Algorithm and Model of Intelligent Classification for Optimizing the Parameters of Beneficiation Technology

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Abstract: Based on the application of the classification control approach, a generalized algorithm for optimization of beneficiation processes is proposed. The results of computer modelling of the classification optimization process on the example of real indicators of magnetite quartzite beneficiation are presented. The results of classification and evolutionary optimization procedures are compared. It was concluded that the proposed intelligent classification method is able to determine the vector of settings and predict the TP beneficiation with satisfactory accuracy. It is confirmed that the developed algorithms and control principles can be applied to determine the required parameter values in modern ICS.

1 INTRODUCTION

The question of optimization of parameters of technological process (TP) of magnetite quartzites (iron ore) beneficiation in industrial conditions of the mining and processing plant (MPP) for the purpose of definition of settings of regulators as a part of intelligent control system (ICS) is considered. The multidimensional and multiconnected mathematical model of TP, which is obtained as a result of the identification procedure using the neural network approach (Kupin and Senko, 2015), is considered to be known. The relevance and general formulation of such a task is presented in the works of the authors (Bublikov and Tkachov, 2019; Kupin, 2014).

Various modifications of gradient algorithms are now mainly used as search methods for multifactor optimization of technological functions of targets, optimal and adaptive automatic control systems (AACS) (Morkun et al., 2018; Livshin, 2019). However, it is well known that in the case of poor conditionality of the optimization problem, which is typical in the case of an attempt to approximate technological functions (especially in non-stationary processes), there are some problems with the coincidence of the extremum search process appear (Livshin, 2019). A good enough alternative to this is the use of intelligent approaches: classification control and evolutionary calculations (Rudenko and Bezsonov, 2018; Trunov and Malcheniuk, 2018).

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2 PROBLEM STATEMENT

Taking into account listed above, in the work (Kupin, 2014) a combined ICS with multi-stage TP beneficiation was developed. Features of the offered decisions are a rational combination of approaches of classification control and genetic optimization. The purpose of this article is to develop a generalized algorithm of intellectual classification, its research by computer modelling and verification on the principle of comparison with the results of genetic optimization.

To implement the classification algorithm in terms of TP beneficiation, we apply the problem statement according to (Rudenko and Bezsonov, 2018). Let the following categories be known in advance:

1) an alphabet of recognition classes for technological situations in the form of a set

$$\left\{X_m^0 | m = 1, M\right\}, \tag{1}$$

which characterizes M functional states of TP and let the class X_l^0 characterize the most desirable

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(search, close to ideal or quasi-optimal) state of TP;

2) a training matrix of the type "object-property", which characterizes the m-th state of ICS in the form

$$\left\|y_{m,i}^{(j)}\right\| = \begin{vmatrix} y_{m,1}^{(1)} & y_{m,2}^{(1)} & \dots & y_{m,l}^{(1)} & \dots & y_{m,N}^{(1)} \\ y_{m,1}^{(2)} & y_{m,2}^{(2)} & \dots & y_{m,l}^{(2)} & \dots & y_{m,N}^{(2)} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ y_{m,1}^{(j)} & y_{m,2}^{(j)} & \dots & y_{m,l}^{(j)} & \dots & y_{m,N}^{(j)} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ y_{m,1}^{(n)} & y_{m,2}^{(n)} & \dots & y_{m,l}^{(n)} & \dots & y_{m,N}^{(n)} \end{vmatrix} \quad (2)$$

$i = \overline{1,N}, j = \overline{1,n}$, where each row is an implementation of the image $\left\{y_{m,i}^{(j)} | i = \overline{1,N}\right\}$ and the column of the matrix is a training sample from the technological database (DB) $\left\{y_{m,i}^{(j)} | j = \overline{1,n}\right\}$; N, n are the numbers of signs of recognition and testing (sample size), respectively.

In the result of training it is necessary to build a division of the feature space into recognition classes Ω in order to optimize and stabilize the functional state of the ICS. In our case, for TP beneficiation according to (Kupin and Senko, 2015), the feature space is formed on the basis of the state vector of the system, which contains all the necessary previously normalized indicators (regime, control effects, output, etc.).

3 RESULTS

Based on the above statement of the problem, the next procedure of intellectual classification will have the following stages.

1. The algorithm of intelligent classification begins to work in case of a special situation (state). This state is fixed when the current values of the initial indicators (qualitative or quantitative i-th stage) at the current (k-th) step of the system $y_i(k)$ are significantly different from the planned settings $y_i^*(k)$. That is, none of the following conditions are met (or several at a time):

$$|\ y_i(k) - y_i^*(k)\ | \le \Delta_y \Leftrightarrow \begin{cases} |\ Q_i - Q^*\ | \le \Delta_Q \\ |\ \beta_i - \beta^*\ | \le \Delta_\beta \\ |\ \beta x_i - \beta x_i^*\ | \le \Delta_{\beta x} \end{cases}, \quad (3)$$

where $Q_i, \beta_i, \beta x_i$ are the current values of stage productivity, the quality of the intermediate or final product and the loss of useful in the tails, respectively. In addition, the yield indicators (γ_i) can be additionally taken into account as similar criteria and separation indicators (ε_i). $Q_i^*, \beta_i^*, \beta x_i^*$ are the corresponding setting values. $\Delta Q, \Delta\beta, \Delta\beta x$ are the maximum permissible values of deviations between the values of the settings and the corresponding output values.

2. The main cause of special situations is perturbations caused by constant fluctuations in the quality composition and properties of primary raw materials (charges) (Bublikov and Tkachov, 2019). The peculiarity is that these effects in the conditions of modern MPP are almost impossible to measure accurately enough during the TP in real time. Therefore, we apply the method of inverse prediction using inverse models of short-term neural network predictors (Kupin and Senko, 2015). For this purpose, on the basis of the known values of the initial indicators $y_i(k)$ from (3), obtained at the k-th step of the system of the i-th stages, the corresponding values of the input perturbations at the previous step $(k-1)$ are predicted. Thus, the inverse model for the neuroemulator has the form

$$v_i(k-1) \approx \hat{v}_i(k-1) = NN^{-1}\begin{pmatrix} y_i(k), y_i(k-1), ..., y_i(k-l_1), \\ u_i(k), u_i(k-1), ..., u_i(k-l_2-1), \\ v_i(k), v_i(k-1), ..., v_i(k-l_2-1) \end{pmatrix}, \quad (4)$$

where $NN(\cdot)$ is nonlinear function that performs neural network transformation (direct or inverse, depending on the direction of study); l_1, l_2 are the numbers of delayed signals at the input and output, respectively.

The rest of the indicators, which are mode or controlled, are determined by direct measurement by appropriate means.

3. To implement the classification procedure, it is necessary to form a sample of data for training (parameterization) of the classifier. Such a sample is formed on the basis of records of the technological database, which is constantly updated during the TP. Therefore, to improve the speed and quality of training classifier with technological database dimension M_{DB} records is selected a limited cluster with the number of C_S records. In the process of ISC, a neural network classifier is used, so the sample size for training can be determined using expressions from (Bublikov and Tkachov, 2019). Therefore, with this in mind, the size of the cluster for classification under TP beneficiation will be $[180 \le C_S \le 900]$. If this amount of information is not in the technological database (for example, at the beginning of the ICS), the classification is impossible.

The selection of the specified number of cluster elements from the technological database is by the method of the nearest neighbours based on the analysis of vectors with a minimum value of the Hamming radius (Rudenko and Bezsonov, 2018)

$$\min_m \left[d_m = \sum_{i=1}^{N} (x_{m,i} \oplus \lambda_i) \right], \quad (5)$$

where $x_{m,i}$ is the i-th coordinate of the reference (current) state vector from (1); λ_i is the i-th coordinate of an arbitrary vector from the technological database that is a candidate for the cluster.

Therefore, as a result of a successful clustering procedure, the C_S of records (vectors) that are closest (similar) to the current technological situation according to criterion (5) will be selected for the training sample (training cluster). In this case, as alternative clustering methods the Kohonen network or the principle of K-means may be used (Rudenko and Bezsonov, 2018).

4. Synthesis and training of the classifying neural network. Artificial neural networks today are one of the most effective means for automatic classification and clustering due to their sufficiently flexible learning capabilities and generalization properties (Kupin and Senko, 2015; Bublikov and Tkachov, 2019).

To solve the problem of classification (1) - (2), a neural network based on a multilayer perceptron is created (figure 1). The network contains 1-2 hidden layers, the size of which is determined by setting up the circuit empirically from a range of $18 \leq n_h \leq 450$ neurons in total (Bublikov and Tkachov, 2019).

As a learning algorithm in the scheme (figure 1) used one of the varieties of the algorithm with inverse error propagation. An example of a two-class classification shows that the root mean square error (MSE) does not exceed 0.4 (Class 1) and 1.2 (Class 2). This indicates a sufficient quality of classification.

5. The main task in the course of classification (or classification optimization) of the current technological situation is the final choice from the cluster of the best vector (X^*), which satisfies the following two conditions:

- according to the input features most corresponds to the current technological situation in the cluster X_l^0 on the basis of the statement (1-2);
- according to the corresponding initial indicators from the technological database best of all corresponds to the value of the global criterion type (7).

Therefore, on the basis of these conditions we obtain

$$X^* = \arg\underset{\bar{u}(k),\bar{v}(k)}{exr} \left[J\left(y_1(k+1), y_2(k+1), y_3(k+1)\right) = J(Q, \beta, \beta_X) \right], \quad (6)$$

where the criterion $J(Q, \beta, \beta_X)$ is selected by the system or operator (technologist, dispatcher, etc.) based on the modification of expression (7), for example,

$$J(Q, \beta, \beta_X) = \begin{cases} Q \to \max \\ \beta^{\min} \leq \beta \leq \beta^{\max} \\ \beta_X^{\min} \leq \beta_X \leq \beta_X^{\max} \end{cases}, \quad (7)$$

where Q is the output of the control stage or section; β; $\beta^{\min}$; $\beta^{\max}$ are the content of the useful component and the corresponding restrictions (minimum and maximum); β_X; ${\beta_X}^{\min}$; ${\beta_X}^{\max}$ are the loss of useful in tails and corresponding restrictions.

The value of the expression of the main (first) local criterion in expression (7) may change in the process of ICS on a marginal principle. For example, $Q \to \max$, $\beta \to \max$, $\beta_X \to \min$ with restrictions on the rest of the local criteria. Therefore, the ideal class formed on the basis of (1-2) and (7) will have the form

$$X_l^0: \quad \left| y_{m,l}^{(j)} \right| = \left\{ Q^{\max}; \beta^{\max}; \beta_X^{\min} \right\}, \quad (8)$$

where $Q^{\max}$ the maximum value of the output performance in the cluster.

With this in mind, the distribution function from the current class analyzed in the classification process will look like

$$S(X_m^0) = \begin{cases} 1(\text{true}), \text{if} \left| \frac{y_{m,l}^{(j)} - y_{m,i}^{(j)}}{y_{m,l}^{(j)}} \right| < \delta_{Ki} \\ 0(\text{false}), \text{otherwise.} \end{cases}, \quad (9)$$

where $\left\{ \delta_{Ki} | i = \overline{1,N} \right\}$ is the limit values of control tolerance fields for normalized recognition features.

After substitution (8) to (9) we obtain

$$S(X_m^0) = \begin{cases} 1, & \left[\left| \frac{Q^{\max} - Q}{Q^{\max}} \right| < \delta_Q \right] \wedge \\ & \left[\left| \frac{\beta^{\max} - \beta}{\beta^{\max}} \right| < \delta_\beta \right] \\ & \wedge \left[\left| \frac{\beta_X^{\min} - \beta_X}{\beta_X^{\min}} \right| < \delta_{\beta_X} \right] \\ 0 \end{cases}, \quad (10)$$

where $\delta_Q, \delta_\beta, \delta_{\beta_X}$ are the limit normalized values of fields of control tolerances on the corresponding signs of recognition (productivity, quality, losses); $\wedge$ is logical conjunction operation.

Functions (9 - 10) take only two logical values of value: 1 (true - true), if the current class belongs (close) to the ideal (8) or 0 (false) – otherwise (technological situation is far from ideal).

6. Making a final decision on the suitability (or unsuitability) of the classification results. For the successful implementation of the automated neural network classification procedure, the following conditions must be consistently met:

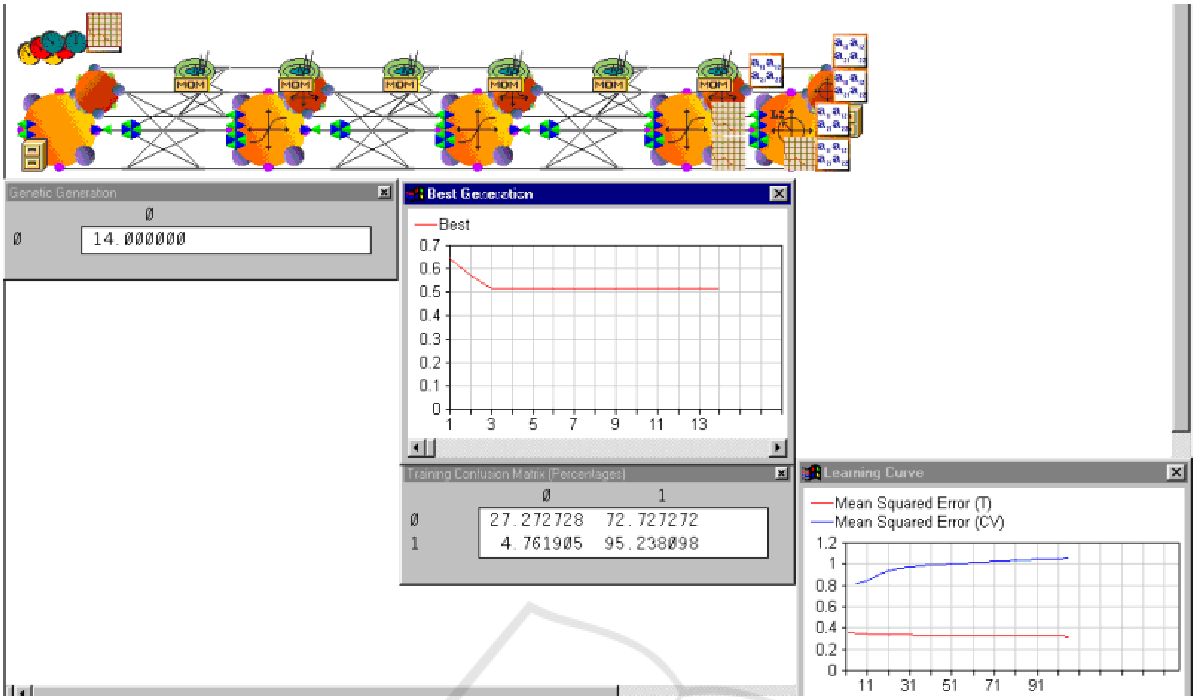

Figure 1: ICS classification neural network implemented in the environment of a specialized package of Neuro Solutions.

- the cluster for parameterization (training) of the classifying neural network must contain not less than the C_S of vectors from the technological database;
- if the precondition is fulfilled, it is necessary to check the quality of classification on the basis of calculating the value of the maximum measure of control tolerance fields for normalized recognition $\{\delta_{Ki}|i=\overline{1,N}\}$ features defined (2) and allowable forecast error ε_f, which according to (Rudenko and Bezsonov, 2018)

$$\begin{cases} \max\left[\delta_{Ki}\right] \leq \delta_K^* \\ \varepsilon_f = \left|y(X^*) - y(X_l^0)\right| \leq \varepsilon_f^* \end{cases}, \qquad (11)$$

  where δ_K^*, ε_f^* are permissible values of tolerance fields and forecast errors respectively.
- it is finally checked whether the obtained classification solution X^* can satisfy the global criterion of type (9), especially by constraints (second and third local criteria).

If all these requirements are met, the final decision on the success of the classification procedure is made (return code 0 – “successful”). Otherwise, the classification is impossible or unsuccessful (returns an error code other than 0).

7. In case of successful classification according to the algorithm, the class closest to the ideal development of the technological situation according to the global criterion is selected as a potential solution (9).

Consider a computer model of the classification algorithm for decision-making in the ISC on the example of one stage of TP beneficiation. To do this, we use a sample of statistical indicators of the second stage in the 14-th section of the ore beneficiation plant (OBP) No. 2 Southern MPP (Kryvyi Rih, Ukraine) (Telenyk et al., 2018).

Table 1 shows an example of the current technological situation (state vector X) at a certain point in time. All factors are divided into three groups:

1) a perturbations – input indicators that are not subject to regulation at the current (second) stage (output for the previous first stage);
2) the control effects and regime indicators that may change or be regulated at the current stage;
3) the initial indicators to be optimized in the ICS at the current stage in accordance with (9).

Therefore, in the first step, according to the above algorithm, the cluster elements are selected according to the degree of their similarity (proximity) to the current technological situation (table 1) on the basis of criterion (7). Table 2 shows a fragment of such a cluster, which was selected from the current technological database. The total volume of the

Table 1: Instant sampling of indicators of the current technological situation.

№	Marking	Explanation	Value
1.1	$d_1, \%$	Particle size distribution of the product at the output of the 1st stage by class -0,074mm	48,57
1.2	$Q_1, t/h$	Processing (productivity) of the 1st stage of ore beneficiation	172,86
1.3	$\beta nn_1(\beta_1), \%$	Mass fraction (content) of total iron (magnetic) in the industrial product of the 1st stage	47,64
1.4	$\beta x_1, \%$	Loss of iron (mass fraction) in the tails of the 1st stage	12,98
1.5	$\gamma_1, \%$	The yield of iron in the industrial product of the 1st stage	57,85
1.6	$\varepsilon_1, \%$	Extraction (extraction) of iron in the industrial product of the 1st stage	85,28
2.1	$C_2, \%$	Circulating load of the second stage	288,65
2.2	$d_2, \%$	Particle size distribution of the intermediate product at the output of the 2nd stage of beneficiation by class -0,074mm	76,08
2.3	$Ph_2, \%$	The solids content in the mill of the 2nd stage	76,85
2.4	$\rho_{k2}, \%$	The density of the pulp in the TP classification of the 2nd stage (hydrocyclone)	17,43
2.5	$\rho_{c2}, \%$	The density of the pulp in the process of magnetic separation of the 2nd stage	20,43
2.6	$Bm_2, t/h$	Water consumption in the mill of the 2nd stage	26,57
2.7	$Bk_2, t/h$	Water consumption in the hydrocyclone of the 2nd stage	102,86
2.8	$Bc_2, t/h$	Water consumption for magnetic separation of the 2nd stage	92,86
3.1	$Q_2, t/h$	Processing (productivity) of the 2nd stage of ore beneficiation	301,46
3.2	$\beta nn_2(\beta_2), \%$	Mass fraction (content) of total iron (magnetic) in the industrial product of the 2nd stage	51,15
3.3	$\beta x_2, \%$	Loss of iron (mass fraction) in the tails of the 2nd stage	10,17
3.4	$\gamma_2, \%$	The yield of iron in the industrial product of the 2nd stage	65,74
3.5	$\varepsilon_2, \%$	Extraction of iron in the industrial product of the 2nd stage	81,64
3.6	$Q, t/h$	Productivity (average) for the processing of ore beneficiation	237,16
3.7	$\gamma, \%$	The yield of iron (average) for the processing of ore beneficiation	61,80
3.8	$\varepsilon, \%$	Extraction of iron (average) for the processing of ore beneficiation	83,46

Table 2: A fragment of a cluster with elements that best correspond to the current technological situation in the vector of input indicators (perturbations).

№	$d_1, \%$	$Q_1, t/h$	$\beta nn_1(\beta_1), \%$	$\beta x_1, \%$	$\gamma_1, \%$	$\varepsilon_1, \%$	Criterion min[d_m]
1	49,51	173,95	47,83	13,36	59,00	85,66	0,0802
2	48,98	178,73	47,59	12,88	57,56	85,18	0,0552
3	48,88	176,67	47,69	13,09	58,18	85,39	0,0433
4	48,82	179,67	47,55	12,80	57,31	85,10	0,0690
5	49,91	173,32	47,92	13,55	59,57	85,85	0,1123
6	49,62	175,61	47,76	13,23	58,61	85,53	0,0727
7	49,56	175,39	47,78	13,26	58,68	85,56	0,0744
8	48,94	171,89	47,93	13,57	59,61	85,87	0,0982
9	48,43	178,58	47,66	13,03	57,99	85,33	0,0416
10	48,55	171,03	47,98	13,66	59,90	85,96	0,1095

specified cluster, taking into account the requirements (Bublikov and Tkachov, 2019) was $C_S = 250$ records.

Therefore, the ideal class of initial (qualitative) indicators, formed using the requirements (10) and the data of table 3 will be as follows

$$\left|y_{m,l}^{(j)}\right| = \left\{Q^{\max}; \beta^{\max}; \beta_X^{\min}\right\} = \{330; 53,3; 9,8\}$$

To automate the classification process, a multilayer neural network of direct propagation is used (figure 2), which is implemented in the Neuro Solutions as neurosimulator. On the basis of sample data from the cluster (tables 2-4) training (parameterization) of the neural network is carried out (figure 2).

To reduce the number of recognized classes in the classification process, it is necessary to rationally

Table 3: A fragment of a cluster with elements that best correspond to the current technological situation in the vector of output.

№	Q_2, t/h	$\beta nn_2(\beta_2)$, %	βx_2, %	γ_2, %	ε_2, %	Limitation [min-max]	
						β_2, %	βx_2, %
1	305,81	52,30	10,66	65,93	82,90	50,3-53,3	9,8-11,1
2	324,93	50,86	10,04	65,69	81,32	50,3-53,3	9,8-11,1
3	316,70	51,48	10,31	65,79	82,00	50,3-53,3	9,8-11,1
4*	328,69	50,61	9,93	65,65	81,04	50,3-53,3	9,8-11,1
5	303,31	52,87	10,91	66,02	83,53	50,3-53,3	9,8-11,1
6	312,47	51,91	10,50	65,86	82,48	50,3-53,3	9,8-11,1
7	311,58	51,98	10,53	65,88	82,55	50,3-53,3	9,8-11,1
8	297,56	52,91	10,93	66,03	83,58	50,3-53,3	9,8-11,1
9	324,34	51,29	10,23	65,76	81,79	50,3-53,3	9,8-11,1
10	294,15	53,20	11,05	66,08	83,89	50,3-53,3	9,8-11,1

Table 4: A fragment of a cluster with the corresponding elements according to the vector of control influences and mode indicators.

№	C_2, %	d_2, %	Ph_2, %	ρ_{k2}, %	ρ_{c2}, %	Bm_2, t/h	Bk_2, t/h	Bc_2, t/h
1	326,75	78,07	78,00	19,33	22,60	27,33	106,67	96,67
2	278,90	75,58	76,56	16,94	19,87	26,37	101,89	91,89
3	299,53	76,65	77,18	17,97	21,05	26,79	103,95	93,95
4**	270,38	75,13	76,31	16,51	19,39	26,20	101,03	91,03
5	345,86	79,06	78,57	20,29	23,69	27,71	108,58	98,58
6	313,97	77,40	77,61	18,69	21,87	27,07	105,39	95,39
7	316,19	77,52	77,68	18,80	22,00	27,12	105,61	95,61
8	347,32	79,14	78,61	20,36	23,77	27,74	108,73	98,73
9	293,27	76,33	76,99	17,66	20,69	26,66	103,32	93,32
10	356,73	79,63	78,90	20,83	24,31	27,93	109,67	99,67

Notes: where (*) is the class closest to the ideal on the basis of the analysis of values of initial (qualitative) indicators; (**) is the corresponding vector of setting values (control effects and mode indicators) to ensure quasi-optimal (close to ideal) output.

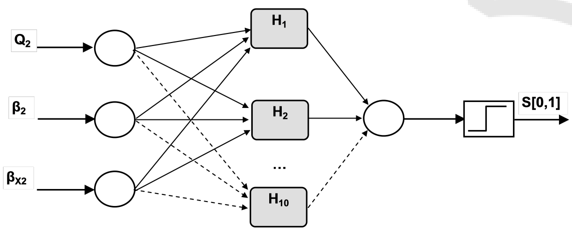

Figure 2: Neural network implementation scheme (3: 10: 1) for classification procedure.

choose the appropriate values of tolerance fields. This can be done by varying the value of the tolerance and its further study (figure 5).

As can be seen from figure 5 the number of classes that are recognized linearly depends on the tolerance values. This is evidenced by the linear trend, which is determined on the basis of the known method of least squares. The value of the coefficient of determination R^2 = 99.8% indicates a sufficiently high reliability of the approximation.

Analysis of the results of intellectual classification

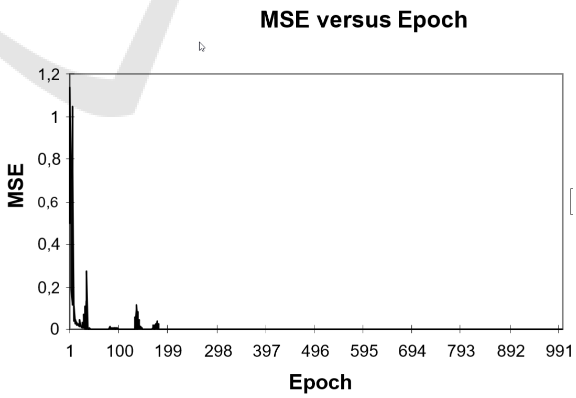

Figure 3: Report on the course of parameterization of the classification process.

(figures 3, 4, 5) and table 5 indicates the sufficient quality of such a procedure. Thus, when changing the normalized average tolerance fields within 4-4.5%, it is possible to determine with sufficient adequacy from 1 to 13 vectors with potentially quasi-optimal settings

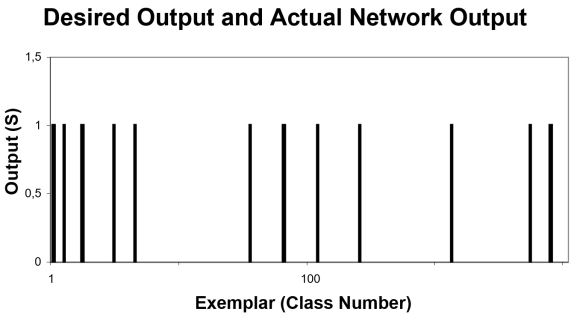

Figure 4: Report on the number of recognized classes in the classification process.

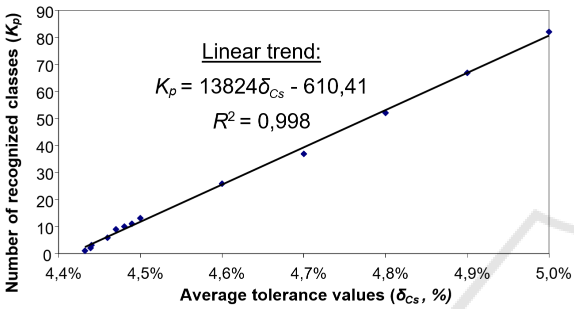

Figure 5: Dependence of tolerance field values on the number of recognized classes in the classification process.

Table 5: The resulting indicators of the adequacy of neural network classification.

Marking (Input/ Output)	S=0	S=1
1. MSE	1,49245E-10	3,78047E-07
2. NMSE	8,6783E-06	7,66892E-06
3. MAE	9,21927E-06	0,000205495
4. Min Abs Error	7,36317E-08	1,70942E-07
5. Max Abs Error	5,31987E-05	0,006554622
6. r	0,999995787	0,999996284
7. S=0 (rejected classes)	237	0
8. S=1 (classes are close to ideal)	0	13

that are close to the ideal sample. In this case, based on the application of the empirical linear dependence of the trend, the quality of such a classification can be significantly improved and brought to 1-3 samples. The rate of convergence in the parameterization of the circuit (figure 3) allows you to apply this approach in real time.

Analysis of the results of the comparison of dependencies (figure 6) shows their satisfactory convergence. As expected, more accurate control results are given by genetic optimization. On the other hand, the classification approach has a higher rate of coincidence. Therefore, both methods have demonstrated the ability to determine the required settings, both in the individual stages of TP beneficiation, and for several stages simultaneously. Depending on the quantity and quality of a priori information in the technological database at the current time it may be appropriate to use a certain method. Therefore, the rational combination and application in the ICS of two alternative strategies (classification control and global optimization using genetic algorithms) is appropriate and justified.

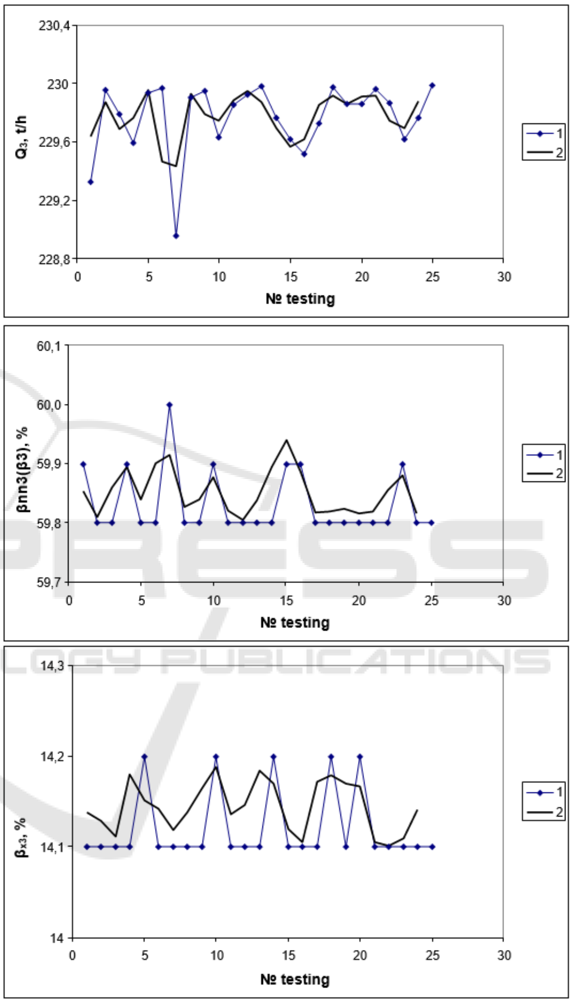

Figure 6: Comparative characteristics of the results of classification and evolutionary optimization of the 3rd stage of TP beneficiation of magnetite quartzites on productivity (Q_3) at restrictions on quality (β_3) and losses in tails (βx_3): 1 – classification solution (Neuro Solutions); 2 – optimization solution (NeuroShell2 + GeneHunter).

4 CONCLUSIONS

The analysis of results of computer modelling allows to make certain generalisations in the form of such conclusions.

1. Intelligent classification using multilayer neural networks and preceding cluster selection of the training sample while ensuring the appropriate number of cluster elements allows to determine the vector of settings and predict the TP beneficiation with satisfactory accuracy, which relative error does not exceed the average normalized tolerance field within 4-4.5%.
2. The results of computer simulation using neurosimulators such as Neuro Solutions, NeuroShell2 and genetic optimizer type GeneHunter proved that the developed algorithms and control principles using evolutionary optimization methods, genetic algorithms and automated intelligent classification can be applied to the practical implementation of modern ICS in conditions of complex multistage TP to determine the required values of the settings.

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