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Neural network modeling of agglomeration firing process for polymetallic ores

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ABSTRACT

While processing polymetallic ores at the non-ferrous metallurgy problems arises connecting with the excellence of production and the efficient applying the technological devices-firing furnace and crusher machine. In earlier time, similar questions were solved due to the big practice experiences and using a mathematical modeling method. The mathematical model for optimizing those operating mode is a very complex and hard to calculation. Performing computations is needed too much time and many resources. Because the control of the agglomeration furnaces and other machines are including complex multiparameter processes. The method of the math modeling for optimization the operating mode to the firing furnace is replaced with modeling based on the neural network that is here a new method. The results obtained have shown that proposed methods based on the neural network modeling of metallurgical processes allow determining more accurate and adequate results of calculations than mathematical modeling by the traditional program. The use of new approaches for modeling the technological processes at the non-ferrous metallurgy gives opportunity to enhance an effectiveness of production excellence and to enhance an efficient applying the heat-energy equipment while a firing the sulfide polymetallic ores of non-ferrous metallurgy.

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1. INTRODUCTION

Background of research is presented to us the actuality of this study that demonstrated in the following works and investigations. As known the neural networks are the present trends for designing of automation with using artificial intelligence (AI) systems, in particularly in the fields of effective operating, optimizing control for manufactory production and business. Within transferring to Industry 4.0 and implementation of the digital technologies in the whole spheres of economics and society the use of neural network technologies is promising ways to optimize the operating modes of technological equipment as well as the innovative development methods of the effective automation control systems for the complex technological processes.

One of the promising areas of application of artificial neural networks tools is the modeling of complex technological processes in the metallurgical manufactories of the mining and metallurgical complex. For this industry and scientific field of research, the use of methods of mathematical modeling is a widely applied approach for control optimization and making high-quality decisions for decreasing the maintenance cost of the technological equipment and self-cost of the production. At the same time, the use of the mathematical models of technological processes is an important tool and an effective method for studying the influence of technology on the final product properties with the appropriate quality.

Nowadays, in the non-ferrous metallurgy while the processing of the sulfide polymetallic ores there are often problems connecting with the quality of the decisions made in the operation and control of the equipment as well as connecting with adequate modeling of technological processes. Because, the decision-making of operation work is mainly dependent on an understanding of the complex chemical-physical processes and multicomponent reactions occurring inside agglomeration equipment, as well as of complexity of calculation and accuracy of results of mathematical modeling.

The problem of statements of the research is given below. Usually, mathematical models of metallurgical processes are often simplified and limited to certain assumptions. As a rule, those models are created on the basis of differential equations and integrating-differential equations, and several approximations. Actually, these simplicities are dependent on many factors, in particular, multi-component ness and high-temperature chemical reactions while the agglomeration firing of the sulfide polymetallic ores. Therefore, the problem of statements of the research is to study and to find a new methods and approaches to the mathematical modeling and optimization of complex technological processes while the processing of polymetallic ores in the non-ferrous production.

The effectiveness of the applied tools for controlling a production technology and a product quality, first, is determined by the accuracy and adequacy of the synthesized models of the technological process. The approximated mathematical models that are linearized in control parameters are not always sufficient and suitable to adequately reproduce the features of continuous technological processes in the lead-zinc production while the processing of polymetallic ores [1]. The practical developments in the use of neural networks for modeling the various kinds of engineering systems in the other economic areas show that they can be used for the metallurgy plants too. Because, they are devoid of several shortcomings which mathematical models have and allow to solve industry optimization problems of any complexity [2], [3].

It is important that while modeling the technological process of agglomeration firing of the sulfide polymetallic ores it is necessary to pay attention to the multiple information and functional dependencies between the production technology and the properties (quality indicators) of the resulting final product. Existing research and practical works are not given good examples of developing and using a neural network to simulation and designing a manufactory process at the metallurgical non-ferrous productions. But a flexibility of neural network models supposes to apply them to simulate a processing and firing the sulfide polymetallic ores in the non-ferrous metallurgy [4]–[6]. Applying an artificial intelligent system for modeling the manufactory production at non-ferrous metallurgy will provide the efficiency enhancing of the production excellence, as well as the efficiency of an automation system to the agglomeration firing of sulfide polymetallic ores.

In this manner this study is proposed the new approach to the modeling of continuous technological processes in the lead-zinc production based on the neural networks. Using this approach there were created a neural network-based models for the processing of polymetallic ores that had provided more accurate results and adequate calculations than mathematical programs. In the same time, it provided to decrease the self-cost of the final products, and also increase the energy effectiveness of the heat-energy equipment operation by optimizing the operating mode.

The relevant literature review is shows us the following situation. The considering study questions and relevant problems presented in this work are investigated and by many modern researchers and practices of industry nowadays. Because artificial neural networks are a convenient and effective tool for representing the information models and their functional defending [7]. In the metallurgical industry, the problem of implementing a novel approaches and techniques is interesting, which can speed up investigations to get a coming metal product, to refine an excellence of the final production, as well as to reduce self-cost [8].

Traditional methods of searching for the composition of new alloys with the required properties are include repeated smelting of prototypes and complex mathematical processing of the results. However, with different content of impurities in the concentrate, the number of necessary industry experiments also is increased. The complex physical-chemical compound of metals while the processing is very strong influence on the changing of the material properties. Therefore, there are complex dependencies between the concentration of metals in the ores, the operating modes of firing, and test conditions in the firing process. In this manner, the opportunity to select the strict mathematical relationship between the compound and characteristics may become impossible and hard. Because of this, the ability to obtain the most promising alloys and metal quality can be complex and difficult to manage [3].

The creation of neural network expert systems is applied to solve a direct problem-predicting the properties of non-ferrous metal alloys by their chemical composition. To solve the inverse problem, the issuance of recommendations on the chemical composition is used, depending on the set of required parameters (taking into account the cost). All this makes it possible to drastically simplify scientific research and come up with the creation of new complex materials based on innovative technologies necessary for the development of modern technologies of the 21st century [2].

A plethora of latest research are aimed to investigation of neural network algorithms, and it is applying to the manufactory equipment. At the same time, there are many studies on the modeling a thermal operation of industrial furnaces in industrial production to ensure the tasks of optimization of control, forecasting, as well as for automated control of energy consumption. Therefore, the work [4] is to consider the problems of designing, training the artificial intelligent systems which design a heat-energy operating to the firing process at the industry manufactory. The artificial intelligent systems can be used both in solving optimization problems and designing automatic control systems.

Neurocomputers are also actively used in energy systems. Last time, the neural network approach has been actively integrated in the tasks of predicting the load of energy and gas consumption [9]. In another study is given a group approach. Here are considering a learning fundamental of the statistical model. This way is helping to forecast the short-term energy expense of a multi house living building [10]. Other approaches are proposed in the work [11], where the investigators proposed a class deep opinion network to forecast energy expense. Here is considered a method that based on the various data and time sets.

In [12], researchers suggested the new learning structure to increase a forecast correctness of short-term energy load. Similarly, in [13], [14], investigators given another forecasting ways. The considering structure is a group of forecasting models called sisters. They have the alike structures but a picking process of data here is various. In [15], [16] have studied a novel approach based on an evolutionary algorithm to forecast small capacity. The developed mixed circuit allows optimum indicators regulation for neural networks, that increasing training and forecasting. Similarly, in [17], [18] are considered factors and initial data used in forecasting the loads on power systems and predict peak electricity consumption.

At the same time, extensive experience has been accumulated in the field of use in quality control in the industry. For example, the neural network used at Intel enterprises to detect defects in the manufacture of chips is a way of rejecting a defective chip with an accuracy of 99.5% [5]. The neural network developed by Mark Waller of Shanghai University specializes in the development of synthetic molecules [19]. Yandex data factory tools help in steel smelting: the scrap metal used for steel production is often heterogeneous in composition. According to Yandex, the introduction of neural networks can reduce the cost of expensive ferroalloys by 5% [20]. A neural network can help for lane detection is proposed using a convolutional neural network (CNN). Proposed approach provides it to use in assistive robotic systems. The use of machine learning technologies in this field will significantly reduce costs [21].

This work showes that a deep transfer learning is feasible to detect coronavirus disease (COVID-19) disease automatically from chest X-ray. This approach is sudgessed a training the learning model with chest X-ray images that is presented mixed with COVID-19 patients, other pneumonia affected patients and people with healthy lungs. [22]. Currently, leading oil and gas companies in various fields are already actively using neural networks. For example, the authors of paper [23] analyzed the global trends of digital technologies' introduction into the oil and gas mining industry. Gazprom Neft, in its project, implemented the concept of "artificial intelligence" -a digital geological model. Processing and interpretation of seismic and exploration drilling data are six times faster and three times more accurate. Nest lab is one of the developers of a digital robotic complex capable of training and optimizing production processes. The combination of simplified physical models and neural network algorithms made it possible to present on the market a product capable not only of automating processes but also of providing operational solutions for managing well regimes. The testing of the "robot program" at the fields of LUKOIL and Gazprom Neft allowed us to achieve significant results [24].

An example of the development and implementation of neural networks in the oil industry is the silicon valley company Tachyus, which combined classical physics and machine learning. The efficiency of field operations, according to the reports of the company's representatives, is up to 20% in mature fields. One of the most striking examples of testing neural network modeling technology developed by Tachyus is one of the large deposits in the Gulf of San Jorge (Argentina). The use of machine learning algorithms allows you to choose the optimal distribution of injection wells corresponding to a limited number of injection distribution options to achieve maximum oil production. So, on the example of the Zapadno-Malobalykskoye field in Kazakhstan, most solutions to the optimization problem provide the current daily production. Simply put, most randomly selected options for the distribution of infectivity of injection wells will allow achieving the current performance of production wells. Neural network algorithms reveal the possibility of creating the necessary conditions that will allow you to realize the full potential of the development system [25].

A review of the other economic and production areas shows that there is a wide range of neural networks applications and artificial intelligence used for the control, automation, and optimization of the processes and plants in the different areas of control. For example, in the work [26] an encode-decode Seg-Net system via deep learning network incorporated with VGG16 has been proposed in order to identify the lane markings on distinct environmental effects. Also, there is a recent work on the development of COVID-19 detection system by a transfer deep learning approach where the state-of-the-art CNN models have been used. The related to coronavirus studies were in the work [27] where a new CNN model has been proposed in order to detect COVID-19 based on X-ray images.

Other work [28] investigates the method for an accurate estimation of solar radiation in Indonesia via a new two-step artificial neural network (ANN). Another paper [6] is demonstated a comparative framework where a suite of long short-term memory (LSTM) recurrent neural networks (RNN) models are implemented to address the existing gaps and limitations of reported wind power forecasting methodologies. Similarly, Salam *et al.* [29] proposed in his research the hybrid SVM-ANN net model. The performance of support vector machine (SVM), ANN, SVM with reduced features, and hybrid SVM-ANN model in the detection of breast cancer have been compared.

Recently published papers of other authors have proposed the use ANNs as an intelligent control strategy for a microgrid energy management system [30]. Similarly, another paper gives the analysis of the performance of the multilayer neural networks with respect to the different activation functions for the purposes of prediction of the production and consumption of electric power [31]. In the other work is investigated the method for the short-term wind speed forecasting system via a deep learning algorithm with applications to wind turbines [32], [33].

Thus, there are many methods for determining the accuracy of mathematical models associated with the energy performance of industrial plants and other industrial production. However, in the non-ferrous production the indicated above methods are not applied. Because there are not found a general-purpose method yet for their application for modeling complex processes for processing and agglomeration firing of multicomponent polymetallic sulfide ores. This analysis supports the relevance of our study within the development of Industry 4.0.

The new value of Research is shown by the next outcomes. The recent development of neural network technologies can provide the creation of an appropriate technologies and approaches to getting the correctness of mathematical systems for automating manufactory equipment. They can be used to make an optimization of the energy expenses of the firing equipment in the lead-zinc production. In this paper, it is proposed the use of neural network technologies for calculating and modeling an agglomeration furnace and crusher machine to increase their efficiency and to reduce production cost. So, this research is proposed the new method is based on the process modeling based on neural networks. In the same time, here is provides a new approach to the optimization of the operation mode and of the control systems for complex multi-component processes in the lead-zinc production, which proves the new value of research. Nowadays there are no proposed methods and approaches in the existing works that are applicable to the technological processes in the metallurgical manufactory for the processing of polymetallic ores.

2. RESEARCH METHOD

This part considers the applying research methods. In the first section, it is given explanation of the proposed methodology of the research problem. The second section is presented a description of the mathematical model and algorithm for calculating the firing process. The third section is demonstrated a description of optimization model of the operation mode for the technological equipment.

2.1. Methodology of the research problem

The research technique of this work involves the use of modern approaches on process optimization such as neural network modeling and mathematical modeling as well as numerical methods and analytical calculations of the obtained results. Also, a method of statistical analysis for decision making and using it while the learning process of neural network models is used in this research work. It is very important to take appropriate mathematical models that reflect the operation of the agglomeration furnace and associated technological equipment. It is given opportunity to make an acceptable choice of the firing equipment. In this matter, the mathematical models used for these goals in the form of computer programs have a complex structure, large volumes, and take a significant amount of time for calculations process.

In this case, using the neural networks technologies for determine an accuracy result obtained when solving heat and energy transfer problems using multi-purpose computing systems is the one best way to solve these kinds of problems. In this work, the methods of modeling are used to solve the optimization of the operating modes of the agglomeration furnace and crusher machine on a firing expense to the burner, energy to a grinder process. In order to define the dependence between the working mode of the firing equipment and grinder machine, a method of determining the dependencies of studied parameters is used. For example, the determination of the dependencies of the influence of changing of the generalized size of polymetallic ores and the parameters of the heating on the time of agglomerating firing.

2.2. Description of the mathematical model and algorithm for calculating the firing process

The sample is designed for a firing furnace working in a fixed mode. The stationary heating flow in the loaded furnace charge should be propose equal to the quantity of heat energy transmitted from the gases to the loaded charge under the convection. Let us assume that the gas volume in the working space of the furnace is isothermal. As far as, the process of loading and unloading the metal charge is continuous, the temperature over all hot area of the metal charge is currently invariable [28].

The math sample is based on the solving of the conjugate question of heat transfer in the gas-charge-agglomerate system. The method of discrete performance of border conditions was taken as a mathematical method of modeling [28], [29]. In Figure 1 is presented the algorithm for solving the studied optimization problem which includes 9 stages. This algorithm provides the calculating the specific consumption of air supplied for the firing and the lowest heat combustion of the fuel for the process. It is given the opportunity to determine the specific outputs and the percentage of combustion products. The realization of this algorithm is made by a set of special computer programs [29], [30].

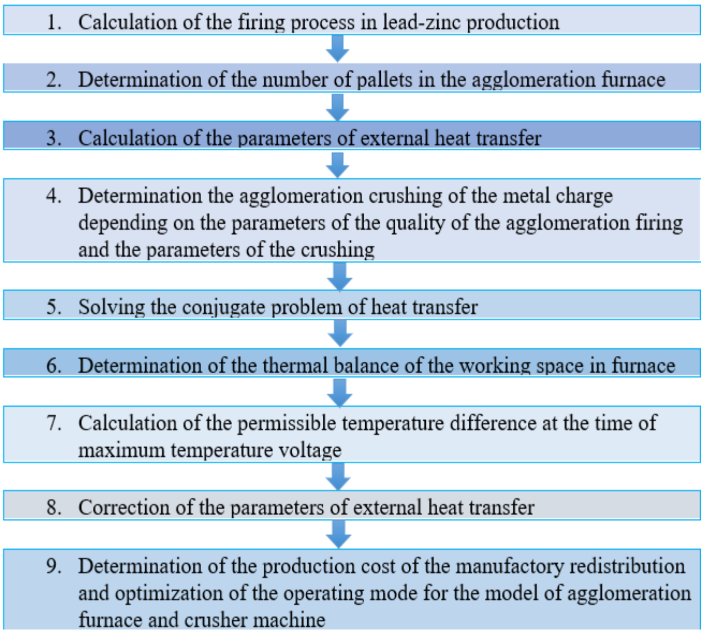


Figure 1. Algorithm of solving the optimization problems and calculating

2.3. Description of optimization model of the operation mode for the technological equipment

Choosing the objective function and operating parameters of the model. For designing an optimization model, it is needed to choose the objective function and parameters of variating for this model. The general-purpose economic argument (the production cost) is one of the appropriate as an objective function to optimize the operating mode of firing furnace. The production cost consists of two types of costs: direct and indirect. Direct costs are divided into basic materials and semi-finished products costs, basic and additional wages. Indirect costs are divided into conditionally variable (proportional) and conditionally fixed expenses [30], [31].

The production costs ($S_{p.c.}$) (*tg/y*) are set for a year and relate mainly to conditionally fixed costs and are determined by the following (1), where $S_{c.m.m.}$-costs of manufactory management, *tg/y*; $S_{c.o.p.}$-costs of other personal, *tg/y*; $S_{a.c.b.}$-costs of buildings and construction, *tg/y*; $S_{c.b.c.}$-costs of maintaining buildings and construction, *tg/y*; $S_{ex.r.b.}$-expenses for current repairs of buildings, *tg/y*; $S_{c.t.e.r.}$-costs for testing, experiments, and research, *tg/y*; $S_{c.lp.s.o.}$-costs of labor protection, and safety, *tg/y*; $S_{c.lv.t.}$-the cost of low-value tools, *tg/y*.

$$S_{p.c.} = S_{c.m.m.} + S_{c.o.p.} + S_{a.c.b.} + S_{c.m.b.} + S_{c.b.c.} + S_{ex.r.b.} + S_{c.t.b.r.} + S_{c.lp.s.o.} + S_{c.lv.t.} \qquad (1)$$

Here the production cost (or self-cost of the product) is the main function of the optimization model for the operating mode.

The costs of maintaining and operating equipment ($S_{c.m.o.eq.}$) related to conditionally variable costs are determined by the formula (2), *tg/y*, where $S_{c.a.eq.}$-the cost of amortization of equipment, transport, and tools, *tg/y*; $S_{c.ad.m.}$-costs for additional materials, oils, and etc., *tg/y*; $S_{e.c.eq.}$-energy costs spent to equipment operation, *tg*/y; $S_{s.s.p.}$-salary of personal servicing the equipment, *tg/y*; $S_{ex.m.r.}$-expenses for maintenance and repair of equipment, *tg/y*; $S_{c.t.s.}$-costs for transportation services, *tg/y*; $S_{c.w.eq.}$-the cost of wear low-value equipment, *tg/y*; $S_{o.c.o.m.}$-other costs associated with the operation and maintenance of equipment, *tg/y*.

$$S_{c.m.o.eq.} = S_{c.a.eq.} + S_{c.ad.m.} + S_{e.c..eq.} + S_{s.s.p.} + S_{ex.m.r.} + S_{c.t.s.} + S_{c.w.eq.} + S_{o.c.o.m.} \quad (2)$$

Thus, the self-cost of the manufactory production is determined by the (3), where $S_{s.m.p.}$ is the salary of the main workers for processing of 1 *kg* of the *i-th* type of product, *tg/kg*.

$$S_{sc.m.p.} = S_{sc.id.ex.} + S_{s.m.p.} \quad (3)$$

Therefore, the optimization parameter while selecting the operating mode of the equipment for the agglomeration firing process is the minimum of the production self-cost. The parameters of operating mode (parameters of the quality of agglomeration) are taken as variable parameters in the model: a temperature on the surface $T(1, Fo_K)$ and a temperature difference at the end of firing $\Delta T_{1-0}(Fo_K)$, as well as the parameter associated with the placement of pallets in the agglomeration furnace (R_m).

Selecting restrictions of the mathematical model and facilitation a number experiment. It is hard to apply the above algorithm to define the optimal working data based on a recitation of versions because the quantity of such calculations is huge. In this manner, the technique is applied, that is presented a set up a computational experiment. This algorithm provides information where an objective function will be changing depending on the various working data sets [1], [32].

To define those a dependency, it is needed to well install the intervals of modification of the operating data. The limits of the various intervals are defined using the following requirements: i) the range of variation of the last firing temperature on the surface, is in the range at which firing cannot be executed and to the melting point of the metal and ii) the acceptable temperature difference at the end of the metal firing is 5-10 °C (the range of variation). In practice, it is advisable to reduce this range somewhat by setting it in the range from 35 to 170 °C. The required dependency and equation of mathematical modeling $y = f(x_1, x_2, x_3)$ is presented in the next form (4), where *y* is an optimization parameter; x_1, x_2, x_3 -variable parameters; b_i,-coefficients.

$$\begin{aligned} y = b_1 + b_2 * x_1 + b_3 * x_2 + b_4 * x_3 + b_5 * x_1 * x_2 + b_6 * x_1 * x_3 \\ + b_7 * x_2 * x_3 + b_8 * x_1^2 + b_9 * x_2^2 + b_{10} * x_3^2 \end{aligned} \quad (4)$$

In order to find the coefficients bi, a second-order orthogonal planning matrix for a computational experiment is constructed for three factors x1, x2, x3. On the basis of a computational experiment using the planning matrix, the coefficients bi are found for the dependence. The optimization problem is solved taking into account 8 constraints as shown in Table 1. Using these data presented in Table 1, we can determine the differences between existing and valid values that are presented in the form of dependencies between constraints and temperature of the firing process.

Table 1. The eight constraints for optimization

Number of constraints	Type of constraints
1	is the temperature of the gases in the working space of the firing furnace
2	is the rate of delivery of agglomeration pallets from the furnace
3	is the allowable temperature difference during the initial firing period
4	are the maximum temperatures of the using furnace materials
5	are the maximum temperatures of the using furnace materials
6	are the maximum temperatures of the using furnace materials
7	is the maximum possible gas flow rate for the agglomeration furnace
8	is the productivity of the agglomeration furnace

The differences between the valid and existing values are determined by the following formula (5), where *i*-current constraint number; y_i-the difference between the valid and calculated values of *i* constraints; x_1, x_2, x_3-variable parameters.

$$\Delta y_1 = b_{1,i} + b_{2,i} * x_1 + b_{3,i} * x_2 + b_{4,i} * x_3 + b_{5,i} * x_1 * x_2 + b_{6,i} * x_1 * x_3 + b_{7,i} * x_2 * x_3 + b_{8,i} * x_1^2 + b_{9,i} * x_2^2 + b_{10,i} * x_3^2 \quad (5)$$

The time for choosing the objective function depends on the adopted step of changing the varied parameters. As the step decreases, the computation time is decreased, and the accuracy is increased. In the optimization model, a technique is used that makes it possible to estimate the accuracy of obtaining the objective function with the adopted step of changing the varied parameters. The entire area of variation of the varied parameters was divided into 1,000 volumes or 10 steps. Then the volume with the minimum cost was determined. Then the calculation was repeated, but already with division by 3,350 volumes or 25 steps. If the results coincided with the specified accuracy, then the calculation was terminated. In other cases, the self-cost of the production was refined for variable parameters with minimization of the objective function.

The value of the optimal self-cost of the product obtained using the model was substituted into the initial data in the computational experiment, which was repeated anew. The dependencies were refining again. Further, the calculation of the objective function optimization was repeated. Refinements were repeated until the specified accuracy was obtained. After that, the calculation was completed. Since additional computational experiments are in the area of the desired values of the objective function, the accuracy of the optimization results increases significantly with a small amount of computer time.

For calculation of these optimization tasks, during the study, it was used several modern computer tools and technics. For example, for analytical solutions were used the programs were designed using the Mathcad packet. The numerical methods were used to solve research questions using the PHOENICS packet. At the same time, for the processing and analysis of the research results, it was used modeling methods based on the neural networks using the Nonresolution's packet.

3. RESULTS AND DISCUSSION

This part of the research is presented the obtained results of program calculations and modeling as well as the experimental data for the agglomeration firing of sulfide ores of non-ferrous metallurgy. In first section is shown the operation results of the mathematical model of agglomeration furnace and crusher machine. In the second section is given the application of neural network technology to simulate a furnace-crushing agglomeration plant. In the third section are presented the algorithm of training of the neural network model.

3.1. Operation results of the mathematical model of agglomeration furnace and crusher Machine

The last part of the study is demonstrated the research outcomes. These outcomes are given for the process of processing polymetallic ores in the Kazakh industry plant. For this purpose, data from real installations of lead-zinc production JSC "Kazzinc" were taken as a basis.

The firing furnace is a chamber lined with refractory bricks and enclosed in a metal frame. The agglomeration furnace is loaded and unloaded manually through a working window framed by a water-cooled frame and closed by a water-cooled steel damper lined with lightweight chamotte. The results of calculating the optimal modes of the real industry plant of Kazakhstan are given in Table 2. Table 2 demonstrates only the main results which are important for optimization of the processing mode in the lead-zinc production. Because they mainly are influencing to the quality and accuracy of modeling results while the processing of polymetallic ores.

Table 2. The calculating results the optimal modes for the firing furnace and the crusher machine

Title of the controlled parameter	1	2	3	4	5	6	7
The temperature of agglomeration furnace (^{0}C)	870	903	815	868	810	780	751
The volume of pallets in the furnace (kg)	560	870	630	660	730	1200	1500
The firing process temperature (^{0}C)	1470	1980	1320	1670	1850	1950	1535
The temperature difference of firing (^{0}C)	99	87	76	68	54	82	79
Gas consumption (m^3/hour)	25	28	22	21	20	19	25
Agglomeration time of firing (sec)	1312	1418	1138	1248	1176	1096	1147
Self-cost of production (tenge/kg)	37,2	38,3	46,9	52,5	50,2	48,3	44,0

3.2. Application of neural network technology to simulate a furnace-crushing agglomeration plant

Neural network modeling approach for optimization of the agglomeration plant. The mathematical model for optimizing the operating mode of an agglomeration plant: agglomeration furnace and crusher machine for processing polymetallic sulfide ores is a rather difficult program that includes several dozen calculation modules. Performing a calculation in the program and obtaining a map of the technological process of agglomeration firing of a metal charge requires a rather large investment of time, and sometimes a decision must be made immediately. Therefore, in this work, the numerical calculation has replaced the program of the mathematical modeling for optimizing the operating mode of the agglomeration plant for firing based on the neural network.

As a result, the designed approach by implementing the process of the so-called network learning that is based on the learning process on the outcomes of computations using the math samples. The neural network has combined up the info received as a functional relationship inside. At the other cases, the math model of the agglomeration firing equipment and crusher machine was changed to model of taking solutions for an optimization of manufacturing plants.

Generation of input and output data for neural network model of the agglomeration plant. For programming using neural networks, it was necessary to solve the problem by collecting data for training using a neural network. A training dataset is a collection of observations for which the values of the input and output variables are specified. The choice of variables (at the initial stage) is intuitive. Initially, training a neural network includes all the variables that can affect the result, and at subsequent stages, they reduce their set. This approach to a neural network program assumes the possibility of flexible and convenient work with a data set. In this manner, the following main data were used as input variables: i) diameter of agglomerating pallets, ii) size of pallets, iii) the estimated size of the agglomeration after the firing operation and iv) permissible temperature difference at the end of agglomeration. The training data set was the database presented by the Microsoft Excel spreadsheet. Each row in table is one supervision that involves the different senses of seven main input variables and a one output quantity.

3.3. Algorithm of training of the neural network model

Training neural network models for the agglomeration process. For the training of the artificial network model in the work, it was resolved the issue of choosing a specific network architecture (the number of "levels" and the amount of "neuro cells" in every of them) when creating a neural network. Since the nature of the phenomenon is not well known at the outset of the analysis, the choice of architecture is difficult and often involves a lengthy process of "trial and error". Therefore, to solve such questions it was created the algorithm that provided the training of the neural network model for the optimization task of the operation mode as shown in Figure 2. Figure 2 is presented the proposed algorithm of training of the neural network models to determine the number of polymetallic ores pallets in the agglomeration furnace.

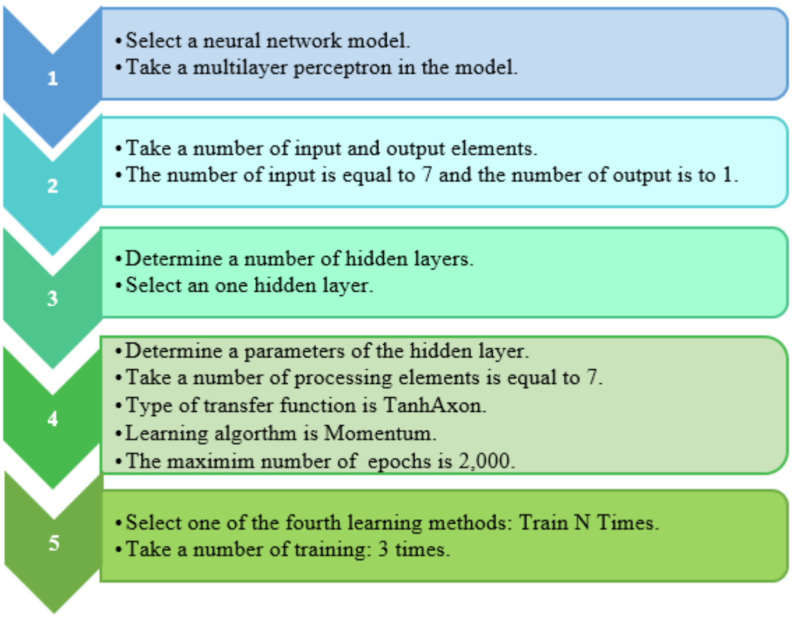
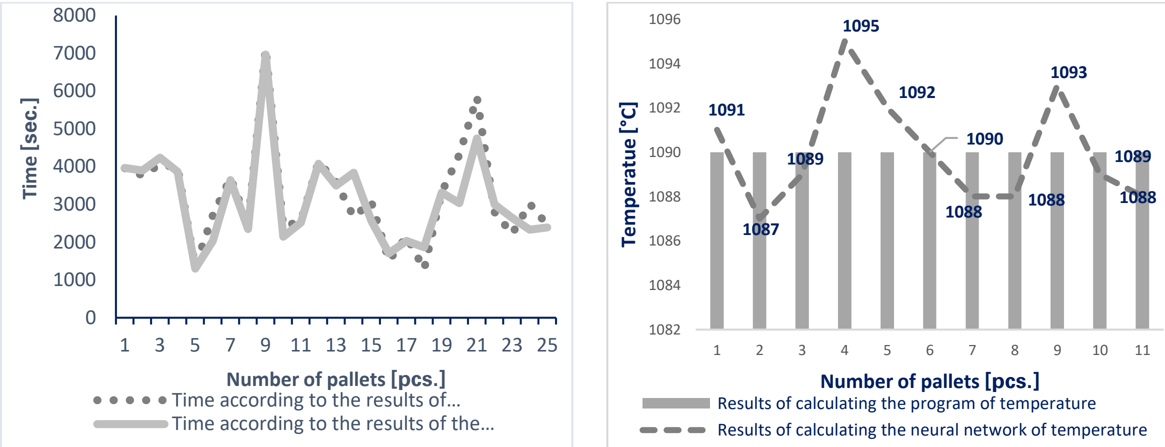


Figure 2. The algorithm of training of the neural network model of agglomeration

Verification of the results of neural network modeling. The training was performed using the data received from the computation on the program for optimizing the operating mode of the firing furnace and crushing plant. Then, the neural network was ready for operation. It was used to make forecasts and make instant decisions. In sum, the better training outputs of neural networks were the training outputs indicated below in the spreadsheet 3 and Figure 3. For example, the Table 3 shows a relative study of the training outcomes and computation according to the computer program to define a number of the metal ores in the firing furnace. Table 3 is demonstrated that the final root-mean-square error is small: MSE=0.0128.



(a) (b)

Figure 3. The Learning outcomes of the neural network according to the proposed algorithm: calculation outcomes of the time for (a) and calculation outcomes of the outside temperature and (b) for firing process

Table 3. The relative study of the training outcomes and computation

Calculation outcomes and learning outcomes	Number of ores pallets
The total number of pallets obtained from the program calculation	1 955
The total number of pallets obtained as a result of training the neural network	1 943

The relative study of the training outcomes of the learning and computation by the computer that provides the defining of the outside temperature for firing process are shown in Figures 3(a) and 3(b). Figure 3(a) has “Time[sec.]” as the vertical axis, and “Number of pallets [pcs.]” as horizontal axis. Figure 3(b) has “Temperature [°C]” as the vertical axis, and “Number of pallets [pcs.]” as horizonta axis. These graphics is showed some of the learning outcomes of the designed neural network according to the proposed algorithm. Thus, according to the numerical experiments and the applying the trained neural network, the little deviations were obtained that are presented in Table 4. As the result, we have obtained the following outcomes of the training and of the little deviations: the neural networks calculation errors in the ore’s pallets number in the agglomeration furnace ranged from 11% to 24%; the neural networks calculation errors in the time of agglomeration of ores pallet blanks ranged from 0.2% to 7%; the neural networks calculation errors in the surface temperature of the ore’s pallet blanks were from 0.09% to 3%.

Table 4. Comparative results of numerical calculations and calculations using neural networks

	Deviations on the number of pallets, pcs.	Deviation on the time of agglomeration, sec.	Deviations in temperature at the end of agglomeration, °C
Maximum deviation	15	302	37
Mean deviation	12	254	25
Minimum deviation	7	9	1

4. CONCLUSION

Within the presented study it was considered the research problems connect with controlling the quality of the final product and optimization of the processing mode for agglomeration firing of the polymetallic ores in the lead-zinc production. Also, this work was paid attention to determining the accuracy and adequacy of the calculation results that are obtained by the numerical methods and mathematical modeling of the processes. Actively used in the study mathematical calculations and programs usually are very complex and required to use more resources and time. At the same time, these approaches as a rule have several constraints and approximations in the models. But for the industry productions and manufactories, it is very important to control all parameters in the required modes and to reduce the self-cost of the production. Therefore, in the work, it was studied the new approaches and innovative methods for solving the optimization questions of the metallurgical plant using neural network technologies. The obtained results of the study are proved our proposed ways and new approaches for solving the problem of the research. The use of neural networks to modeling a technological process of firing of polymetallic sulfide ores at the non-ferrous metallurgy provided to enhance the efficiency of production quality control systems and automation systems for firing of sulfide metals, decreasing a manufacturing cost by 3%. In addition, it increased the effectiveness of energy reproduction. Operation of heating equipment by optimizing the operating mode of equipment is provided the increasing of effectiveness 10%.

Thus, from the above results, it is obvious that a getting neural models correctly describe the real processes while the processing t and the firing of polymetallic ores in the furnace. And this is proving that the research goals of this work are obtained. Future, it can be recommended to use for study the process of the firing of the other ores on the metallurgy plant and for calculating the design features of a heating and power plant. This way also could be applied to forecast and take good solutions to design any other heating tools as well as for its optimal regulation. Finally, these results in this work are adding the new value of research to the existing scientific results and knowledge in particular to problems of the modeling and optimizing the technological processes in the metallurgical manufactories. The novelty of this research lies is presented in the following. The new technique has been developed to determine the accuracy of calculation results and the adequate of modeling the modes of continuous technological processes of the loading and unloading concentrates into agglomeration furnaces and firing of the sulfide polymetallic ores. It was created the neural network model of the agglomeration furnace and crusher machine solving the problem of calculating the needed parameters of the furnace and crusher machine. It was proposed the new approach to optimizing the operating mode of energy equipment in lead-zinc production that provided a decrease in the production cost.

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