neural network work error were slightly higher. For the level of natural “bed”, the mean absolute percentage error was (7.4%) and for the pulsation frequency of the jigging compartment – 6.1%. Therefore, a fuzzy algorithm can be successfully used to determine the optimal value of the key jigging variables.

7.CONCLUSION

This paper describes the results of the development of intelligent algorithms for determining the key variables of the chrome ore jigging process. Classical methods of controlling the dressing process of small and thin grades of ore do not allow achieving the maximum content of the useful component in the end product. Thus, in this study, using fuzzy logic and neural networks, experimental algorithms were obtained that allow formalizing the knowledge of experienced technology experts. The check of the adequacy of the algorithms showed that the minimum discrepancy between expert data and model data is inherent in a fuzzy algorithm. The RMSE (Root Mean Square Error) value for the test sample of expert and model data was 0.036 and 0.055, respectively. In its turn, the RMSE values for the neural network made 0.082 and 0.063. The fuzzy algorithm can be used as an autonomous expert system or integrated into the overall control system of the jigging machine. This eliminates the influence of the human factor and allows achieving high technological indicators of dressing.

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