# Application of neurocontrol principles and classification optimisation in conditions of sophisticated technological processes of beneficiation complexes

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Abstract
This paper contains formalisation of a typical technological beneficiation complex as a sophisticated object for automation of control processes (in the context of beneficiation of iron ore - magnetite quartzites). On the basis of application of the classification control approach the generalised algorithm of optimisation of beneficiation processes is offered. Results of computer modelling of classification optimisation process in the context of actual indicators of magnetite quartzites concentration were shown. Comparison of results of classification and evolutionary optimisation procedures is carried out.
**Keywords:** NEUROCONTROL, CLASSIFICATION CONTROL, BENEFICIATION TECHNOLOGY, IRON ORE, MAGNETITE QUARTZITES.

## 1. Introduction

The general problem of control processes automation in conditions of industrial complexes of beneficiation technology has been considered. Such technological processes contain first of all beneficiation of ferrous, nonferrous and precious metal ores coal, etc. Similar manufactures actively work for several centuries in different countries around the world (for example, Australia, the USA, Canada, Sweden, Ukraine, Russia, Southern Africa, etc.). Thus necessity of constant improvement of manufacture, increase of competitiveness, minimisation of technological environmental impact demands application of complex automation systems is based on modern information technologies (IT) and intelligent control systems (ICS) [1].

Let us consider the complex of technological processes of iron ore beneficiation (magnetite quartzites). As the object of control such complex is characterised by sufficient complexity (multichanneling, nonlinearity, non-stationary, illegibility and incompleteness of information along with great value of transport delay of output parameters, presence of noise and disturbance, presence of recycles on the majority of stages, etc.) [2]. Taking into account these properties, statement of a problem and potential approaches to their decision such complex can be considered as typical [3].

Works of V.Z. Kozin, O.M. Maryuta, V.O. Ulshin, V.S. Protsuto, V.S. Morkun, I.M. Bogaenko, C.L. Karr, D.A .Stanley, B. Weck, B.J. Scheiner, M.A. Reuter and others are of great importance for the development of intellectual management theory of concentrating technology objects. At the same time, despite of considerable quantity of research and development, existing systems of automation do not always meet modern requirements and do not provide the effective decision of difficult tasks in actual conditions in beneficiation process line.

**2. Review of existing decisions and task setting**

Taking into account multidimensionality, illegibility and incompleteness of technological information on all levels of control it is necessary to use ICS to support operators' (controllers, technologists and other) decision making and increase their quality [1].

It is known that for the optimal management of beneficiation TP in the conditions of technological line it is necessary to take into account a number of parameters that may be represented as a set of the state vector of the system.

For example

$$\overline{X} = \left\{ \begin{array}{l} \overline{\alpha}, \overline{\xi}, \overline{\rho}, \overline{g}, d_0, Q_0, \overline{Q}, \overline{C}, \overline{d}, \overline{P}_m, \overline{B}_m, \overline{B}_k, \overline{B}_s, \overline{\rho}_k, \overline{\rho}_s, \overline{\beta}_{pp}, \\ \overline{\beta}_x, \beta_k, \overline{\gamma}, \gamma_k, \overline{\varepsilon}, \varepsilon_k \end{array} \right\}, \quad (1)$$

where $i = 1...N_r$ is a number of industrial variety of ore; $N_r$ is quantity of industrial varieties; $\overline{\alpha} = \{\alpha_i\}$, is estimated raw ore grade; $\overline{\xi} = \{\xi_i\}$ is specific gravity of every variety of ore; $\overline{\rho} = \{\rho_i\}$ is an index or a group of indices that characterize physical and chemical properties of ore (for example, density of corresponding varieties of ore, strength, grindability, etc.); $\overline{g} = \{g_i\}$ is index that characterizes mineralogical and/or morphological properties of ore (for example, averaged size of magnetite dissemination in ore after varieties); $d_0$ is averaged ore coarseness before beneficiation; $Q_0$ is an ore consumption on the first stage of beneficiation; $j = 1...N_s$ is number of beneficiation stage; $N_s$ – is quantity of stage; $\overline{Q} = \{Q_j\}$, is processing output of each stage; $\overline{C} = \{C_j\}$ is circulation load; $\overline{d} = \{d_j\}$ is averaged product coarseness; $\overline{P}_m = \{P_{mj}\}$ is a solid content in pulp; $\overline{B}_m = \{B_{mj}\}$, $\overline{B}_k = \{B_{kj}\}$, $\overline{B}_s = \{B_{sj}\}$ are consumption of water to the mill, classifier and magnetic separation respectively; $\overline{\rho}_k = \{\rho_{kj}\}$ is a pulp density in the process of classification; $\overline{\rho}_s = \{\rho_{pj}\}$ is a pulp density before magnetic separation; $\overline{\beta}_{pp} = \{\beta_{pp\,j}\} = \{\beta_j\}$ is an estimated grade in the industrial product; $\overline{\beta}_x = \{\beta_{xj}\}$ is loss of a commercial component in tails; $\beta_k$ is a quality of concentrate; $\overline{\gamma} = \{\gamma_j\}$ is an output of useful component in an industrial product; $\gamma_k$ is an output of useful component in concentrate; $\overline{\varepsilon} = \{\varepsilon_j\}$ is an extraction of useful component in an industrial product; $\varepsilon_k$ is an extraction of useful component in a concentrate.

It should be noted that indexes as $\overline{\alpha}, \beta, \gamma, \varepsilon$ can be monitored for a few products (for example, total iron and magnetic, etc.). In addition, the factors $\overline{\alpha}, \overline{\xi}, \rho, \overline{g}, d_0$ of set number (1) originally can be referred to as a priori information. They are determined in technological processes that preceded to beneficiation (ore output in an open-pit, crushing on a crusher) and are not controlled (actually they can be considered as disturbance). Other indices from (1) appear directly in the process of beneficiation and there can be changed of regime or regulated. Monitoring of these factors is carried out, but not always with the necessary discreteness and exactness (especially for qualitative indicators). Taking this into account and (1) we obtain

$$\overline{X} = \{\overline{U}, \overline{V}, \overline{Y}\} = \left\{ \begin{array}{l} \overline{V} = \{\overline{\alpha}, \overline{\xi}, \overline{\rho}, \overline{g}, d_0\} \\ \overline{U} = \{Q_0, \overline{Q}, \overline{C}, \overline{d}, \overline{B}_m(\overline{P}_m), \overline{B}_k(\overline{\rho}_\kappa), \overline{B}_s(\overline{\rho}_s)\} \\ \overline{Y} = \{\overline{\beta}_{pp}, \overline{\beta}_x, \beta_k, \overline{\gamma}, \gamma_k, \overline{\varepsilon}, \varepsilon_k\} \end{array} \right\} \quad (2)$$

where are accepted $\overline{V} = \{v_1, v_2, v_3, ..., v_{n_v}\}$ is a vector of input disturbing parameters (input a priori information); $\overline{U} = \{u_1, u_2, u_3, ..., u_{n_u}\}$ is a control vector (control actions and/or regime parameters); $\overline{Y} = \{y_1, y_2, y_3, ..., y_{n_y}\}$ is a vector of output parameters of the system; $n_v$, $n_u$, $n_y$ are corresponding amount of factors.

For further application of multidimensional models such as (1)-(2) with usage of artificial intelligence technology a number of typical neural network structures that were examined in researches [1, 4] were offered by the author. The results of tests of such intelligent systems have proved the possibility of their application in the beneficiation of TP. At the same time, to ensure their operation it is necessary to determine the values of settings and / or trends in their paths. Further studies have shown that the determination of the required setting values it is necessary to carry out by combination of the following [5]:

1. Classification control, that is founded on the basis of permanent accumulation of technological parameters history database (DB), their grouping on certain signs (clustering) and determination of value of setting for the measure of closeness (similarity) to the current values of vectors: input, output and internal parameters[6, 7].
2. Optimal control, which requires the design of general purpose functionality for the system and the application of global optimization methods [3, 8].

The conducted researches and industrial tests [1, 4-5] proved that application of neural networks schemes on the basis of inverse models and neuro emulators as regulators of separate channels of beneficiation of TP has a sufficient dynamics (reasonable time of settings exercise on condition of its presence), the possibility of the proper disturbance rejection at 10% level and operation on the conditions of nonlinear limitations (changes of controller parameters) on the basis of satiation principle. Thus, the task of this work is the verification of possibilities of classification strategy for reliable determination of optimal values of current parameters of TP (in the form of the relevant tasks or setting for controllers), that will provide stable work of local regulators in the above-mentioned terms.

**3. Implementation of the intelligent control method using clustering procedures and neural networks classification**

Application of classification approach (also found as "classification or situation control") when creating the intelligent control systems is relatively new direction that appeared on the basis of combination of classic theory of patterns recognition and modern technologies of artificial intelligence (neural networks, fuzzy logic, evolutional methods, etc.) [6]. It is known that on condition of proper application of modern computing the classification strategy is quite a powerful tool for increasing the ICS performance.

For classification algorithm implementation on conditions of beneficiation of TP the approach, which is similar to [7], will be applied. Such categories are known:

1. The alphabet of recognition classes as a set of $\left\{X_m^0 \mid m=1, M\right\}$, (3)

which characterizes $M$ functional states of TP, where class $X_l^0$ characterizes the most desirable (searching) state of TP;

2. Educational matrix as "object-property" that characterizes the state of each ICS as

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

(4)

where $m$ is number of the state, and each line is the realization of pattern $\left\{y_{m,i}^{(j)} \mid i=\overline{1,N}\right\}$; matrix column is a training set from the technological DB $\left\{y_{m,i}^{(j)} \mid j=\overline{1,n}\right\}$; $N$, $n$ are amount of recognition features and tests (sample size) respectively.

It is necessary as a result of training to design a subset of space of features $\Omega$ into classes for recognition with the aim of optimization of the functional state of ICS.

In our case for beneficiation of TP according to (1) space of features is formed on the basis of vector of the system state and for most cases it will include input parameters only. So

$$\Omega: \overline{V} \cup \overline{U} = \left\{\overline{\alpha}, \overline{\xi}, \overline{\rho}, \overline{g}, d_0, Q_0, \overline{Q}, \overline{C}, \overline{d}, \overline{P}_m, \overline{\rho}_k, \overline{\rho}_s\right\}$$

(5)

The corresponding values of output indexes (qualitative and quantitative) are determined by comparing the key fields of technological DB.

In some cases, to improve the quality of the classification procedure a variety of advanced features can be used. It is formed by adding a certain amount of output indexes (eg, qualitative indexes of the previous beneficiation stages)

$$\Omega^0: \left\{\overline{\alpha}, \overline{\xi}, \overline{\rho}, \overline{g}, d_0, Q_0, \overline{Q}, \overline{C}, \overline{d}, \overline{P}_m, \overline{\rho}_k, \overline{\rho}_s, \overline{\beta}_{pp}, \overline{\beta}_x, \overline{\gamma}, \ \overline{\varepsilon}\right\}$$

(6)

Also it should be noted that it is necessary to normalize the value of all technological parameters before application of classification procedure [1].

On the basis of the above-mentioned task setting the next intelligence classification procedure will have the following.

**Stage 1.** The intelligent classification algorithm starts to work in the case of certain "special situation" (state). Such state is fixed, when the current values of output indexes (qualitative or quantitative of the corresponding stage) on the current *k*-step of operation of $y_i(k)$ system are significantly different from pre-arranged settings $y_i^s(k)$. So any of such terms (or a few simultaneously) are not executed:

$$\left|y_i(k) - y_i^s(k)\right| \le \Delta_y \Leftrightarrow \begin{cases} \left|Q_i - Q_i^s\right| \le \Delta_Q \\ \left|\beta_i - \beta_i^s\right| \le \Delta_\beta \\ \left|\beta x_i - \beta x_i^s\right| \le \Delta_{\beta x} \end{cases} \qquad (7)$$

where $Q_i, \beta_i, \beta x_i$ are current values of stage productivity, quality of intermediate or end product and useful losses in tails; $Q_i^s, \beta_i^s, \beta x_i^s$ are corresponding values of settings; $\Delta Q, \Delta\beta, \Delta\beta x$ are maximum allowable deviation between the values of settings and corresponding output indexes.

**Stage 2.**The main reason of special situations is disturbance factors that are caused by the permanent variations of qualitative composition and properties of primary raw material [3, 8]. The feature is in the fact that these influences on conditions of modern mine enterprises can not always be accurately measured during TP in real-time. Therefore in most cases the indirect methods of measuring, computing or predicting are applied for this purpose [3, 5].

In our case on conditions of ICS the reverse prediction method with application of inverse models of short-term neural networks predictors will be used [5, 6]. For this purpose on the basis of well-known values of output indexes of $y_i(k)$ (7), that are obtained in the process of the direct measuring on the *k*-step of system operation of the current stage, the corresponding values of input disturbance on the $v_i(k–1)$ previous step are predicted. So, an inverse model for the neuroemulator in the form of

$$v_i(k-1) \approx \hat{v}_i(k-1) = NN^{-1}\begin{pmatrix} y_i(k), y_i(k-1),..., y_i(k-l_1), \\ u_i(k), u_i(k-1),..., u_i(k-l_2-1), \\ v_i(k), v_i(k-1),..., v_i(k-l_2-1) \end{pmatrix} \qquad (8)$$

are used, where in accordance to (1) the set of disturbance influences $\hat{v}_i(k-1)$, includes such indexes: $\overline{V} = \{\overline{\alpha}, \overline{\xi}, \overline{\rho}, \overline{g}, d_0\}$. As architecture model in the process of prediction of one-step autoregressive predictors $NN^{-1}(\cdot)$can be applied, it is shown [5, 6].

The other regime or controlled indexes ( $\overline{U} = \{Q_0, \overline{Q}, \overline{C}, \overline{d}, \overline{P}_m, \overline{\rho}_k, \overline{\rho}_s\}$) are determined by the direct measuring of appropriate means [8].

**Stage 3.** For implementation of classification procedure it is necessary to form sample data for training (parameterizations) of classifier. Such sample is formed on the basis of records of technological DB that is constantly updated during TP. Therefore to increase speed and quality of classifier training a limited cluster with the amount of $K_c$ records is taken from technological DB. In the process of ICS operation a neural network classifier is used, that's why a sample size for training can be defined on the basis of recommendations [9]. Thus, taking this into account the cluster size for classification on conditions of TP beneficiation will be $180 \le K_c \le 900$. If such information is not in technological DB (for example, at the beginning of ICS operation), the classification is impossible.
Selection of the specified amount of cluster elements from technological DB occurs after the nearest neighbor method [10] on the basis of vectors analysis with the minimum value of Hamming radius [7].

$$\min_m \left[ d_m = \sum_{i=1}^{N} \left( x_{m,i} \oplus \lambda_i \right) \right], \qquad (9)$$

where $x_{m,i}$ is *i*-coordinate of standard (current) vector of the $x_m$ state from (3); $\lambda_i$ is *i*-coordinate of arbitrary vector from technological DB, that is a candidate in a cluster.

Thus, as a result of successful procedure of clustering $K_c$ records (vectors) that after criterion (9) are the nearest (similar) to the current technological situation will be selected to the teaching selection (training cluster). As alternative methods of clustering it is possible to apply the Kohonen's maps or on the principle of K-middle [9, 10].

**Stage 4.** Synthesis and training of classifying neural network. At present time artificial neural networks are among the most effective means for implementation of automatic classification and clustering due to their flexible learning opportunities and generalization properties [6, 9].

To solve the classification problem (3) - (4) a neural network based on multi-layer perceptron is designed (Fig. 1). The network contains 1-2 hidden layer, the size ($n_h$) is determined on the basis of recommendations [9] and chosen empirical at circuit adjusting from the range $18 \le n_h \le 450$ of neurons in a general amount.

As an algorithm of training one of varieties of back error propagation algorithm is applied in a circuit (Fig. 1). The example of classification for any two classes shows, that the average quadratic error of MSE does not exceed 0,4 abs. (1th class) but 1,2 abs. (2th class). This shows a sufficient quality of classification.

**Stage 5.** The main task during the classification decision (optimizations) of current technological situation is the final choice from the cluster of the best vector ($X$*), that satisfies the following conditions:

- on input features it mostly answers a current technological situation in a cluster $X_l^0$ on the basis of (3) - (4);
- on corresponding output indexes from technological DB better than all answers the value of chosen global criterion.

Thus, based on these conditions, we obtain

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

(10)

where a criterion $J(Q,\beta,\beta_x)$ is chosen by the system or operator (technologist, controller), for example.

$$J(Q,\beta,\beta_x) = \begin{cases} Q \to \max \\ \beta^{\min} \le \beta \le \beta^{\max} \\ \beta_x^{\min} \le \beta_x \le \beta_x^{\max} \end{cases}, \qquad (11)$$

where $Q$ is the productivity on the output of the control stage or section; $\beta; \beta^{\min}; \beta^{\max}$ are content of useful component and corresponding limitations (minimum and maximal); $\beta_x; \beta_x^{\min}; \beta_x^{\max}$ are losses of useful component in tails and corresponding limitations.

The value of expression of basic (first) local criterion in expression (11) can be changed in the process of ICS operation on marginal principle. For example, $Q \to \max, \beta \to \max, \beta_x \to \min$ at limitation on other local criteria. Thus, the ideal class formed on the bases of (3) (4) and (11) will be as follows

$$X_l^0 : \quad \left|y_{m,l}^{(j)}\right| = \left\{Q^{\max}; \beta^{\max}; \beta_x^{\min}\right\}, \qquad (12)$$

where $Q^{\max}$ is a maximal value of the outcoming productivity in the cluster.

Taking this into account the distributive function from a current class $S(X_m^0)$, that is analysed in the process of classification, will take the following form:

$$S(X_m^0) = \begin{cases} 1(\text{true}), \text{if } \left|\dfrac{y_{m,l}^{(j)} - y_{m,i}^{(j)}}{y_{m,l}^{(j)}}\right| < \delta_{K\,i} \\ 0(\text{false}), \text{otherwise.} \end{cases}, \qquad (13)$$

where $\left\{\delta_{K\,i} \mid i = \overline{1,N}\right\}$ are limits of the acceptance tolerance fields on the normalized characteristics of recognition.

After substitution (12) into (13) we will obtain

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

(14)

where $\delta_Q, \delta_\beta, \delta_{\beta_X}$ are normalized limits of the acceptance tolerance fields on the corresponding characteristics of recognition (productivity, quality, losses); $\wedge$ is a logic operation of conjunction.

Functions (13) - (14) accept only two logical values: 1 (true), if a current class belongs (near) to ideal (12) or 0 (false) - in opposite case (a technological situation is far from ideal).

**Stage 6.** The final decision about the suitability (or unsuitability) of classification results. .For successful implementation of procedure of the automated neural network classification the following conditions are to be executed:

- a cluster for parametrization (training) of classifying neural network must contain no less than $K_c$-vectors from technological DB;
- at implementation of previous condition it is necessary to check the quality of classification on the basis of value calculation of maximal measure of the acceptance tolerance fields on the normalized characteristics of recognition $\left\{\delta_{K\,i} \mid i = \overline{1,N}\right\}$, given (4) and tolerated forecast error $\varepsilon_f$, that according to [7] are defined as

$$\begin{cases} \max_i\left[\delta_{K\,i}\right] \le \delta_K^{'} \\ \varepsilon_f = \left|y(X^*) - y(X_l^0)\right| \le \varepsilon_f^{'} \end{cases}, \qquad (15)$$

where $\delta_K^{'}$, $\varepsilon_f^{'}$ are acceptable value of tolerance fields and forecast error accordingly, and all arguments are normalized.

- finally checked whether the resulting classification decision $X^*$ satisfies global criterion of the type (11), especially after limitations (second and third local criteria).

If all marked requirements are executed, then a final decision about success of classification procedure (returning of a 0 code is successful) is accepted. Otherwise, the classification is impossible or fail (returns the error code different from 0).

**Stage 7.** In the case of successful algorithm classification the class that is the nearest to ideal development of technological situation on a global criterion (11) is chosen as a decision.

**4. Computer modelling of the decision-making process using intelligent procedures of clustering and classification**

Let us consider the computer model of operation of decision-making classification algorithm as a part of ICS through the example of one stage of TP beneficiation. For this purpose sample statistics indexes of the second stage operation in the conditions of section No14 of the second factory of the South beneficiation complex (Kryvyi Rih, Ukraine) [5] will be applied. All factors are divided into three groups:

1. Disturbance is input indexes that are not subjected to adjusting on the current (second) stage (outgoing for the previous first stage); influences
2. Control influence and regime indexes that can be changed or regulated on the current stage;
3. Output indexes, that can be optimized in ICS on the current stage in accordance with criteria as (11).

Thus, on the first step according to the above-mentioned algorithm the selection of cluster elements by their degree of similarity (proximity) to the current technological situation on the basis of criterion (9) is carried out. As a key selection fields the value of indexes of group 3 ( $\left|y_{m,l}^{(j)}\right| = \left\{Q^{\max}; \beta^{\max}; \beta_X^{\min}\right\}$) have been applied.

Other values have been made by the indexes of the first two groups of the state vector. Total volume of mentioned cluster taking into account technological requirements was $K_c$=250 records.

For classification process automation the multi-layered neural network of direct distribution (Fig. 1), realized in the software environment of Neuro Solutions neuroemulator is used. On the basis of sample data from the cluster the training (parametrization) of this neural network is carried out.

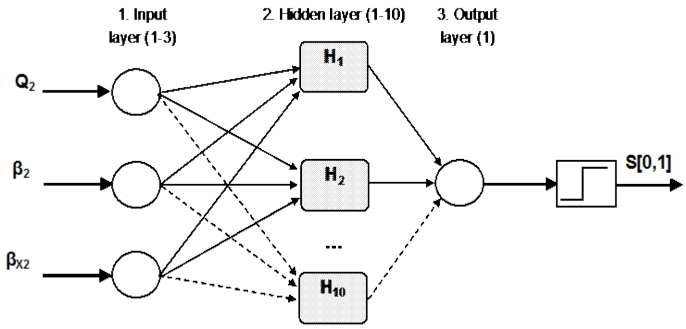


**Figure 1.** A Structure of neural network realization (3: 10: 1) for classification procedure

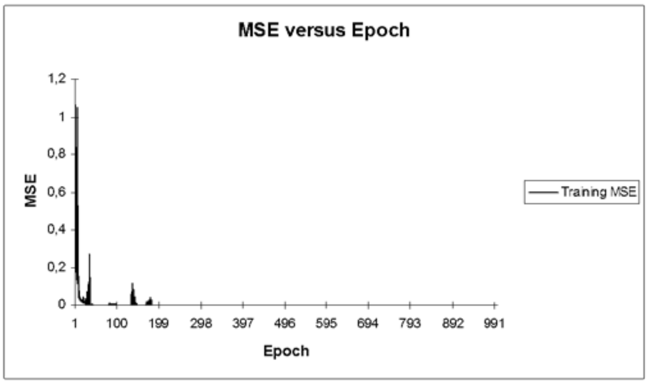


**Figure 2.** A progress report on the parametrization of classification process

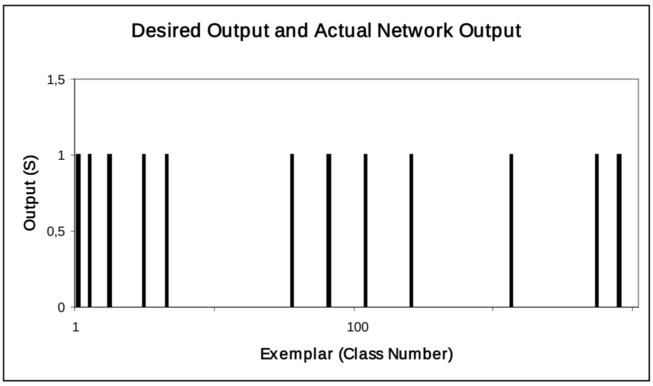


**Figure 3.** A report about the amount of the recognized classes in the classification process

For the reduction in the number of recognized classes in the classification process it is necessary to choose rationally the corresponding values of the tolerance fields. This can be done by varying the values of tolerance and further research

(Fig. 3-4). As noticeable from Fig. 4 the amount of classes, that is recognized linearly, depends on the values of tolerance. A linear trend that is obtained on the basis of application of least squares method has shown it [10]. Thus about high enough authenticity of approximation a value to the coefficient of determination is $R^2$=97%. In this case, the coefficient of determination $R^2$ = 97% gives a rather high reliability of approximation.

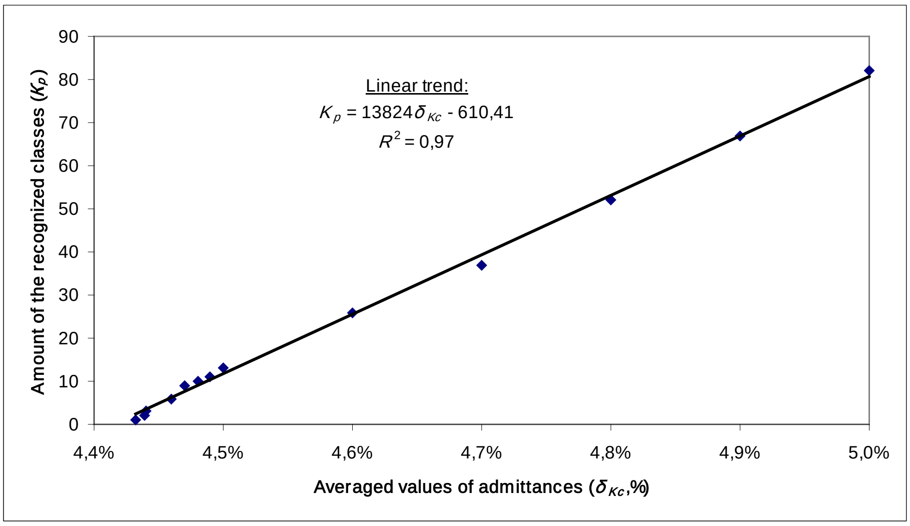


**Figure 4**. Dependence of values of the tolerance fields on the amount of the recognized classes in the classification process

**Table 1**. Resulting indexes of neural networks classification adequacy

| Index (Input/ Output) | S=0 | S=1 |
|---|---|---|
| 1. MSE (Normalized Mean Square Error) | 1.49245E-10 | 3.78047E-07 |
| 2. NMSE (Mean Square Error) | 8.6783E-06 | 7.66892E-06 |
| 3. MAE (Mean Absolute Error) | 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 (coefficient of correlation) | 0.96787 | 0.97284 |
| 7. S=0 (improper classes) | 237 | 0 |
| 8. S=1 (classes are close to the ideal) | 0 | 13 |

Analysis of results of intelligent classification (Fig. 2-4) and Table 1 indicates the sufficient quality of such procedure. So, when changing the normalized averaged tolerance fields within 4-4.5% it is possible to choose with sufficient adequacy from 1 to 13 vectors with potentially quasioptimal settings that approximate to the ideal model. In this case, based on application of empiric linear dependence trend quality of such classification can be considerably improved and brought to 1-3 standards. Speed of matching at circuit parameterization (Fig. 2) allows to apply given approach in real time.

To compare the operation efficiency of the classification control and global optimization computer simulation under identical conditions has been carried out. Comparative results of simulation are shown in Fig. 5 In the process of comparison for global optimization genetic algorithm (GA) has been used.

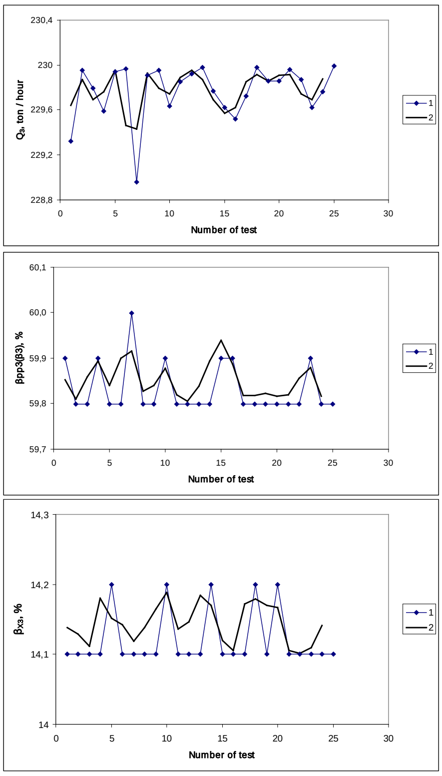


**Figure 5.** Comparative analysis of results of classification and evolutional optimization (1 is a classification decision; 2 is an optimization decision with application of GA)

The analysis of comparative results of dependences (Fig. 5) testifies to their satisfactory convergence. As expected, genetic optimization gives more accurate results of computing. On the other hand, classification approach has higher match speed. Thus, both methods have shown the ability to determine the required settings both for certain stages of TP beneficiation and for a few stages simultaneously. Depending on the amount and quality of a priori information in a technological database at the current time application of certain method may be appropriate. Therefore rational combination and application of two alternative strategies (classification control and global optimization) as apart of ICS is appropriate and ground.

## 5. Conclusions

Intelligent classification using multilayer neural networks and the previous cluster sampling of the training selection, while ensuring the proper amount of cluster elements allows to define the setting vector and predict necessary indicators of TP beneficiation with sufficient accuracy that according to ratio error does not exceed the average normalized tolerance field within 4-4.5 %.

The results of computer modelling and industrial tests have proved that developed algorithms and neurocontrol principles using automated intelligent classification, evolutionary optimization methods (GA) can be applied for practical realization of hierarchical ICS in complex multi-stage TP for determination of necessary values of settings.

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