АВТОМАТИЗАЦІЯ ПРОЦЕСІВ ТА СИСТЕМ

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APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR DETERMINATION OF THE ADDITIVES AMOUNT IN THE AUTOMATED PROCESS CONTROL SYSTEM OF STEELMAKING IN BASIC OXYGEN FURNACE

This paper describes an algorithm of determining the amount of deoxidizing and alloying materials that are loaded into the basic oxygen furnace (BOF) and steel ladle on the base of information about burdening of melting and chemical composition of the steel using artificial neural network (ANN). The analysis of resent researches and publications regarding mathematical modeling of BOF melting and application of ANN as such models was made. This analysis show that selected topic has novelty and relevance. The schematic of interaction of different kinds of mathematical models in the system of automated control of BOF melting is offered. The research of applicability of artificial neural networks for determination of quantity of deoxidizing and alloying components is performed. The place of the obtained artificial neural network in the overall system of automated control of basic oxygen melting is described. The description of the multistep selection process of the ANN architecture is given. The correlation coefficients and mean square deviations for all parameters are found. The results of performed analysis are considered satisfactory. The recommendations for replacement of alloying and deoxidizing components in the absence of any of them in stock are given.
Keywords: *modeling, artificial neural network, steel industry.*

Сокол С.П., Симкин А.И. Применение искусственной нейронной сети для определения количества присадок в системе автоматизированного управления выплавкой стали в кислородном конвертере. *В статье приводится алгоритм определения количества раскисляющих и легирующих материалов, загружаемых в кислородно-конвертерную печь и стальковш, на основании информации о шихтовке плавки и химическом составе стали с использованием искусственной нейронной сети (ИНС).*
Ключевые слова: *моделирование, искусственная нейронная сеть, сталеплавильная промышленность.*

Сокол С.П., Сімкін О.І. Використання штучної нейронної мережі для визначення кількості присадок в системі автоматизованого управління виплавкою сталі в кисневому конвертері. *У статті наводиться алгоритм визначення кількості розкислюючих та легуючих матеріалів, що загружаються до киснево-конвертерної печі та стальковша, на основі інформації про шихтовку плавки та хімічний склад сталі за допомогою штучної нейронної мережі (ШНМ).*
Ключові слова: *моделювання, штучна нейронна мережа, сталеплавильна промисловість.*

Description of the problem. The most widespread process of steelmaking at the modern steel plants is BOF process with the top blowing of the bath with oxygen. Due to the sufficient complexity of technological process of melting of quality steel with the given chemical composition and temperature it is impossible to do without application of an automated control system of melting. Due to the

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lack of the continuous monitoring of parameters of a melt in the BOF and liquid steel in a ladle the software of the system must include a complex of mathematical models which purpose is calculation of values of technological parameters for a melting process. Nowadays a large amount of models for an assessment of a process of BOF melting is developed, and the majority of them are related to the blowing period. However the stage of deoxidizing and alloying of the steel while releasing from the BOF has essential impact on steel quality too. Usually the quantity of deoxidizing and alloying components is defined from the balance equations or by empirical way that does not always provide enough accuracy. Authors considered the possibility of using of ANN for determination of quantity of deoxidizing and alloying components.

Analysis of the last researches and publications. The problem of application of statistic models on the basis of artificial neural networks in control system of BOF melting was partially considered in [1]. The authors developed the complex model consisting of a dynamic model intended for determination of temperature at the end of a blowing based on a heat balance of melting, and ANN serving for setup of coefficients of a dynamic model. In [2] the same authors offered the algorithm of training of ANN that allows to slightly increase the accuracy of results.

In [3], [4] the authors described the process of selection and training of ANN for a prediction of temperature of steel at release from the BOF based on information about chemical composition of the initial components and a required chemical composition of finished steel. The obtained results matched the experimental data with enough high precision.

In article [5] the authors described the original idea of application of ANN for prediction of end time of blowing using the analysis of images of the converter obtained by photographic camera.

In [6] the authors put forward the idea of determination of amount of components loaded in steel on the furnace ladle aggregate. The authors of article also suggest using an artificial neural network for determination of mass of components. The correlation and regression analysis of initial data is carried out, the justification for a choice of architecture of ANN which is most suitable for an objective is given and the analysis of the received results is realized in the article. The obtained accuracy of determination of amount of components is satisfactory that allows using the obtained artificial neural network in system of automation of the furnace ladle aggregate.

Among the most known and widely used static models it is possible to mention the models developed by CRIFM together with CDB [7], B.C. Bogushevsky (VNPP "KIA") [8], A.M. Bigeev (Magnitogorsk state metallurgical institute) [9]. The balance method is supposed to be a basis of all these models in which the equations of the chemical reactions taking place in the BOF are worked out. Quantities of the initial components are defined proceeding the material and heat balance of these reactions. Thus these models allow defining a melting burdening knowing a chemical composition and temperature of the initial components both a required chemical composition and temperature of ready steel. However there is not always an opportunity to define precisely a chemical composition of the initial materials because its analysis is not made for all components. So it is usually impossible to define an exact chemical composition of the scrap covered in the converter, for example. Errors in operation of static model of calculation of a burdening lead to the need of further blowing that increases duration of melting and reduces BOF productivity. For reduction of influence of unaccounted factors to the accuracy of results a number of the correction coefficients determined by an empirical way on the basis of experience of the previous melts are used in mathematical models. Thus the last melts are considered rather than earlier ones. It allows increasing the accuracy of models but doesn't exclude completely a randomness factor.

The balance equations, allowing calculating quantity of the deoxidizing and alloying materials added during draining of metal from the BOF are given in [8] also. First masses of deoxidizing and alloying materials are defined on the base of the material balance of chemical components by equations offered by authors. Then the corrections considering experience of the previous melts are entered into them. The developed model allows obtaining saving on account of more exact determination of necessary amount of expensive ferroalloys (to 25 kg for melting) according to the authors.

The objective of the article is describing an algorithm of determining the amount of deoxidizing and alloying materials using artificial neural network (ANN); pointing the place of the obtained ANN in the overall system of automated control of BOF melting; giving the recommendations for replacement of alloying and deoxidizing components in the absence of any of them in stock are given.

Basic material. ***Application of models in process control system of BOF melting and a prob-***

lem definition. As it was justified above, the software of the modern process control system of melting of steel in the BOF must include implementation of several mathematical models required for calculation of different parameters based on which the subsystem of melting control works. The diagram of interaction of these models is shown in figure 1.

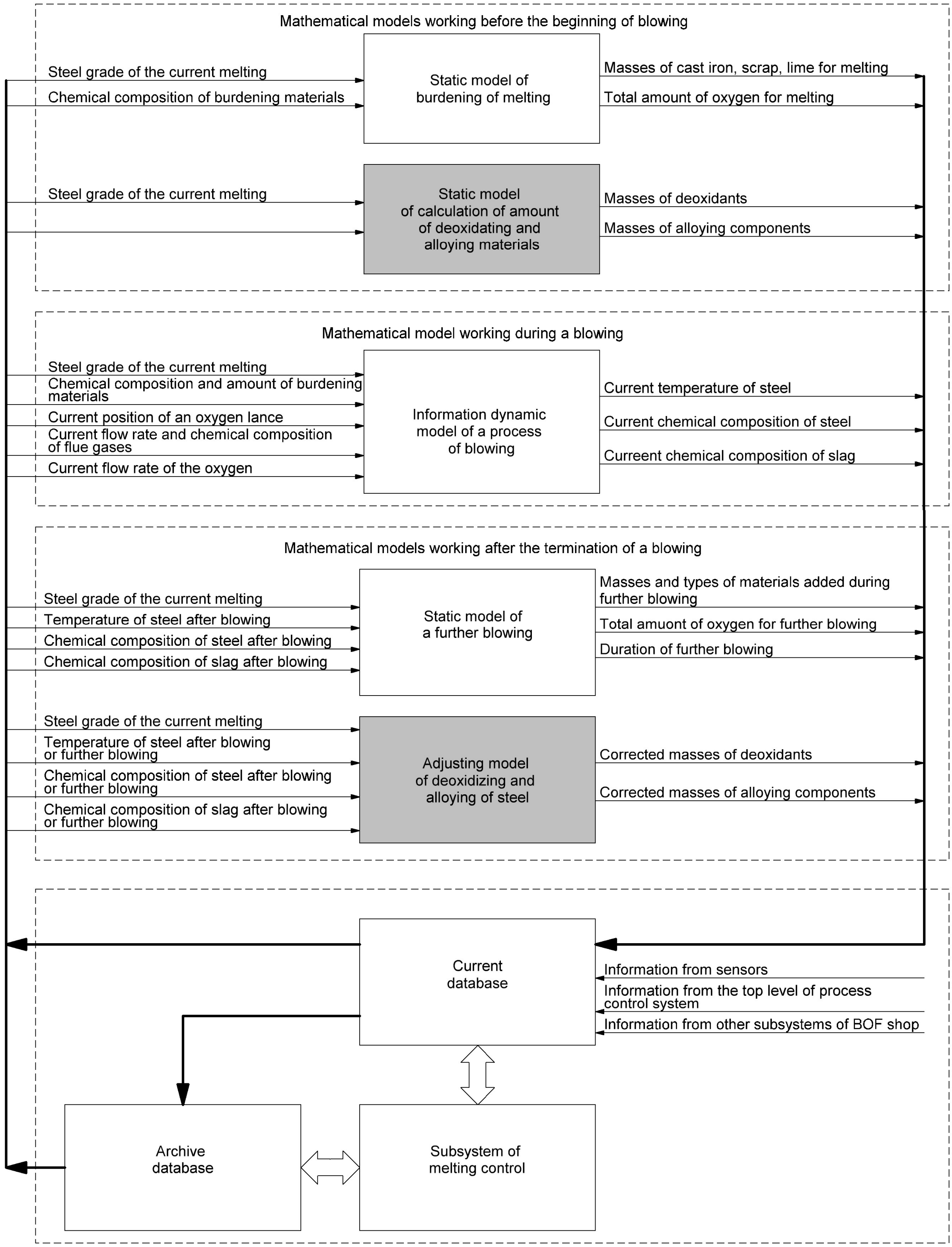

Fig. 1 – The diagram of interaction of mathematical models

Initial data for static model of a burdening of melting are: required chemical composition and temperature of finished steel determined by the given steel grade; chemical composition and temperature of cast iron; chemical composition and properties of the available steel scrap. This model calculates the summary flow of oxygen required for a blowing and masses of cast iron, scrap, lime and coolers (for example, iron ore, pellets) for a current melting.

At the same time with burdening model the initial information arrives to model of interim quantity of deoxidizing and alloying materials. It is known that most of them are added on a stream during the pouring of steel from the converter in a ladle and only pure metals (for example, nickel, molybdenum, etc.) are loaded directly into the converter together with steel scrap.

The blowing begins after required quantity of solid and liquid components are loaded into the oxygen converter. Then information dynamic model of a process of a blowing begins operation. It calculates the current temperature of steel, the chemical composition of steel and slag on the base of current flow rate of the oxygen moving through a lance, the current position of an oxygen lance relative to the level of quiet metal in the BOF, the current chemical composition and the flow rate of flue gases and so on. This information is required for operation of a subsystem of melting control and for determination of the end time of a blowing in case of achievement of the given temperature and a chemical composition of steel.

After the termination of blowing the turning of the converter is executed and selection of probe of liquid steel and temperature measurement is made. If results of measurement of temperature and chemical composition of steel after blowing meet the requirements the blowing is considered as finished and steel pours from the converter in a ladle. If not, further blowing is made.

The static model of a further blowing which is similar to static model of a burdening is used for determination of duration of a further blowing, amount of necessary oxygen and mass of added materials. But this model operates with information about chemical composition of steel after blowing but not composition of cast iron and scrap. The turning of the converter and measurement of temperature and chemical composition of steel is made again after further blowing. If they are kept within the specified limits steel is poured. In other case one more further blowing is made.

After all further blow downs, correction of masses of deoxidizing and alloying materials that are loaded into steel during its pouring in a ladle is made. It is based on the known temperature and chemical composition of the steel and the given chemical composition determined by a steel grade by means of adjusting static model of a deoxidizing and an alloying of a steel. The same model can consider absence of some materials in a warehouse and their replacement with others that have the same influence on a finite chemical composition of steel.

As it was told above all mathematical models have the correction coefficients allowing considering the undefined factors which are permanently leading to appearance of an error.

During their functioning all above-mentioned mathematical models communicate with the current database in which information about the current melting gathers from all possible sources: from sensors and the transformers situated on object, from the top level of process control system; from control systems (mixer section, scrap section, section of furnace ladle, pouring section) or the automated monitoring system of the BOF department parameters. Mathematical models receive information required for their working from a database, and the values calculated by them also are sent to a database. Information about last melting moves from the current database to the archive after termination of melting. Information about previous melts is required for operation of some models (especially for static models of a burdening). They receive it from an archive database.

The subsystem of melting control controls a blowing process based on all information arriving from sensors, mathematical models, other subsystems of process control system, results of previous blow downs Its task is calculating and setting of all parameters of melting in each moment to receive the greatest productivity of the BOF.

The authors of this article offer to replace two static models of calculation of deoxidizing and alloying materials (they are highlighted with gray color in fig. 1) with one statistical model based of ANN in addition with the module of calculation of amount of materials depending on their existence in a warehouse. The advantage of such approach is that instead of two different mathematical models only one is used. And it is developed on a different principle, than calculating of the material balance of melting. There are only some linear equations in ANN that replace the difficult balance equations. This allows considerably simplifying the software of process control system of melting of steel in the

BOF. The following material is devoted to the question of applicability of the offered approach.

Research of applicability of artificial neural networks for determination of quantity of deoxidizing and alloying components. The authors of this article carried out the researches using real parameter of more than 2000 melts carried out on one of steelmaking plants of Ukraine from January till July, 2012.

The input parameters obtained from databases of blowing which was first decided to use for ANN creation are: the parameter values known before the beginning of a blowing (cast iron mass, scrap mass, lime mass, cast iron temperature, chemical composition of cast iron (Mn, Si, S, P) the total volume of oxygen for melting, the maintenance of O_2 in oxygen, the oxygen temperature, sequence number of melting in converter campaign), and the parameter values received after the termination of a blowing: temperature and chemical composition of finished steel (C, Si, Mn, S, P, B, N, Al, Ca, Ti, V, Cr, Ni, Cu, As, Nb, Mo). Output model parameters are masses of deoxidizing and alloying components.

Before development of a model on the basis of ANN correlation analysis was carried out in which correlation coefficients between input and output parameters were defined. The part of output values are not practically related to any of input parameters. It turned out that there are those components which are used quite seldom (less than in 1% of melts). Before developing the ANN it was decided to exclude those melts in which these components were used, and the components themselves from reviewing. As a result the data of 1900 melts was used for development and training of ANN. The total quantity of output values thus decreased from 40 to 22.

Besides, as the result of correlation analysis it was noted that for part of input parameters there was no relation to other input and to all output parameters. It was decided to exclude them for simplification of structure of a network and for avoid of creation of destabilizing factors during training ANN.

As a result the following parameters were left after correlation analysis as input values:
- cast iron mass,
- lime mass,
- cast iron temperature,
- chemical composition of cast iron (Mn, Si, P),
- pure O2 content in technical oxygen,
- oxygen temperature,
- number of melt in converter campaign,
- chemical composition of steel (C, Si, Mn, P, B, Al, Ti, V, Cr, Ni, Cu, Nb, Mo).

For creation and training of model on the basis of ANN program Statistica v.8 was used. As the exact nature of dependence between input and output parameters is unknown preliminary search of the most suitable architecture of an ANN was carried out first. Multi-layer perception (MLP) and networks of radial basis functions (RBF) types of ANN took part in reviewing. The quantity of neurons of the hidden layer changed from 70 to 100 and functions of activation of neurons of the hidden and output layer for MLP were selected from the list provided in table 1:

Table 1

Types of activation functions of neurons

Name of the function	Identity	Logistic	Exponential	Hyperbolic tangent
Function look	$y = x$	$y = \dfrac{1}{1-e^{-x}}$	$y = e^{-x}$	$y = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$

The single available activation function of neurons of the hidden layer for RBF is the normal distributions function $y = \dfrac{1}{\sqrt{2\pi\sigma}} \exp\left(\dfrac{(x-\mu)^2}{2\sigma^2} \right)$ and the identity function is available for neurons of the output layer.

While creating of ANN 70% of melting passports were used for training, 15% were used for test and 15% were used for validation. All parameters of ANN were selected from the above mentioned

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list in a random way. 50 ANN were trained in total. General parameters of the best ten of which are summarized in table 2.

Table 2

Parameters of the ANN after preliminary search

Index	Network name	Training performance	Test performance	Validation performance	Training error	Test error	Validation error	Hidden activation	Output activation
1.	MLP 22-52-22	0.77139	0.72165	0.65486	0.12307	0.15052	0.15487	Logistic	Tanh
2.	MLP 22-88-22	0.77100	0.70938	0.66083	0.12717	0.15912	0.16140	Exponential	Identity
3.	MLP 22-91-22	0.77046	0.70402	0.65426	0.12518	0.15651	0.15567	Logistic	Tanh
4.	MLP 22-75-22	0.76397	0.71014	0.64726	0.12958	0.15277	0.16747	Tanh	Identity
5.	MLP 22-90-22	0.75402	0.71743	0.65274	0.13285	0.15697	0.15743	Tanh	Tanh
6.	MLP 22-81-22	0.75219	0.70337	0.66188	0.13307	0.15909	0.15605	Logistic	Identity
7.	MLP 22-36-22	0.72803	0.68709	0.65496	0.14143	0.16208	0.15809	Exponential	Tanh
8.	MLP 22-36-22	0.71627	0.68782	0.64924	0.14516	0.16257	0.15808	Logistic	Sine
9.	MLP 22-55-22	0.69757	0.62998	0.59638	0.11738	0.15532	0.16261	Logistic	Logistic
10	RBF 22-57-22	-0.02490	-0.0144	-0.0222	25977.8	29173.3	23449.8	Gaussian	Identity

Index is the sequence number of an ANN in the table 2.

Network name is the name of a neural network. Where MLP or RBF is the network type, the first number is the quantity of neurons of an input layer (it is equal to quantity of input variables); the second number is quantity of neurons of the hidden layer (it is selected in a random way from the given range from 70 to 100); the third number is quantity of neurons in an output layer (it is equal to quantity of output variables).

Training performance, Test performance and Validation performance are network performances for training, test and validation sets (70%, 15% and 15% from total number of melts, respectively). Performance shows the average correlation coefficient of all output variables. Therefore the higher performance corresponds to the better quality of an ANN.

Training error, Test error and Validation error are errors of ANN training for a training, test and validation sets, respectively. In this case the error of training is defined as the sum of squares of differences between the real value of output parameter and the value calculated by ANN. When training an artificial neural network all variables are normalized to the range [0; 1] therefore the values of errors are not equal to real sum of squares of errors. The less error of training corresponds to the better quality of an ANN.

Hidden activation and Output activation are activation functions of neurons for the hidden and output layers of neurons, respectively. Tanh is a hyperbolic tangent function, Logistic is logistic function, Identity is the linear function, Gaussian is a normal distribution function, and Exponential is exponential function (see table 1).

As one can see from table 2, neural networks of multi-layer perceptron type better cope with the task of determination of additives quantity. The network of radial basis functions having the best in the class performance is shown in line 10 for comparing. As it is possible to see, errors of this network exceed the errors of networks of multi-layer perceptron type in many times. Those ANN which have the greatest performance and the smallest error are highlighted by the gray color in table 2.

The secondary search was carried out after primary search. MLP networks type were left only

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with such parameters:

- activation functions of neurons of the hidden layer are Exponential, Tanh and Logistic,
- activation functions of neurons of the output layer are Tanh, Logistic and Identity,
- quantity of neurons of the hidden layer are in range from 50 to 100.

From results of secondary search it was also left 10 ANN with the best performance which are provided in table 3.

Table 3

Parameters of the ANN after secondary search

Index	Network name	Training performance	Test performance	Validation performance	Training error	Test error	Validation error	Hidden activation	Output activation
1.	MLP 22-94-22	0.78003	0.71669	0.65179	0.12354	0.15322	0.16216	Tanh	Identity
2.	MLP 22-55-22	0.77872	0.70120	0.65520	0.12282	0.15793	0.15892	Exponential	Tanh
3.	MLP 22-80-22	0.77426	0.71977	0.65058	0.12497	0.15290	0.15749	Tanh	Tanh
4.	MLP 22-81-22	0.76319	0.70648	0.65013	0.12990	0.15628	0.16125	Tanh	Tanh
5.	MLP 22-64-22	0.76243	0.69657	0.65402	0.12740	0.15876	0.15630	Logistic	Tanh
6.	MLP 22-92-22	0.74364	0.71093	0.65221	0.13695	0.15950	0.15827	Logistic	Identity
7.	MLP 22-61-22	0.70420	0.63791	0.60608	0.12642	0.16672	0.17377	Exponential	Logistic
8.	MLP 22-93-22	0.69622	0.64851	0.62385	0.12399	0.15066	0.16298	Logistic	Logistic
9.	MLP 22-88-22	0.64609	0.60249	0.58054	0.12280	0.14871	0.16480	Tanh	Logistic
10	MLP 22-93-22	0.64493	0.61589	0.60667	0.14611	0.16633	0.16518	Exponential	Logistic

As one can see from tables 2 and 3 all ANN having the smallest error of training and the greatest performance have different structure but in general their indices do not differ from each other. Finally it was succeeded to ensure in it after one more search which results aren't given here because of their similarity with the results given in tables 2 and 3. Therefore the network at number 1 from table 2 was selected for further use as having the best indexes in general. Besides it has less quantity of neurons in the hidden layer than another trained ANN that allows to reduce computation time and to reduce risk of retraining of a network in case of which the network is set up only for those values on which it was trained giving out incorrect results for any other values. As it is possible to see the retraining didn't occur though productivity and an error for test and validation sets are worse than for a training set.

Analysis of the selected ANN. Let's consider more detailed results of operation of the selected network (table 4), estimating correlation coefficients and mean square deviations for all 22 output parameters. As the materials used in BOF shop for a deoxidizing and an alloying of the steel represent a trade secret they will be called simply "Material 1", "Material 2", etc. in the further analysis. As one can see from table 4 fourteen of twenty two output parameters have correlation coefficient higher than 0.7 both for test and for a training set (they are highlighted with gray color in the table 5) that points to the strong functional dependence. Remaining eight parameters have correlation coefficient from 0.3 to 0.7 that points to average functional dependence. Correlation coefficients for a validation set are slightly lower than for teaching and test sets in general. This can be explained by small quantity of the meltis involved in a validation set and by the principle put in a basis of ANN.

For example dependences between the experimental data and the results obtained by ANN for materials 7 and 9 are given in figures 2 and 3.

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Table 4

Analysis of the selected ANN

Output parameter	Correlation coefficient			Mean square deviation		
	Training set	Test set	Validation set	Training set	Test set	Validation set
Material 1	0.76899	0.77974	0.57209	0.04448	0.04404	0.05343
Material 2	0.74875	0.68749	0.56797	0.15966	0.18607	0.17500
Material 3	0.78629	0.75613	0.58742	0.08064	0.07835	0.10963
Material 4	0.76417	0.77127	—	0.00308	0.00623	0.00317
Material 5	0.93808	0.85471	0.95292	0.15052	0.14303	0.17500
Material 6	0.69887	0.60587	0.50969	0.37053	0.35810	0.38568
Material 7	0.98474	0.98838	0.96793	0.04016	0.03422	0.06393
Material 8	0.88922	0.88100	0.91720	0.21944	0.24967	0.21936
Material 9	0.84578	0.78534	0.86580	0.72917	0.78507	0.65370
Material 10	0.91181	0.85708	0.90523	0.91931	1.14433	0.97760
Material 11	0.88430	0.86943	0.85795	0.33377	0.33916	0.29261
Material 12	0.34961	0.29878	0.22091	0.02188	0.00770	0.01103
Material 13	0.61470	0.50337	0.36792	0.36267	0.38460	0.45655
Material 14	0.71139	0.64810	0.56977	1.20984	1.32512	1.29019
Material 15	0.91726	0.83154	0.82987	0.02726	0.03719	0.03995
Material 16	0.88491	0.91967	0.84880	4.96193	4.61206	5.78238
Material 17	0.37744	0.14388	0.24060	2.38177	2.64120	2.53834
Material 18	0.74173	0.70976	0.69574	0.48303	0.52499	0.51263
Material 19	0.95469	0.91671	0.79243	0.16262	0.15863	0.19265
Material 20	0.59626	0.54415	0.63970	1.20031	1.29421	1.17129
Material 21	0.97343	0.97368	0.98060	2.64705	2.38687	2.34316
Material 22	0.62811	0.55012	0.51628	2.00322	2.15873	2.35054

As one can see from figure 2, results for a material 7 match the experimental data with high accuracy. For a material 9 (fig. 3) results have more dispersion however it is possible to recognize them satisfactory in general.

The obtained results can be explained as follows. First, the part of components is added quite seldom and only for specific steel grades therefore ANN isn't possible to find the functional dependence for determination of their quantity. Secondly, it was clarified by the authors that though some materials are added quite frequently but almost unsystematic because of the poor organization of production. In that case because of absence of correlation between quantity of this material and input parameters of ANN also can't find the dependence that allows defining mass of this material. Thirdly, basic data for training of ANN could contain erratic parameter values because of signal processing errors from sensors and failures of sensors that also could add the share of an error.

The place of the developed model in process control system of steel melting in BOF. This model can be applied before the beginning of blowing using results of operation of the static model of

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a burdening of melting and also a required chemical composition and steel temperature as input data. In this case it calculates preliminary quantities of deoxidizing and alloying materials. The same model can be applied after termination of blowing too. Real parameter values of ready steel are used as basic data in such case. This allows obtaining the specified masses of added materials.

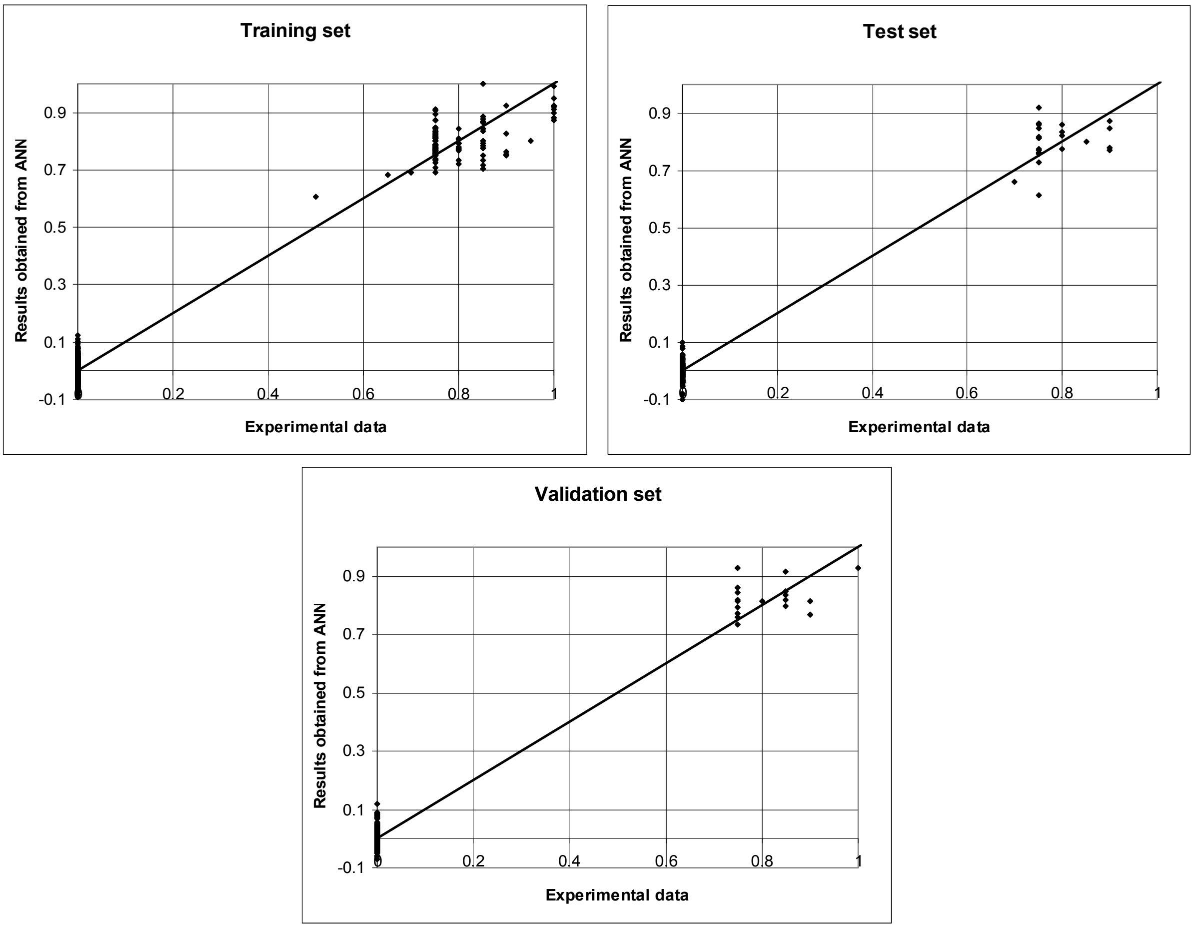

Fig. 2 – Results of calculation of mass of material 7

Trained ANN can be saved as the file written in the C language that allows integrating it into any shell program easily. The source code of the program is intended for operation in command line therefore the interface of the program should be overworked for more comfortable operation with it.

The program should be added with the subprogram receiving information about existence of the required materials in a warehouse for increasing of functionality. In case of the absence of any material calculated by model on the basis of ANN it is possible to recalculate the masses of added materials based on the material balance of chemical components considering materials that are available in a warehouse.

For example, the neural network calculated that 1 ton of the material having the following chemical composition is required for melting: 70% of manganese and 30% of iron. But only a material containing 80% of manganese and 20% of iron and the steel scrap containing 95% of iron is available in a warehouse.

Thus it is required of 1000x70/100 = 700 kg of manganese and 1000x30/100 = 300 kg of iron for melting. Percentage of manganese in a material containing in a warehouse is 80% then it is required 700/80x100 = 875 kg of this material. 875x20/100 = 175 kg of iron contains in this mass of a material. In order to material balance tally it is necessary to add the steel scrap. The mass of iron obtained from steel scrap must be equal to 300 - 175 = 125 kg. Then there is required of 125/95x100 = 131.58 kg of steel scrap. So, instead of 1 ton of the ferroalloy calculated by ANN it is possible to take 875 kg of available ferroalloy and 131.58 kg of steel scrap.

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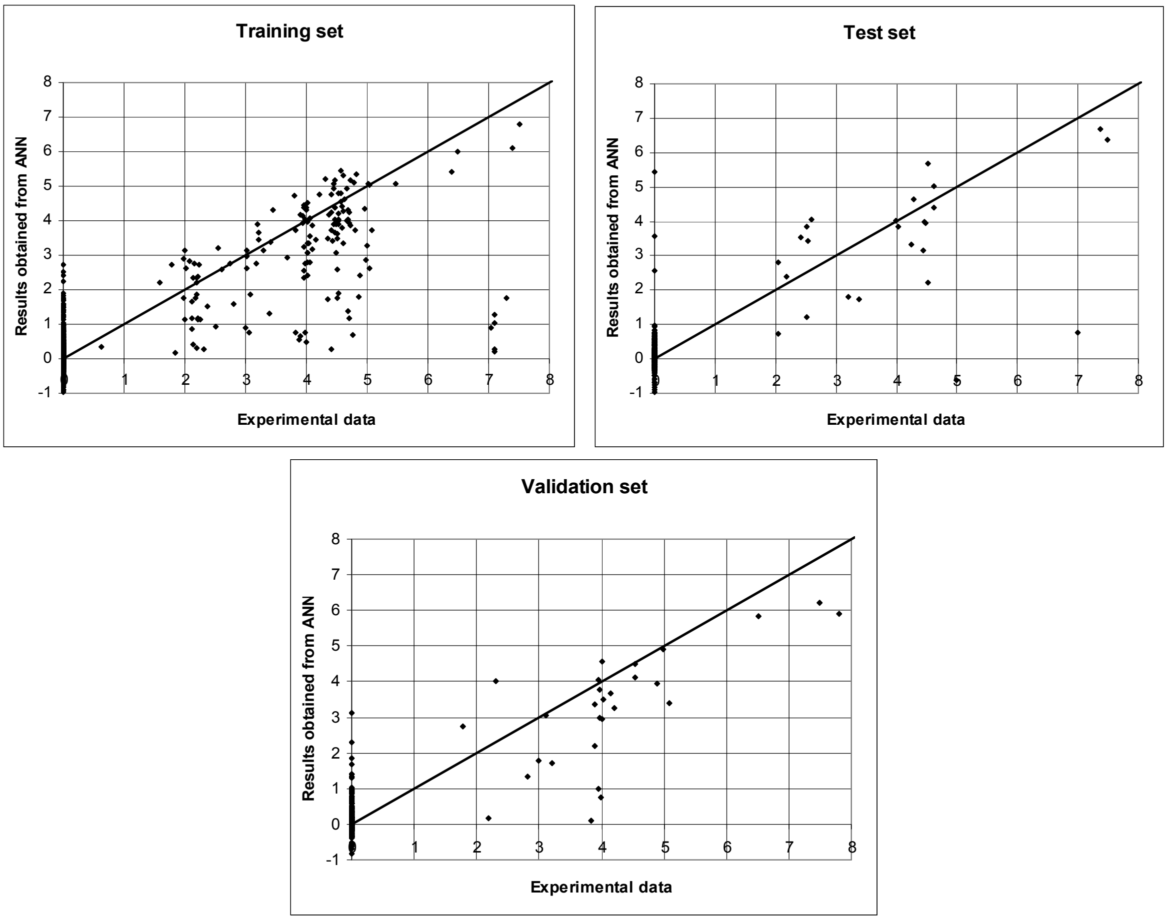

Fig. 3 – Results of calculation of mass of material 9

Only one variant of calculation is given here but there can be a great number of them considering of materials available in a warehouse. In that case calculation of materials should be carried out considering economic factor with selecting variant with the smallest cost. This task is comes to search of a minimum of the multiple-factor function including cost of materials, the frequency of their use, residual of materials in a warehouse. As the result this task represents a subject for separate research.

Conclusions

The research directed on establishment of possibility of application of ANN for determination of mass of deoxidizing and alloying components being used in BOF melting was carried out in this work. Correlation analysis of initial data was carried out as a result of which the part of input and output parameters that are not correlated with other parameters was discarded. Then preliminary search of the best architecture of ANN for determination of mass of the remained output parameters was carried out. As a result networks of radial basis function were excluded from reviewing and multi-layer perceptrons are left. Then secondary search was carried out as a result of which activation functions of neurons of the hidden and output layers were defined in case of which ANN has the greatest performance and the smallest error. Then it was defined that even in case of randomly selected architecture of ANN their parameters differ from each other slightly. After that ANN having the best parameters and the smallest quantity of neurons was selected in order to avoid retraining. Selected ANN has the following architecture:

- network type – multi-layer perceptron;
- quantity of neurons of an input layer – 22;
- quantity of neurons of the hidden layer – 52;
- quantity of neurons of an output layer – 22;
- activation function of neurons of the hidden layer – logistic;

- activation function of neurons of an output layer – hyperbolic tangent.

The correlation coefficients and mean square deviations for all output parameters were found for selected ANN. Based on the obtained values a conclusion was made that selected ANN is suitable for determination of mass of the most part of added materials.

For better integration into process control system of steel melting in the BOF the selected ANN was saved in the C-language format. As basic data for training of model are based on the equations of the material balance, coefficients of a network don't need continuous adaptation. Updating of a network is required only in case of appearance of new deoxidizing or alloying materials which initial weren't in a database.

It is planned to add the module of calculation of quantity of materials considering existence of them in a warehouse and economic indexes into the obtained model in the future. Besides it is planned to equip model with the intuitive and clear graphic interface for convenience of operation with it.

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