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Optimal control of copper concentrate blending and melting based on intelligent systems

Abstract. *The possibilities of use of intelligent systems in automation of production and technological processes are considered. The intelligent system for optimal control of copper concentrate blending and melting is developed. The paper presents the results of the investigation of the intelligent system for optimal control of copper concentrate blending and melting using neural network (Matlab NNTool), adaptive neuro-fuzzy (hybrid network Matlab Anfis) and fuzzy inference (Matlab Fuzzy Logic) modelling.*

Streszczenie. *W artykule opisane zostały możliwości wykorzystania inteligentnych systemów sterowania w automatyzacji procesów produkcyjnych I technologicznych. Przedstawiony został system do optymalnego sterowania topieniem i wzbogacaniem koncentratu miedzi. W artykule przedstawiono również wyniki badań symulacyjnych przedstawionego systemu z wykorzystaniem sieci neuronowych (Matlab NNTool), rozmytych (sieć hybrydowa Matlab ANFIS) i logiki rozmytej (Fuzzy Logic) (**Sterowanie optymalne procesem rozdrabiania i roztapiania wsadu miedzianego w oparciu o systemy inteligentne**).*

Keywords: copper concentrates, charge, electromelting, modelling, intelligent control systems.
Słowa kluczowe: koncentraty miedzi, wsad, roztapianie elektryczne, modelowanie, inteligentne systemy sterowania.

Introduction

The control of blending and melting of copper concentrates is conducted in conditions of information uncertainty connected with the complexity of physical and chemical processes. In this case, traditional control methods are not effective enough. Therefore, instead of traditional control methods the intelligent networks could be used. The intelligent networks are the most effective when the traditional calculations are time-consuming or physically inadequate. The use of intelligent models in control has several advantages: reducing of the amount of computation, the intelligent model is easier to understand than the equivalent mathematical model based on differential or difference equations, and simpler implementation of the modelling results compared with the classical control algorithms.

The aim of this work is the development of optimal control of copper concentrate blending and melting using the intelligent systems in the Matlab program, that is to minimize the content of Cu, SiO_2, Fe in the dump slag at minimum specific energy consumption.

The input variables (material flows) are characterized by some combination of input variables dependent on the constructive and technological features of the furnace and the process, such as the content of Cu, Fe, SiO_2, S in the charge, specific copper losses in dump slags and specific energy consumption.

For optimal control of blending and melting of copper concentrates the following systems in the MatLab program could be used: neural network (Matlab NNTool), adaptive neuro-fuzzy (hybrid network Matlab Anfis) and fuzzy inference (Matlab Fuzzy Logic) modelling. For the solution of the task by means of intelligent systems the input and output variables and their terms should be determined, for each term the membership function should be chosen, the base of rules required for connection of input and output variables should be created.

Ore-smelting electromelting of copper concentrates belongs to the objects characterized by multidimensionality, unsteadiness, large delays, random nature of the variables, etc. It is possible to allocate four main stages: creation, training, testing, and modelling of a network.

Modelling approach and considerations

We have analysed the blending and melting of copper concentrates in the six-electrode ore-smelting electric furnaces. The quality of the end product first of all depends on four main variables: X_1 (the content of Cu in the charge); X_2 (the content of Fe in the charge); X_3 (the content of SiO_2 in the charge); X_4 (the content of S in the charge). The output variable Y is the expected optimal losses of copper in slags at minimum specific energy consumption.

Thus, the control system, considering the main features of object, should be based on the model describing the change of all main variables of a process (quantitative characteristics of material and electric power flows, qualitative compositions of charge), taking into account the available aprioristic information. The estimates of input and output variables are usually set by experts and are represented in a numerical (point scale) form. Each operator conducts the process intuitively, basing on the experience and knowledge. However, despite the observable differences in control of the charge loading in practice, the average data of charge loading in all shifts are practically identical. The purpose of technological control is the fulfilment of the production plan during one shift as well as during any long period of time for all parameters (e.g. the composition and amount of the charge). Ensuring of this function is performed by the technological personnel of workshops and plants. Research of the main regularities of performance of this control function is conducted according to an operating check for a long period with discretization level not less than the time of production and operational analysis of melting products.

For intelligent networks the empirical rule "garbage in, garbage out" is true, so the pre-processing of the input data for network training is very important. The training data set we define as x_{ij}, where i is the parameter number, j is instant of time.

An unknown quantity x_j at instant of time t_j is calculated as follows [1]:

$$x_i = \frac{t_j(x_{j-1} - x_{j+1}) + (t_{j-1}x_{j-1} - t_{j+1}x_{j+1})}{t_{j-1} - t_{j+1}}. \tag{1}$$

After completion of the research of models received by different methods the comparative analysis on their adequacy is made. The approximation error is the value of the deviations of the actual and calculated values of the effective feature y-$\hat{y}_x$ for each observation [2].

In order to estimate the quality of the model the average approximation error is determined from relative deviations for every observation:

$$\sigma = (\frac{1}{N} - \sum \left| \frac{y - \hat{y}_x}{y} \right|) \cdot 100\% . \qquad (2)$$

The approximation error is calculated for the models obtained by different methods. Then comparative analysis of the models is made. The model with the lowest approximation error is considered to be the most adequate. Every membership function uses three parameters c, s, b to be adapted. If accept that every variable x_i is characterized by own membership function, then for *M* inference rules we will receive $3MN$ nonlinear parameters. The sum of rules equals to $M(4N+1)$ linear and nonlinear parameters which values have to be chosen during the training of a network. A task of the system is determination of the optimal modes of the process: $Y1$ depending on composition of the input charge (components $X1, X2, X3, X4$).

If accept that each variable x_i has m different membership functions the maximum number of rules which can be created at their combinations equals: $M = m^N$ (three-level evaluation (0.0; 0.5 and 1.0) for four input variables, that is 3^4= 81 inference rules) [3].

In this paper for creation of the intelligent control system for blending and melting of copper concentrates we use a full factorial experiment for fuzzy, neural network and neuro-fuzzy (hybrid) methods.

For modelling we use the pre-prepared data (files with the extension *dat in Matlab), that is the training file, which contains 5 columns (the first four columns $X1, X2, X3, X4$ contain the values of the input variables, and the last (fifth) column contains $Y1$ output values).

To create the effective models the filling of the survey matrix by expert is necessary. A fragment of such matrix in Matlab is given in the form of files with the extension *dat.

Each column describes one set of characteristics used for training the network. Similar rules are set as a result of the testing results for each set of input variables included in the training file used for training, which allows the neural network to update and optimize the weights of copper concentrate blending and melting for the best representation of the control system of production processes [4].

Below, the results of investigations of the intelligent system for optimal control of copper concentrate blending and melting, using neural network (Matlab NNTool), adaptive neuro-fuzzy (hybrid network Matlab Anfis) and fuzzy inference (Matlab Fuzzy Logic) modelling are described.

Results

The neural network for optimal control copper concentrate blending and melting using Matlab NNTool

At creation of neural analytical models it is necessary to remember that the value of the prediction error of neural network depends on the amount and reliability of the input data, and the completeness of accounting the factors influencing the responses.

To create the intelligent systems it is desirable to consider the characteristics of the melting process, such as the content of Cu, Fe, SiO_2, S in the charge, the losses of copper in slags, the content of Cu, SiO_2, Fe in the dump slag, specific energy consumption and other technological parameters.

For modelling of neural networks we used the Matlab NNTool. After formulating the task, it is necessary to prepare the data for network training (a fragment of such matrix is given in the form of files with the extension *dat in Matlab). The types of input data are binary numbers (0 and 1), bipolar (-1 and +1) numbers, integers or real numbers from a certain range.

As it can be seen from Fig.1 the training was finished when the aim function achieved the given value (goal = 0). It should be noted that for perceptrons with hard-limiting activation function the approximation error in Matlab is calculated as the difference between the target value and calculated output value [5]. The program visualizes the training process and the result of the training, as given in Fig.1.

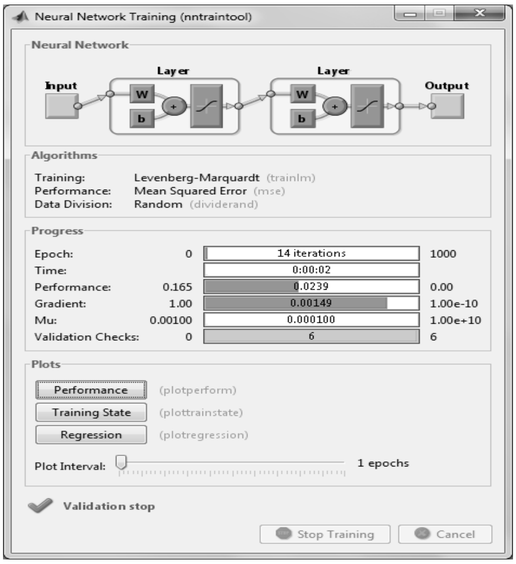

Fig. 1. The training process: change of the network error during the training

Now it is possible to evaluate the constructed fuzzy inference system for the expected optimal losses of copper in dump slags at minimum specific energy consumption [6]. For this purpose we enter values of input variables for the case when the content of Cu in the charge is equal to 0, the content of Fe in the charge is equal to 0, the content of SiO_2 in the charge is equal to 1, the content of S in the charge is equal to 0.5.

The calculated value of the output variable, i.e. the expected optimal losses of copper in dump slags at minimum specific energy consumption is equal to 0.72. The result (output) of training the neural network is given in Fig.2.

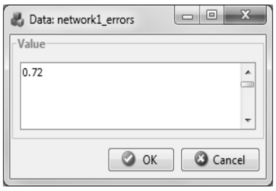

Fig. 2. The result (output) of neural network training

The adaptive neuro-fuzzy model (hybrid network) for optimal control of copper concentrate blending and melting using Matlab Anfis

Therefore, instead of fuzzy and neural network models the hybrid networks models, such as neuro-fuzzy (ANFIS) models, can be used. The basic idea underlying the hybrid networks model is to use existing data sample to determine the characteristics of membership functions that best fit a given fuzzy inference system. In this case, for finding the characteristics of membership functions the known procedures for training neural networks are used.

The training process is visualized in the form of the graph dependence of the result on the number of training cycles. In order to choose a method of training of a hybrid network we do not change the method settings (hybrid) and the level of the error (0) set by default, but we set the big enough number of training cycles (81). At three-level evaluation (0.0; 0.5 and 1.0) for four input variables there are $3^4 = 81$ inference rules.

Experimental data and modelling results are displayed as a set of points in two-dimensional space. For the given example, the neuro-fuzzy inference system contains 4 input variables, each with 3 terms, 81 rules of neuro-fuzzy outputs with 81 terms, and one output variable with 81 terms. As an illustration, the neuro-fuzzy network with four input variables and one output variable is given in Fig. 3.

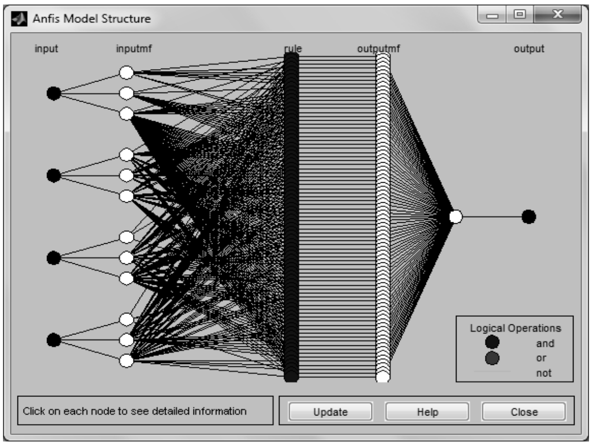

Fig.3. The structure of the generated neuro-fuzzy inference system

We continue to train system until the error (Training Error) reaches its minimum value. The results visually showed the reverse distribution network superiority in comparison with other reverse distribution networks after training of 81 epochs, that is this structure is optimal. As it can be seen from Fig.4 the difference between the network output value and true value is rather small.

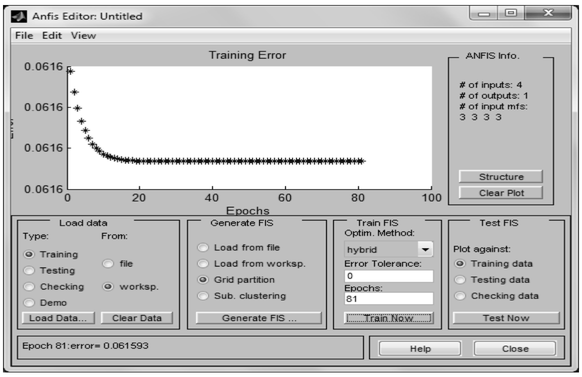

Fig.4. Result of training

The training of a network consists in representation of a variety of input sets until value of the error would be less than desirable value. When the training is complete, weight vectors of each connection remain invariable for this model. By means of the neuro-fuzzy model given in Fig.4 the values of the expected optimal losses of copper in dump slags at minimum specific energy consumption were calculated. For the same values of input variables as for the case of neural network the calculated value of the output variable, i.e. the expected optimal losses of copper in dump slags at minimum specific energy consumption is equal to 0.0616. As it can be seen from Fig.5 the value of the output variable is 0.0616 that is much better in comparison with neural modelling (value of the output variable equals 0.72).

The fuzzy model for optimal control of copper concentrate blending and melting using Matlab Fuzzy Logic Toolbox

Further settings of created and trained hybrid network can be performed using Matlab Fuzzy Logic Toolbox.

Now we can evaluate the created fuzzy inference system for the expected optimal losses of copper in dump slags at minimum specific energy consumption.

For the same abovementioned values of the input variables the calculated value of the output variable, i.e. the expected optimal losses of copper in dump slags at minimum specific energy consumption is equal to 0.87 (Fig.5).

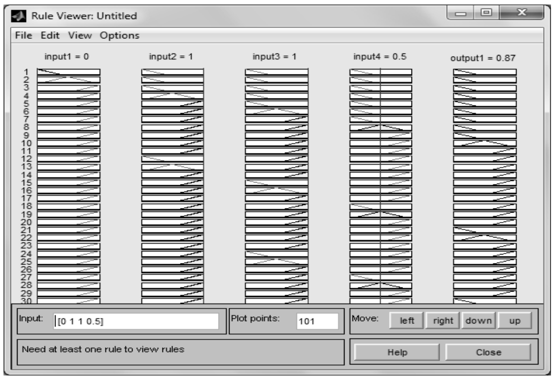

Fig.5. The window Ruleview to display the simulation results

Thus, when constructing intelligent models for control in electric furnace one can create the dependence of the output variables on the input variables using three-dimensional graph and analyse it. As it can be seen from Fig.5 the calculated value of the output variable 0.87 is higher compared with the calculated values of the output variable for neural models (0.72) and adaptive neuro-fuzzy networks (0.0616). Thus, the adaptive neuro-fuzzy model is better than fuzzy and neural models.

Discussion

Depending on given limits it is possible to receive optimal characteristics of the charge. We calculate the modelling results for all models from data of FFE matrix at the three-level evaluation (0.0; 0.5 and 1.0) using the approximation error equal to 0.93 in the range from 0 to 1. As it can be seen from figures 2, 4 and 5, the neuro-fuzzy (hybrid network) model is the most accurate (0.0616), comparing with. fuzzy model (0.87) and neural network model (0.72). Therefore, in our further research we will use the adaptive neuro-fuzzy model. To check the efficiency of the network and its capabilities during the training samples, a variety of neural network architectures were investigated and tested. Each of these neural networks was created in short time to ensure the maximum efficiency of neural network when processing applications. The reverse distribution networks were used during testing. For evaluation of the productivity of a network the general error (a difference of input and desirable target output value at transformation of the error function in every layer) was calculated for all epochs of training for every architecture.

The results show that the adaptive neuro-fuzzy models are the most effective for developing the system for optimal control of copper concentrate blending and melting using intelligent systems in Matlab.

Thus, the possibilities of the optimization of neural network architecture considering the peculiarities of the production process are analysed in the paper. The obtained results allow to substantiate the possibility of using the neural networks to remove the contradiction between the increasing demands of adaptation and time constraint required to set automatic systems for control of production processes. This study allows to consider the possibilities of neural network models in the control of various technological processes, and emphasizes the importance of neural networks in stimulation of complex technological processes.

From Fig.4 it follows that the optimization of the blending and melting using the training was succeeded. The error value and its deviation were considerably decreased. Therefore, the use of a neural network based on adaptive neuro-fuzzy inference system is quite reasonable for the optimization of copper concentrate blending and melting.

Conclusions

The correct operation of intelligent systems as systems for control of technological processes of copper concentrate blending and melting depends on the competence of specialists, operators, technologists involved in the formation of the FFE matrix, membership functions and the formulation of the rule base of an intelligent system. The described intelligent system is designed for operation in conditions of high uncertainty. Its decision-making mechanism is based on neural network methods, adaptive neuro-fuzzy control, fuzzy models and additionally can use heuristic methods for the correction of the control algorithm when new functions or control purposes appear during operation. Contrary to neural networks and fuzzy models, the adaptive neuro-fuzzy models are more flexible, allowing to predict a variety of dependent variables with high accuracy. The results show that the neuro-fuzzy models are the most effective for control systems of production processes. The use of Matlab Anfis for the solution of the optimization problem is rather perspective. In our work we considered the use of intelligent systems in automation of production and technological processes, we have developed an intelligent system for optimal control of blending and melting of copper concentrates. This intelligent system can be widely used not only in automation and control, but also in various fields of science and industry, such as metallurgy, electric power supply, engineering industry, etc.

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