UDC 004:

NEURAL NETWORK MODELING AND OPTIMISING OF THE AGGLOMERATION PROCESS OF SULPHIDE POLYMETALLIC ORES

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Abstract: During the operation of the lead-zinc production while processing of polymetallic ores, problems arose related to the quality of products and the efficient use of equipment – agglomeration furnace and crushing apparatus. Previously, such issues were resolved due to the experiences and based on mathematical modeling of processes. The mathematical model for optimizing unnecessary such operating mode is a difficult program. Performing calculations is required a fairly large investment of time and resources. Therefore, the program of the mathematical model for optimizing the operating mode of the agglomeration furnace and the crushing device for sinter firing was replaced with a neural network by implementing the process of training the network based on the results of calculations on a mathematical model. The results obtained showed that neural network models were more accurate than mathematical models, which made it possible to solve production optimization problems of great complexity. The use of neural networks for modeling technological processes has made it possible to increase the efficiency of product quality control systems and automatic control systems for the roasting of sulfide polymetallic ores.

Keywords: neural network technology, modeling of technological processes, optimizing the mode, agglomeration furnace, control system and industrial automation

Introduction

In metallurgical industries, the task of introducing innovative technologies is attractive, which can accelerate research in obtaining new promising metallurgical alloys, improve the quality and safety of methods for obtaining smelted metal, and reduce its cost. Due to the complex nature of the change in material properties, depending on the chemical composition of the ores being processed, the concentration of metalsin the ores, heat treatment modes, and test conditions, the ability to choose the exact mathematical relationship between the composition and properties quickly decreases and may become impracticable [1].A further solution to the problem of optimizing the control of metallurgical processes for the processing of polymetallic sulfide ores is possible by solving the problems of controlling large melting units (roasting and agglomeration furnaces, oxygen converters, etc.) including complex multiparametric processes. The introduction of automated neural network systems for melting process control will improve the quality of the smelted metal, reduce its cost (including the prime cost) and increase the safety of the technologicalprocess.

Proposed Approach and the New Value of Research

This paper proposes the use of neural network technology for calculating and modeling a furnace-crushing heat-technological installation to increase their efficiency and reduce cost. Modeling based on neural networks provides a new approach to the design of control systems for complex processes in lead-zinc production, which ensures the innovativeness of the study.

The novelty of the research lies in the fact that: a new technique has been developed for using neural networks to simulate the modes of continuous technological processes of loading and unloading concentrates into roasting furnaces and processing of sulfide polymetallic ores; a neural network model of furnace-crushing was created to solve the problem of calculating a roasting furnace, crushing, as well as new technology to optimize the operating mode unit to increase their efficiency in lead-zinc production.

Description of the mathematical model of the furnace

The model is designed for an agglomeration furnace operating in a stationary mode. The stationary heat flux in the loaded furnace charge can be considered equal to the amount of heat transferred from the gases to the loaded charge by convection. Under these assumptions, the loaded charge from the point of view of radiation heat transfer can be considered as an ideal lining. Let us assume that the gas volume in the working space of the furnace is isothermal. Since the process of loading and unloading the metal charge iscontinuous, the temperature over the entire heated surface of the metal charge is currently constant [3].

The mathematical model is based on the solution of the conjugate problem of heat transfer in the gas–charge–agglomerate system. The method of discrete satisfaction of boundary conditions was adopted as a mathematical method of modeling [2-3]. The algorithm for solving the problem includes 9 stages and is presented below, in figure 1.

The calculation determines the specific consumption of air supplied for combustion, the lowest heat of combustion of the fuel, the specific output, and the percentage of combustion products. To calculate the combustion process, a set of programs is used [4-5]. The parameter that needs to be optimized when selecting the operating mode of the furnace-sinter crushing plant is the minimum cost of the workshop redistribution.

Description of the model, optimization of the operating mode of the furnace-agglomeration crushing plant

A universal economic parameter (workshop cost) is most suitable as an objective function to optimize the operating mode of the agglomeration furnace. The workshop cost consists of two types of costs: direct and indirect. Direct costs are divided into basic materials and semifinished products, basic and additional wages. Indirect costs are divided into conditionally variable (proportional) and conditionally fixed[4-5].

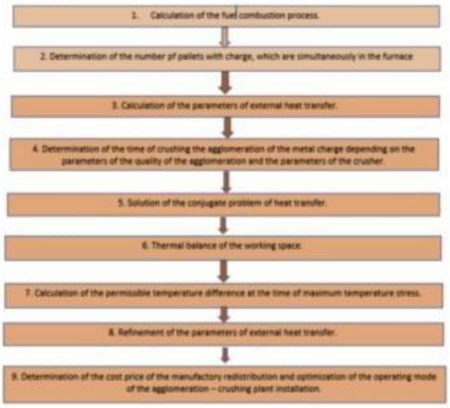

Fig. 1. Algorithm for solving the problem for modeling an agglomeration furnace

Choosing the Limitations of the Mathematical Model and Setting up a Computational Experiment It is difficult to use the above algorithm to determine the optimal operating parameters based on an enumeration of options, the amount of computation is large. Therefore, an algorithm is used, the essence of which is to set up a computational experiment. It is necessary to know how the objective function will change from changing operating parameters [6].

To determine such a dependence, it is necessary to reasonably set the intervals of variation of the varied parameters. The boundaries of the various intervals are determined based on the following conditions:

1) For the final heating temperature of the metal on the surface, the range of variation is in the rangefrom the temperature at which firing cannot be performed (the metal loses its plasticity) to the melting point of the metal (the metal turns into a liquid state).

2) For the permissible temperature difference at the end of metal heating, the range of variation isfrom a temperature drop close to zero (5-10 ˚C) to the temperature difference between the melting point ofthe metal and the temperature of the beginning of firing. In practice, it is advisable to reduce this rangesomewhat by setting it in the range from 15 to 150 ˚C.

Here, an algorithm is used, which is to set up a computational experiment. It is necessary to know how the objective function will change from changing operating parameters [4,5, and 6].

To determine such a dependence, it is necessary to reasonably set the intervals of variation of the varied parameters. The required dependence $y = (x_1, x_2, x_3)$ is in the form (Eq.1):

$$y = b_1 + b_2x_1 + b_3x_2 + b_4x_3 + b_5x_1x_2 + b_6x_1x_3 + b_7x_2x_3 + b_8x_1^2 + b_9x_2^2 + b_{10}x_3^2 \quad (1)$$

Where y is an optimization parameter; x_1, x_2, x_3– variable parameters.

The optimization problem is solved taking into account 8 constraints: is the temperature of the gases in the working space of the sintering furnace, which cannot exceed the actual combustion temperature of the fuel; use the rate of delivery of pallet blanks from the kiln, which should not be less than the firing time.; is the allowable temperature difference during the initial sintering period, determined by the allowable temperature stresses; are the maximum temperatures for use of refractory and insulating materials from which the three-layer masonry of the furnace is made; is the maximum possible gas flow rate for the furnace; is the productivity of the agglomeration furnace.

The Structure of the Mathematical Model of the Furnace-Crushing Agglomeration Plant

The proposed unit model is designed to optimize the operating mode of the agglomerationcrushing furnace system, calculate the rates of energy consumption for the unit at a minimum cost of the workshopredistribution. Figure 2 shows the interaction of the components of the furnace-agglomeration crushing plantmodel.

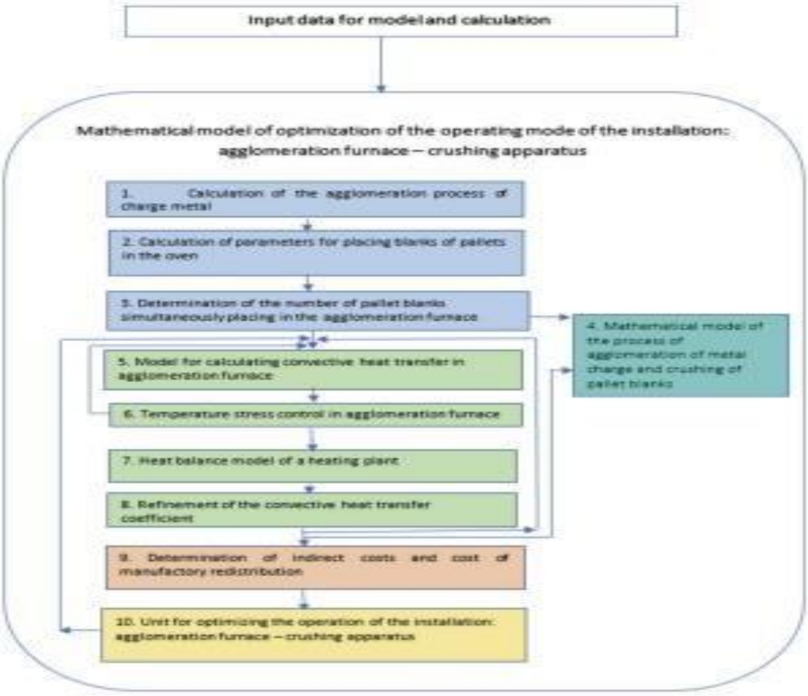

Fig. 2. Block diagram of the model: agglomeration furnace – crusher

Results and Discussion

We replaced the program of the mathematical model for optimizing the operating mode of the industrial plant: agglomeration furnace and crushing device with a neural network by implementing the process of the so-called network learning based on the results of calculations on a mathematical model.

The neural network has generalized the information received in the form of functional connections within itself and in some cases has replaced the mathematical model of the furnace-sinter crushing plant for decision-making.

The learning set is a database in the form of a Microsoft Excel spreadsheet. Each row in the table is one observation that includes the various values of seven variable input variables and an output quantity.

1. The training of the neural network to determine the number of pallet blanks in the agglomerationfurnace was carried out in accordance with our own algorithm.

2. After training on the data obtained from the calculation in the program for optimizing the operatingmode of the furnace-crushing sinter plant, the neural network is ready for operation and was used to make forecasts and make instant decisions. As a result, the best learning outcomes of neural networks were thelearning outcomes presented in table 3.

Table 3. Comparative analysis of the learning outcomes and calculation of pallet blanks in the agglomeration furnace

Calculation and learning outcomes	Number of pallet blanks in a furnace
The total number of pallets obtained from the calculation in the program for optimizing the operating mode of the installation: agglomeration furnace crushing apparatus	-1955
The total number of pallets obtained as a result of training the neural network	-1943

For this training, it was obtained that the final root-mean-square error was: MSE = 0.0128.

Table 4 presents a comparative analysis of the results of training and calculation according to the program for determining the agglomeration time of the metal charge and pallet blanks. Table 5 presents a comparative analysis of the results of training and calculation according to the program for determining the surface temperature of the metal charge at the end of agglomeration.

Table 4. Comparative analysis of the results of training and calculation according to the program for determining the agglomeration time of the pallet blanks

Calculation and learning outcomes	Agglomeration time of pallet blanks
The sum of the agglomeration time numbers of pallet blanks for all experiments, obtained by calculation in the program for optimizing the operating mode of the sintering furnace-crusher	- 232 844
The sum of numbers obtained after training the neural network	-232 347

With such training, the final root-mean-square error was: MSE = 0.0109 to determine the time ofagglomeration of the metal charge and pallet blanks.

Table 5. Comparative analysis of the results of training and calculation according to the program for determining the surface temperature of the agglomeration

Calculation and learning outcomes	Number by surface temperature of pallet blanks at the end of agglomeration
The total number of the temperature of the metal surface at the end of sintering, obtained from the calculation in the program for optimizing the operating mode of the sintering furnace-crusher	-109115
The total number of the surface temperature of the pallet blanks at the end of the agglomeration, obtained as a result of training the neural network	-109090

With this training, the final root-mean-square error was MSE = 0.011311147 to determine the surface temperature of the metal charge at the end of the agglomeration.

Thus, according to the results of the experiments, as a result of using the trained neural network, the following deviations were obtained between the results calculated in the installation optimization program: agglomeration furnace-crusher and the neural network (Table 6).

Table 6. Comparing results calculated in the installation optimization program: agglomeration furnace-crusher and the neural network

Deviation	**Deviations in the number of pallet blanks in the agglomeration furnace, pcs**	**Deviation in timeof agglomeration of pallet blanks, sec.**	**Deviations in sinter surface temperature at the end of agglomeration, C**
maximum deviation	16	682	37
mean deviation	12	497	25
minimum deviation	1	8	1

For clarity, figure 6 shows the dependences of the workshop cost on the surface temperature of thepallet blanks at the end of sintering, obtained on the model of the installation: agglomeration furnace-crusherfor two different versions.

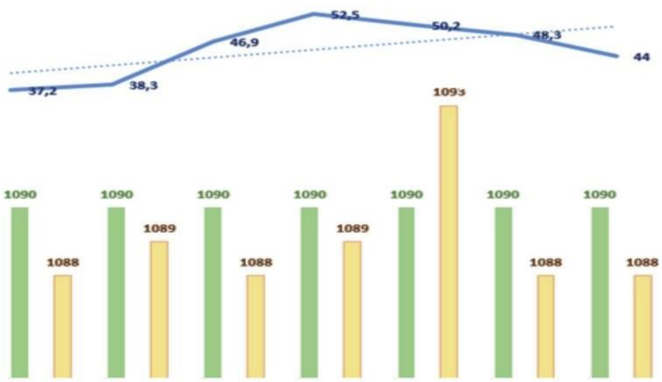

Fig. 6. Dependences of the workshop cost on the surface temperature

For clarity, figure 6 shows the dependences of the workshop cost on the surface temperature of thepallet blanks at the end of sintering, obtained on the model of the installation: agglomeration furnace-crusherfor two different versions.

Based on the obtained results of training the neural network, the following results were obtained:

- the network error in terms of the number of pallet blanks in the agglomeration furnace rangedfrom 11% to 43%;
- the network error in terms of the time of agglomeration of pallet blanks ranged from 0.2% to 29%;
- the network error in terms of the surface temperature of the pallet blanks was from 0.09% to 3%.

According to the obtained tabular data in tables 3-5 and the plotted graphs shown in figures 5-6, it can be concluded that in the proposed model of the agglomeration kiln, the temperature distribution of the kiln, pallet blanks, and a metal charge is close to the experimental data. The range of relative error in temperature is 0-4.16%.

Thus, the obtained neural model adequately describes the real processes during the agglomeration of the charge and the firing of pallet blanks in the furnace. It can be used to make forecasts and make instant decisions in the design of heating equipment and control.

Conclusion

During the operation of heating and power plants in metallurgical production, in particular, lead-zinc production in the processing of polymetallic ores, problems arise associated with the quality of products and the effective use of agglomeration furnace and crushing apparatus. Recently, mathematical modelling of the processes occurring in heat-technological installations has begun to be actively used for these purposes. However, the mathematical model for optimizing the operating mode of the installation is a complex program, which includes several dozen calculation modules.

Therefore, we replaced the program of the mathematical model for optimizing the operating modeof the agglomeration kiln and the crushing device for firing with a neural network. The use of neural networks to simulate technological processes in lead-zinc production ensured an increase in the efficiency of product quality control systems and automatic control systems for roasting of polymetallic ores, optimizeproduction costs (by 3%), and also increase the efficiency of energy production.

In addition, neural network models turned out to be more accurate and more adequate than mathematical ones, and make it possible to solve production optimization problems of any complexity in lead-zinc production. Thus, neural network modelling of technological processes for processing and agglomeration roasting of polymetallic ores provides an innovative approach to the design of controlsystems and their modelling for optimization problems and increasing production efficiency.

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