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DEVELOPMENT OF THE HYBRID CONTROL SYSTEM FOR A THREE-STAGE IRON ORE ENRICHMENT BASED ON MULTI-AGENT CONTROL AND REGRESSION ANALYSIS

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Abstract. Development issue on the automated control system for the enrichment of iron ore in a view of complexity of the relations between mechanisms is considered. The object of the research is a model of the automated control in the enrichment process at the enrichment enterprise section.

Aim. Development of the multi-agent control system for the enrichment enterprise through the advanced control means and measurement of the performance functions of the equipment and the product processed.

Methods. The processes of the iron ore enrichment in terms of the automated control are considered. It is established that changes in characteristics of iron ore on a feeder significantly impact both the technological processes of a concentrating mill and the characteristics of the outputs. Complexity of measurements, non-stationarity and inertia of processes requires the use of combinations of advanced intelligent automated control. The tasks regarding characteristic measurement of the processed product and the parameters of technological mechanisms are of great importance. The effectiveness of the multi-agent control in combination with the intelligent control means in comparison with the methods used today is proved. The expediency of the intelligent control means including the means of a regression analysis for the control of technological equipment is proved.

Scientific novelty. The method for controlling a three-stage enrichment based on relations between agents, as well as methods for experiment planning and regression analysis are proposed.

Practical significance. A block diagram of the control system for three-stage grinding and enrichment of the iron ore is developed. The control system for the second enrichment through a hydrocyclone on the base of the above-mentioned methods is developed. An analytical model for controlling the iron ore enrichment section in general is developed. The performed analysis suggests the use of the multi-agent control to significantly improve the control accuracy, as well as make it more adapted to the real conditions and requirements for the quality of a concentrate. Improvement of the method for modeling the technological process of enrichment through a regression analysis will significantly upgrade the accuracy of control in terms of non-stationary processes of a concentrating mill. Further research is to develop the control systems for each mechanism, to make more precise the rules in databases of fuzzy networks and to study the possibilities of relations between agents.

Keywords: enrichment, iron ore, automation, multi-agent control, system approach, hydrocyclone, separation, regression analysis.

Introduction. The prime objective of the production is to reduce the cost price of the product in view of important directions of modern global market development. This goal may be attained by a comprehensive optimization of a production processes through introduction of modern technologies. Improving the quality of industrial processes automation is the main factor in industrial energy efficiency.

Processing complex includes many technological mechanisms having various operations, as well as different construction. Therefore, different approaches to develop the control systems are required. Besides, the enrichment devices are directly interrelated and affect each other, as well as require the use of measuring instruments for recording the values of a different physical nature. This increases the required computational power [1-4].

The use of modern means of intelligent systems such as methods of optimal and adaptive control, fuzzy logic or artificial intelligence, is one of the most promising directions in the development of factory automation. The powerful regulators are constructed on the basis of these means. They are generally characterized by fast performance, improved resistance to disturbance variables and ability to operate more effectively with the use of incomplete data. In [5], the method for normalizing a power consumption of the enrichment enterprise based on the intelligent control was proposed. The system of effective neuron-fuzzy power consumption forecast was suggested in order to achieve a set goal. Based on industrial tests results, this system through modern control means has reduced power consumption by 2% through the structural subdivisions of the enrichment enterprise.

Traditional automation means in combination with fuzzy logic methods not by using limited numerical values, but by using linguistic variables, which is expedient for controlling a three-stage enrichment complex. The whole complex is considered then a more adequate system, close to real conditions. It allows one to perform a full control through some expert knowledge base in real-time. [6-9].

Diagnosis of technological tools is truly effective in preventing emergency situations and provides planned check-ups precisely. Thus, that would significantly extend the life of equipment and reduce the repair and maintenance costs in the future. However, the processes at the concentrator takes place in the closed constructions. A pulp passes from mechanism to mechanism in the pipelines (except spiral classifier channels), and it makes impossible to visually control the processes inside the mechanisms like measuring the data on the state of these mechanisms and the raw materials processed.

That is why the non-contact measuring instruments are widely used in mining and processing industry. The radiometric, ultrasonic, thermographic instruments can be installed outside the mechanisms and pulp pipelines. However, the radiometric sensors, despite their high accuracy, require a special maintenance and availability of an appropriate service at the enterprise. The thermographic means of measurement do not provide sufficient accuracy [10-13].

The table 1 shows the degree of influence of qualitative properties of the ore on the efficiency of its processing (a degree of influence is measured from 1 to 4, as from a minor impact to very high) [14].

Table 1. The degree of influence of qualitative properties of ore on processing process efficiency

Property	Grinding	Magnetic separation
Hardness of the ore	1	-
Textural characteristics	2	3
Content of the magnetic product	-	1
Granulometric composition of the ore and products	3	2
Density of the ore	-	4

Such mechanisms as mills, separating apparatuses and magnetic separators are normally researched by scientists separately They develop new methods for measuring and controlling the parameters of the processed ore, diagnose the state of technological tools to extend their life cycle, examine in detail a physical nature of the ore processing processes, offer new constructions of the ore processing equipment or add-ins. It is the control of ball mills at the first stage of grinding has been given top priority in most works on automation of grinding processes. The very first stage is supposed to determine the preparation for enrichment and have the greatest impact on the enrichment results, while the subsequent stages of grinding are often ignored. This is also due to the fact that losses at the first stage are large and account to 30-55% of the total loss of the iron in tailings through changes in the physical and mechanical properties of the ore [68].

However, automation process requirements of the first and subsequent stages are different. The first stage is the process of ore preparation. The following stage is to disclosure ore clusters obtained from the previous stage. The reason for neglecting the second and third stages of grinding was previously high cost and complexity of control and automation, which were used only in priority tasks. In addition, a grinding cycle is a complex system in which several processes are simultaneously carried out, therefore, their adequate examination is a rather difficult task. However, real-time control means increasing speed of performance make possible to accurately monitor and include the parameters of the following stages of enrichment from the first one in the calculations of the control algorithm. The proposed solutions to individual problems, undoubtly, make it possible to achieve a significant positive effect. However, the operation of the mechanisms in main modes of interaction and their possible impact are not sufficiently studied by scientists. In addition, the implementation of most developments is either too complex or too expensive.

The aim of the study is to develop a multiagent system for the automated control of the iron ore processing enterprise by using modern control means. For this purpose, the following specific objectives have been pursued: to analyze the modern methods for controlling the concentrating mechanisms separately, as well as the mining and enrichment section as a whole; to improve the method for modeling the technological process at each stage of grinding and enrichment, as well as the relations between them for their further use in the control system.

Materials and methods. Taking into account a large number of measured data on the state of mechanisms and processed raw materials, it is expedient to simulate a distributed control system to solve the first problem. Distributed control system greatly facilitates a modeling process and improves the system performance. Distributed control system is defined as a complex of technical and software solutions for constructing automated process control systems, which enables decentralized data processing and availability of the distributed input and output systems, increased fault tolerance, standard and unique database structure.

Interest in distributed control systems arose in the process of increasing the number of sensors, production areas, modernization and complication of standard algorithms for monitoring technological processes. Controllers, input and output modules, sensors, actuators are separated in space. Each PLC operates with its sensors and actuators, works with a specific part of the control object, and does not depend on other PLCc. However, it interacts with other circuits and devices to perform a common task and achieve specified quality metrics. The distributed system sections can be located at any distance from each other, and communication between them will be supported by industrial communication protocols.

The main advantages of the distributed control system are fault tolerance, scalability, simple configuration and development.

However, the distributed control has its own drawbacks, the main of which is a certain "Command Center". While the distributed control mechanisms work independently from each other, the center processes all the obtained data on regulating the interaction between the controlled mechanisms contained significant design resources. In case of control center failure, the objects of the system will not be able to interact.

Multi-agent control (MACs) allows to avoid this disadvantage. It implies full decentralization of a control, absence of some main system and free operation of each control system (agent) by technological mechanisms independently from each other. However, agents interact harmoniously and share information among each other. The characteristic feature of the approach based on the principles of the collective multiagent control is a relatively low design complexity of the algorithms, as well as quick and optimal decision-making in dynamically changing circumstances. Each agent operates autonomously resulting in substantially increasing the efficiency of the system and controlling each mechanism required specifically for its operation.

An agent structure can be used to optimize complex control problems, choosing the best possible solution with the most efficient use of limited resources; to reduce costs, resources and maintenance by performing all the analytical tasks on a single platform; to improve the preparation of data [9]. The use of the multi-agent control significantly increases the productivity of the overall control system, its immunity and flexibility.

The main difference between classical distributed control and multi-agent control lies in what aspect of the process control system is as distributed one. Controlled mechanisms and / or their parameters are specific to the distributed control. The multi-agent control is a characteristic of the control systems of mechanisms that are considered to be distributed, i.g., distributed are relations without changing their physical relations. It is multi-agent controls that operate with the process parameters in the iron ore enrichment section based on recycling and extensive relations.

Establishing relations between control agents (technological mechanisms) necessitates making models directly by agents. Each of them is a subsystem and is modeled as a separate control system. First of all, a developed model of the mechanism will be ideal, since it is constructed on the analogy of a real physical model; prognostic, since the model predicts behavior of a control object; and a formal mathematical model, since mathematical regularities are used for its construction and research.

In view of nature of the processes at the concentrator, the created model should be stochastic, continuous, nonlinear, optimization and analytical.

Advanced automated control means like fuzzy logic tools, optimal and adaptive control methods, genetic algorithms, object space representation (matrix representation) and experiment planning methods (regression analysis) are advisable to be used for modeling technological mechanisms.

Advantages of fuzzy logic are the following: ability to operate with input data that are not specified clearly, for example, values (dynamic tasks) change continuously in time, as well as cannot be uniquely determined (statistical research results); option of fuzzy formalization of the evaluation and comparison criteria: operation with "majority", "possibly ", "predominantly"; possibility of the qualitative assessments of both input data and output results: not only operating the actual values but their degree of reliability and its distribution; ability to perform rapid modeling complex dynamic systems and their comparative analysis with a given degree of accuracy: operation with the system principles described by fuzzy methods save much time on a precise calculation of variables values and an equation formation described, as well as evaluation of different option for the input values.

Optimal control enables to monitor the technological mechanism for optimizing a certain criterion. The criterion can be various -technical, economic and other functional indicators of the object. Behavior of an object is represented mathematically, by equations. The basis for the application of optimal control is planning. Its main condition is to compare expected results and costs when allocating resources to solve critical problems, as well as when distributing production tasks and resources between the industries. Optimal control ensures the output of given production volume with the least expenditure or maximization of the economic result, coherence of economic interests.

Mathematical models for mechanisms of the optimal control include: development of goal control, expressed through a quality criterion; determination of differential equations describing all possible ways of movement of a control object; establishment of restrictions on resources that can be used in the form of irregularities or equations [11-12].

Adaptive control synthesizes control systems that change regulator parameters or regulator structure in terms of change of control object parameters or external disturbances acting on the control object. This approach considers the changing operating conditions of technological mechanisms and raw materials supplied for processing.

Genetic search algorithms are used for optimization and modeling problems by sequential selection, combination and variation of the desired parameters. This is rather an auxiliary means of the intellectual control which is applied in combination with other methods. For example, to optimize or configure a function, and train a neural network.

The above-mentioned means of the modern intelligent automated control have their advantages and disadvantages in the model of the technological mechanisms at the enterprise. However, they do not include the effect of the parameters of a pulp to be treated at different stages. In order to achieve a required optimum (maximum quality, maximum productivity or minimization of losses of a useful component), it is necessary to establish dependence of the optimized parameter on the parameters of a pulp at the inlet and between the stages. The identification of characteristic, whose modification mostly influences the change in the result, enables to more accurately select the required control actions and effectively use them.

However, direct relation between inputs and outputs of the product almost never happens, especially in view of non-stationary and dynamic processes at the enrichment plant. In this case, regression dependence is used. Most of the parameters of a pulp processing at the enrichment plant are difficult or impossible to measure. Therefore, with the problem of maximizing iron content in the concentrate at the section outlet, it is only possible to establish dependence of iron content in the final product on characteristics such as strength or granulometric composition of a pulp in theory, since in practice these parameters are not measured during the operation of the mechanisms.

In this case, regression analysis should be used. After the presentation of relations between variables quantitatively in some combinations of these variables, the resulting combination is used to predict the value that can make the target (dependent) variable, which is calculated on a given set of input values (independent) variables. In the simplest case, the standard statistical method such as linear regression is used. In general, regression analysis measures the extent to determinism variation of the criterion (dependent) variable by predictors (independent variables); it predicts value of the dependent variable by means of independent variable; it determines the contribution of individual independent variables to variation of dependent variable.

Modeling of mechanisms is a more complex task because of the lack of real data on the mechanisms, which makes it difficult to identify transfer functions. Therefore, it is advisable to provide regression equation for each mechanism, as well as to set a fuzzy controller before each stage section. The regulator changes the coefficients of regression equations of mechanisms depending on perturbations, changes of work or operation mechanisms modes. On the base of the technological map of enrichment, the initial regression equations are compiled, whose coefficients are corrected by a fuzzy regulator in the further work. Multi-agent control ensures the transfer of information between mechanisms and autonomous operation of control systems.

A general description of MAS can be shown through the algebraic system

$$MAC=(A,E,R,ORG), \qquad (1)$$

where A – a set of agents, i.e. a set of generators; E – a set of MAS, i.e. a communication environment in which MAS interacts with other MAS; R – a set of interactions between agents, i.e. a variety of configurations; ORG – representation of current MAS as image.

In this model, the i-th agent (generator) from the perspective of its interface with other elements of the system can be described as a trio:

$$A_i=(E_i,R_i,ORG_i), \qquad (2)$$

where E_i – MAS of communication tnvironment, in wich agent snteracts ($E_i \in E$) Ri - a subset of agentrelation of current MAS as image.

Relation between technological mechanisms at the enrichment plant is important, since it has to be considered as a unified process of enrichment and to be controlled according to the entire situation.

Under the proposed scheme (Figure 1), four operations are carried out in the concentrator section: grinding, classification, desliming, and wet magnetic separation of the iron ore. There are such technological mechanisms as mills, magnetic separators, deslimers and extending mechanisms. For the first stage it is a spiral classifier, for the next stage are hydrocyclones. The diagram shows the parameters of the processed product (flow of a pulp, its density) needed for monitoring and calculating control actions. The parameters were calculated in terms of recycle and sumps between some mechanisms in the section. Also, the amount of output iron is measured, which in this case makes up 64.23%.

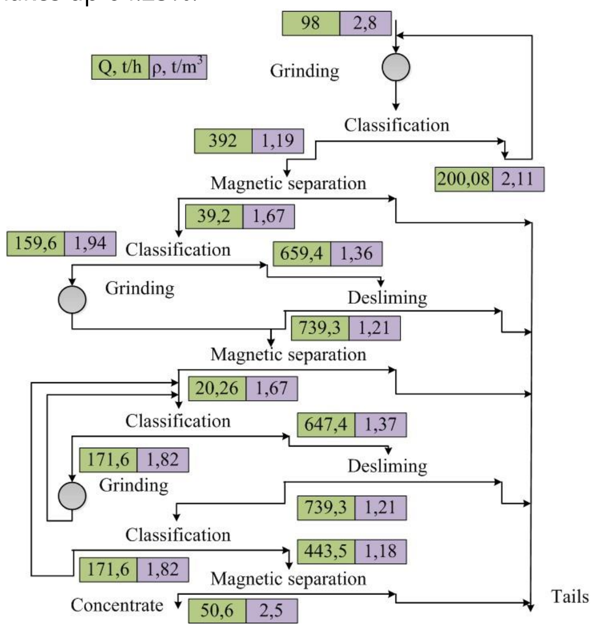

Figure 1. Technological scheme of the three-staged enrichment of iron ore

Consider in detail the difference between classical calculations of the mechanism parameters and its operation as an agent.

A hydrocyclone feed comes from a sump, to which a pulp under industrial conditions comes directly from several mechanisms and is mixed. In this case, there are fluctuations in the parameters of a pulp like density, the amount of solids, etc. For example, in order to calculate the average content of solids in the mixture of pulps entering the sump with known flow rates (measured by flowmeters), the solid content and the iron content in the solid phase, the following calculations are to be made.

$$\delta_0 = \frac{1}{a - b\alpha'},$$
$$a = \frac{1 - \delta_0^* \alpha_0^* / \delta_M \alpha_M}{\alpha_0^*\left(1 - \frac{\alpha_0^*}{\alpha_M}\right)}, \qquad (3)$$
$$b = -\left(a - \tfrac{1}{\delta_M}\right)/\alpha_M,$$

where α,α_M, α_0^* - iron content in the enriched pulp, in the input ore and the calculated iron content in the enriched pulp; δ_M, δ_0^* - density of magnetite and density of the input ore.

$$T_0 = \frac{\sum\left(\hat{c}_i'\delta_i T_i\right)/T_i + (1 - T_i)\delta_i)}{\sum\left(\hat{c}_i'\delta_i\right)/T_i + (1 - T_i)\delta_i)} \qquad (4)$$

where T_i – a content of solid phase by weight in the i-th flow of pulp (i=1, 2,...,n); δ_i – density of a solid phase in the i-th stream; $\hat{c}_i'$ - a relative part of solid and liquid phases by volume in the i-th flow.

$$\delta_0 = \frac{\sum \hat{Q}_i' \dfrac{\delta_i T_i}{T_i + (1 - T_i)\delta_i}}{\sum \hat{Q}'} \qquad (5)$$

where $\hat{Q}'$ - a volume flow rate of a pulp flow in the i-th stream.

$$T' = \frac{T}{T + (1 - T)} \qquad (6)$$

First, density of solid phases of the pulp flows entering the sump ($\square_0$), is determined by the formula (3), then the average solid content in the mixture by mass (T_0) is calculated by the formula (4). After calculating the density of the solid phase in the mixture according to the formula (5), the mass content of solid in the mixture of pulps is directed to the volume content by the formula (6).

Consider the method for modeling the input product classification based on the consideration of the hydrocyclone after the mill [15]. The function of the input product of the final discharge of the hydrocyclone is given in the equation (7):

$$c_i = \frac{1}{1 + (x_i/d_{50})^{-\gamma}} \qquad (7)$$

where c_i - a classification function value for i-th interval size, x_i – a representative size for i-th size class interval, d_{50} - a specified size at which c_i is equal to 0.5 and γ is constant. The fractional mass which returns to the mill through the classification output, s_i, is calculated by the equation (8):

$$s_i = a + (1 - a)c_i\,. \qquad (8)$$

Where a - a mass of the fraction returned to the mill through a bypass, or short circuiting phenomenon occurs in the classifiers. If a=0, which is normally a correct assumption for the classification output, then s_i=c_i and the following equation is obtained (9)

$$s_i = \frac{1}{1 + (x_i/d_{50})^{-\gamma}} \qquad (9)$$

The constant value γ in this special case is represented by γ_1, which is related to separation precision SI by the equation (10):

$$\gamma_1 = \frac{0{,}9553}{-\log(SI)}\,. \qquad (10)$$

All the above-mentioned operations are used to calculate only one of many characteristics of the pulp required. They can be greatly simplified by presenting the main functioning parameters of the technological mechanism as control agent parameters, and simulating less important parameters based on the information already measured. The system is much simpler and faster in the form of agent.

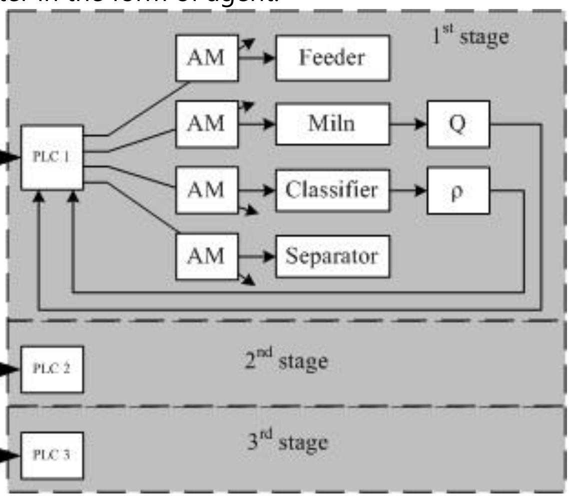

Figure 2. Control of agents at the first stage of enrichment

The figure 2 shows the control of the first stage of enrichment. PLC (Programmable logical controller) receives signals from the sensors of density (ρ) and productivity (Q based on the information received, the fuzzy network trains the regulators of control actuators of a feeder, a classifier, a wet magnetic separator and water supply to the mill. The essence of the agents is their autonomy with communication, therefore, a communication between them should be involved. Within one stage, this exchange may be carried out by software in the PLC. The data is transmitted using the PLC of each stage in order to exchange information between stages.

However, direct relation between input and output parameters of the product almost never happens, especially with the non-stationary and dynamic processes at the concentration plant. In this case, correlations must be used. Methods of experiment planning (multifactorial analysis) show quite accurate results [16]. The most famous experiment planning methods are the Box-Wilson method, stochastic balance method, simplex planning and the Scheff's plans method. The choice of method depends entirely on the conditions of the problem.

The most widespread is the Box-Wilson method. The method is to conduct a series of small experiments and to determine the shortest route traffic to the area extreme based on the results. In the study of complex multifactorial process the researcher has to deal with a large number of parameters, although most of them are minor in the future. At the same time, it is unable to make a qualified selection of the most significant parameters as this choice is based solely on intuition. The stochastic planning method helps to identify and exclude the parameters from the calculation that insignificantly influence the final result. During the studies, change of values in the uncontrolled variables, such as raw material's quality or equipment characteristics, shifts the optimum position. In this case, it is advisable to use such a strategy for optimum's search, which permits all the time to adapt to changing conditions. Simplex planning takes into account these changes. The Scheff's plans method is appropriate to apply for tasks of ore averaging.

Characteristics of the section's final product (concentrate) are clustered to determine the mineralogical variety of the processed ore. Final decision on process control in the section is made after verification of the clustering process result with technological maps and based on a variety of the processed iron ore and the desired characteristics of the concentrate.

Clustering can also be used for fault detection and diagnosis.

Clustering is a training algorithm, which has strong robustness for random signal and important application in diagnosis and fault detection. In the detection of fault data, the application of clustering algorithm can reduce the dimension of data errors and keep down the training time of a subsequent recognition model.

Selection of the clustering algorithm is very important. Consider the current clustering methods which are used in the industry. Issam applied kernel K-means into the preprocessing the fault data [17]. Hesam proposed the online fault detection method based on WFCM clustering [18]. However, they both need to specify the number of clusters in advance, and K-means can only discover spherical clusters. Li Yamin introduced affinity propagation clustering algorithm [19], which did not need to specify the number of clusters but can't handle noisy data very well. DBSCAN is a density-based clustering algorithm, which can discover clusters of any shape [20, 21], but does not operate well, when the density of data space is not uniform [22, 23].

As for fault pattern recognition, fault diagnosis is considered a problem of multiclassification after the fault data detected online. Various approaches developed for this purpose can be mainly divided into two categories. The first one is mathematical, based on the models, and includes multinomial logistic regression [24] and Bayesian networks [25]. The second one is related to the artificial intelligence, like fuzzy classifier [26], artificial neural networks (ANN) [27], SVM [28] and ELM [29]. Recently, more attentions have been paid to development of artificial intelligence. Most of artificial intelligence approaches are based on ANN which has great capabilities in modeling of nonlinear systems. For example, an approach to motor rolling bearing fault diagnosis by using neural networks and

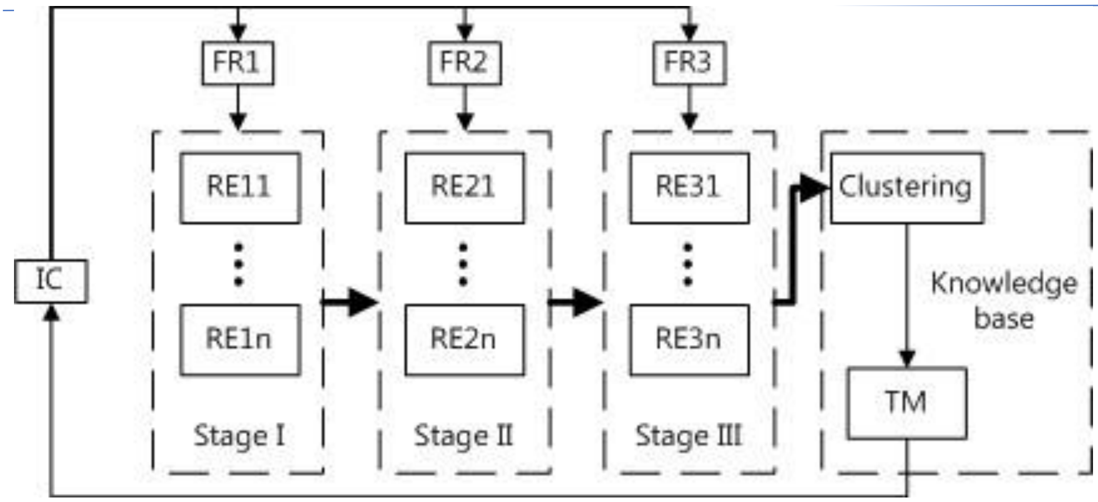

Figure 3. General view of the model

time/frequency-domain bearing vibration analysis is presented [30]. The bearing vibration frequency features and time-domain characteristics were applied into neural network in order to recognize the fault patterns. Mahdieh and Farhad proposed a hybrid neural network for soft fault diagnosis of the circuit under test, avoiding the local optimum by using a genetic algorithm and obtaining the accurate optimal solution quickly through the rapid convergence of back propagation algorithm [31]. S. S. Tayarani presented a dynamic neural network for fault diagnosis of a dual spool aircraft jet engine, which uses an infinite impulse response filter to generate dynamics between the input and output of neuron and consequently entire network [32].

Xiaoyue and others introduced probabilistic neural network as a classifier of fault diagnosis [33]. However, they are only based on empirical risk minimization principle, and the experiment data of CBMWE or BW are difficult to collect.

In the figure 3, the following notations are used: IC – intelligent controller, RE - regression equation, n – a number of output parameters of the mechanism, FR – fuzzy regulator, TM - technological map.

$$Y = b_1X_1 + b_1X_1 + ... + b_nX_n + b_{12}X_{12} \times X2 + ... + b_{(n-1)n}X_{(n-1)}X_n + b_{11}X_1^2 \quad (11)$$

Where b_1, b_2, ..., b_n – regression coefficients.

$$b_1 = \frac{\partial f}{\partial X_1};\ b_2 = \frac{\partial f}{\partial X_2};\ b_{12} = \frac{\partial^2 f}{\partial X_1 \partial X_2};\ \frac{\partial^2 f}{\partial X_1^2}. \quad (12)$$

This dependence takes into account the impact of each of the indicators on the final result separately and together. Thus, volume

In the figure 3, three stages of enrichment section represent control agents. Agents have different amounts of regression equations depending on nature of mechanisms and measurable characteristics of the products. The characteristics of the section's final product (concentrate) are subject to clustering to determine the mineralogical variety of processed ore. After reconciling the clustering result of the technological map on the basis of the processed variety of iron ore and the desired characteristics of the final product, a decision is made to control the technological processes in the section. According to the received information, intelligence controller affects the fuzzy regulators. Fuzzy regulators affect the control actions of agents, controlling the processes of grinding, separation and enrichment. Control actions in this case include the reference signals (the amount of ore incoming to the section, initial settings of the operation) and directly controlled quantities (the amount of process water, control of the pump motors).

Final products of each mechanism have some measurable parameters. Presenting output parameter Y as dependent on a number of input parameters X_1, X_2...X_n can be got response function $Y=f(X_1,X_2...X_n)$. After its decomposition into a Taylor series is regressive dependence:

calculations increase exponentially with the increase of the indicators used for calculation. First, it is assumed that the desired function can be approximated by a polynomial of the first degree. However, this approximation is usually adequate only for the areas studied surface. When an area where there is extreme is reached, the desired function is approximated by a polynomial containing nonlinear terms.

The planning matrix is made for the experiments. The parameters included in the matrix have several levels. Two levels are provided in order to achieve the extremum:

$$X_{i.min} \le X_i \le X_{i.max} \quad (13)$$

where X_i - average value parameter; $X_{i.min}$, $X_{i.max}$ - a minimum and maximum value of the i-th parameter, respectively. After normalizing the parameter values, symbols - "+" and "-" corresponding to the assignment setting its maximum or minimum value are introduced in the table experiment.

For each parameter of the input product mechanism is compiled a regression equation. For example, it will be hydrocyclone's density and productivity at Over-and Underflow. However, multi-agent-based control information from adjacent mechanisms reduces the cost for measuring all parameters by modeling some values. So, for a hydrocyclone it is advisable to measure only the characteristics of the overflow, modeling characteristics of the underflow that reduce the number of regression equations for the control agent to two. Hydrocyclone's productivity for the overflow and density of the overflow depend on such control actions as pump power adjustment and amount of additional water to the hydrocyclones. The experiment tables for studying the effects on performance and density of the overflow are as follows.

Table 2. Experiment table for finding dependence of underflow's productivity on control actions

№ of experiment's point	Parameter			Q
	W	*P*	*W*P*	
1	-	-	+	Q_1
2	+	-	-	Q_2
3	-	+	-	Q_3
4	+	+	+	Q_4

Table 3. Experiment table for finding dependence of underflow's density on control actions

№ of experiment's point	Parameter			ρ
	W	*P*	*W*P*	
1	-	-	+	ρ_1
2	+	-	-	ρ_2
3	-	+	-	ρ_3
4	+	+	+	ρ_4

Regression coefficients are calculated by the formula:

$$b_0 = \frac{\sum_{j=1}^{N} Y_j}{N};\ b_i = \frac{\sum_{j=1}^{N} X_{ij} Y_j}{N};\ b_{ie} = \frac{\sum_{j=1}^{N} X_{ij} X_{ej} Y_j}{N},\ i \ne e, \quad (14)$$

Where i, *e–a* number of a factor, *j–a* number of the experiment's point.

Thus, the regression equation for the above parameters takes the form:

$$Q = b_0 + b_1W + b_2P + b_{12}WP; \quad (15)$$

$$\rho = b_0 + b_1W + b_2P + b_{12}WP. \quad (16)$$

In this case, agent hydrocyclones have two inputs (control actions) and two outputs (overflow characteristics), which serve as input variables to the next agents.

Results. The analysis suggests that, the use of the multi-agent control in development of objects control systems at the enrichment plant significantly improves the accuracy of control and generally makes control more adapted to the real conditions, as well as requirements for the quality and quantity of a concentrate. The use of such advanced control means as fuzzy logic and artificial intelligence will improve the quality and accuracy of control.

Improvement of the method for modeling technological process at every stage of grinding and enrichment, as well as relations between them through the regression analysis and experiment planning methods will significantly upgrade the accuracy of control in terms of non-stationary processes at the enrichment plant.

Further research provides more study of the relations between technological mechanisms of the various enrichment stages and their impact on the parameters of the final product. **References**

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