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The use of artificial neural networks for the prediction of a chemical composition of hot metal produced in blast furnace

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ABSTRACT

Purpose: The paper presents the possibilities of using neural networks for the prediction of chemical composition of hot metal produced in blast furnace.

Design/methodology/approach: Three blast furnaces in ArcelorMittal, Unit in Dąbrowa Górnicza, provided the data for the model construction. The data reflect a number of variables, which describe the blast furnace process.

Findings: The results obtained, based on input parameters, show that the construction of such neural networks is viable. There is a good correlation between expected and actual results.

Practical implications: The model can be used as an auxiliary tool for blast furnace operators.

Originality/value: Prediction of a chemical composition of hot metal at the stage of adjusting hot metal process parameters.

Keywords: Artificial Neural Networks; Blast furnace; Chemical composition

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

Currently computers are broadly used in materials technology. Prediction of materials properties is a source of success of many undertakings. Different models, more and more often used in industry, give their users information they expect. Prediction of the materials properties brings significant money and time savings and minimizes time required for the research [1-3].

Models help engineers at their everyday work. They clear the way for predicting the physical and mechanical properties of materials or phase transitions, they help in making thermodynamic calculations. Solution of this type can also be used for calculations of e.g. factors, which have an impact upon aircraft landing or for reduction of a waiting time in hospital admission rooms [4-6].

Nowadays a demand for steel is higher than ever. Fast technological progress stimulates a demand for steel in a building and automotive industries. Continuous increase in customer requirements motivates the steel branch to follow the line of a constant development and innovation, directed at a reduction of production costs and improvement of a product quality [7].

Blast furnace process includes numerous complicated chemical, thermal and mechanical reactions. The process complexity, number of variables and continuously changing temperature in a blast furnace are the main reasons, for which a development of mathematical model is extremely complicated [8].

Neural networks is a tool, thanks to which modeling of processes – whose correlations have not been completely examined so far – is possible. A network recognizes and learns the interrelations between input data and target values. Upon the completion of a training process, the network can independently predict the result, based on a new set of loaded data. An important advantage of networks is their ability of adaptation through training, which eliminates a time-consuming re-programming [9-10, 13].

2. Tested material

Hot metal is melted in blast furnace and makes an input charge for the steel plant. Hot metal is an alloy of iron and carbon and other elements, where the carbon content amounts to ca. 4%. Hot metal is breakable and not plastic, therefore it cannot be subject to mechanical working. Hot metal chemistry has been shown in a Table 1 [11].

Table 1.
Hot metal chemistry

Range	Chemistry, %				
	Si	Mn	P	S	C
min	0.2	0.3	0.1	0.0	4.0
max	1.2	0.7	0.2	0.1	5.0

In a blast furnace process charge materials are cyclically loaded through a BF throat, by means of a top charging system. Top charging system distributes the charge material inside the BF with a charge material distribution runner and tightly closes the BF. Top charging system currently used in modern BFs consists of two receivers into which coke and sinter are loaded. Blast furnace is a type of a shaft furnace; each segment of the furnace – going from the top to the bottom – is characterized with its own geometry (Fig. 1). This is connected with processes, which take place inside the BF [12].

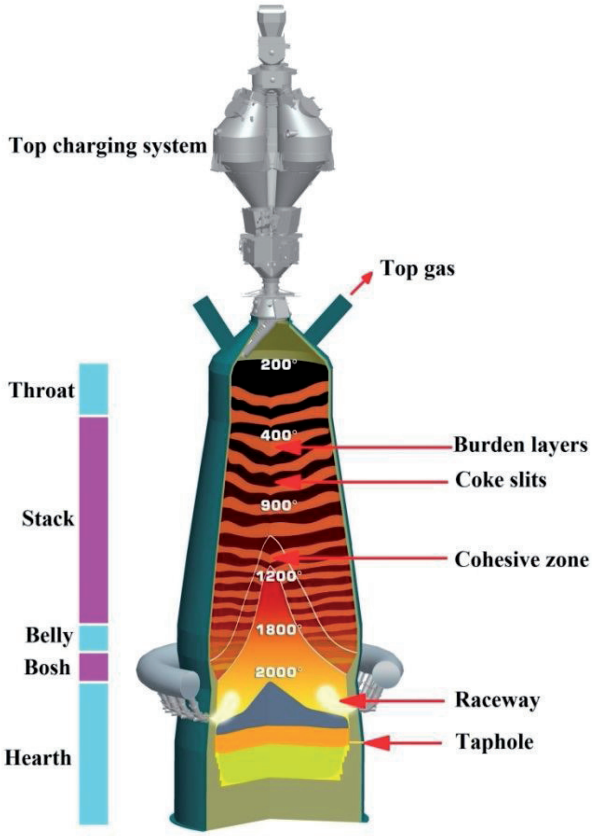

Fig. 1. Blast furnace (BF)

BF charge is a mix of sinter, iron ore, coke and fluxes. Charge materials are distributed inside the BF in such a way as to ensure the efficient heat exchange and required permeability. Incorrect charge distribution disturbs a BF operation and reduces hot metal output. Charge materials continuously move down and absorb heat from gases, which flow in the opposite direction [14].

Hot blast at ca. 1200°C, with the oxygen added, is supplied through the tuyeres. Cold blast, at the temperature of ca. 100°C, produced by turbo-blowers is forced through hot stoves to be heated. Hot stove construction includes a combustion well and a stove checker built of ceramic blocks. Hot stove is operated in a heating cycle and blast cycle. Heating cycle is finished when the waste gas temperature gets at 350°C or when the temperature at the hot stove dome is 1350°C. When the hot stove has been heated, a cold blast is passed through it, which absorbs heat accumulated in the checkers. At the beginning of a blowing cycle, before the hot blast is blown to the BF, it is mixed with a cold blast, in order to maintain a constant temperature throughout the blowing cycle. Then the hot blast is blown through a bustle pipe to the tuyere sets and, finally, to the blast furnace [14].

Coke is the main source of heat in the blast furnace and is burned in the raceways, in a BF hearth. Hot blast blown through the tuyeres oxidizes the coke. Combustion or decomposition products are: CO_2, CO, H_2 and N_2. In a coke burning process a high amount of heat is released and the temperature goes up to 2000°C. The burning process in raceways effects in a constant descent of burden from the BF top downwards. Burning of coke in a hearth modifies the character and speed of a burden descent, which also depends on a gas flow distribution and heat exchange between the burden and gas [16, 17].

Gases generated in a tuyere breast, in a BF hearth, flow upwards through the burden layers to the top within 3-6 sec. At that time the gas heat should be transferred to the burden and iron oxides should be reduced. Most of gas is produced in a coke burning process in the raceways, therefore a gas flow is directed towards the BF walls. Gas distribution pattern depends on a raceway size. A depth and size of raceways modify gas penetration towards hearth center. The gas ascend in the boshes area depends on coke granularity and slag viscosity, whereas the gas flow in a shaft depends on a charge materials size composition and a distribution pattern of charge materials in a BF throat. The ascending gas flow compensates for 55-60% of burden weight and reduces friction between pieces of burden. [15]

Some amount of fuel can be replaced with coal dust, coke-oven gas, natural gas and oil added to the hot blast. Simultaneously, hot blast can be enriched with oxygen. All these result in an increase and change in a chemical composition of gases escaping from the raceways, as well as in a reduction of a flame temperature. The temperature of fuels blown to the BF is low, whereas the temperature of coke in raceways amounts to ca. 1500°C. The only exothermic reaction, which proceeds in a combustion zone is a combustion of C to produce CO. Other reactions absorb heat. The amount of coke which can be saved by charging 1 kg of alternative fuel to a BF is defined as a replacement factor. This factor is related to a fuel chemical composition but does not depend on blast furnace operational conditions [14].

3. Artificial Neural Networks (ANNs)

Neural networks are used in many industrial branches. They are an alternative for the analytical approach to the problem solving. Neural networks can be used for all problem areas connected with prediction, classification or control. The idea to construct artificial neural networks appeared in the 40s of the previous century. The work started from a simplified mathematical description of neuron [18].

While constructing the model, numerical coefficients, called the weights, which are equivalent to the amount of substance released once at particular synapses, can be attributed to the cell inputs. If the weights are real, positive numbers, then a cell is activated; if the weights are negative, neuron activation is inhibited by other synapses. If the activation-inhibition balance is negative, a cell returns to the initial state and no change can be observed at its output [13].

Neurons are most often arranged in layers (Fig. 2). First neuron layer is called an input layer and is responsible for the data propagation in the network. The number of neurons in this layer is equivalent to the number of values simultaneously introduced to the network. The last neuron layer, called the output layer, helps determine the output layers of a network. Also there may be hidden layers between the layers mentioned above. In a hidden layer there are elements of a network, which cannot be directly observed, either from the input, or from the output sides. Neurons, which are in the adjacent layers, are interconnected. These connections make the links, along which information is transferred in a network. [18].

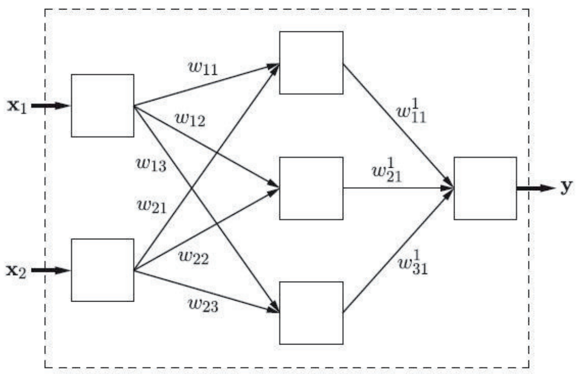

Fig. 2. An example of a two-layer ANN

Artificial neuron can be regarded as a specific signal converter (Fig. 3). A number of inputs with weights, an output signal, activation and activation function are the basic elements of an artificial neuron. There are many types of activation functions. The choice of a function mostly depends on a type of data in a training set and a type of a network selected to solve the problem.

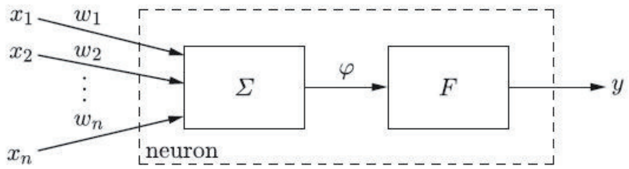

Fig. 3. Artificial neuron model

In order to use an artificial neural network for solving a given problem it is required to set the weights of inter-neuronal connections for neurons in the adjacent layers. The weights setting consists in a multiple presentation of simulated phenomenon set of patterns to the network. Setting the weights is called training. A method of training depends on a goal, which is equivalent to a formulated problem. Training takes place at the level of particular neurons [19].

4. Methodology of modeling

For the purpose of simulation the data including 7333 rows have been collected. There are 38 variables, which describe the blast furnace process, in each row, plus hot metal chemistry data. Parameters have been shown in Table 2. The data have been selected for the period from January 1, 2001 to December 31, 2013 and represent all three blast furnaces in ArcelorMittal Poland, Unit in Dabrowa Gornicza (former Huta Katowice). The models of artificial neural networks have been used to predict the Si content in hot metal.

All rows have been randomly divided into three groups. The first group, making 70% of the whole, has been used for a network training. The remaining two groups, 15% each, have been used fir the network validation and testing. While designing the network, a multi-layer network has been selected. This type of a network can better and more correctly predict the results, for which the input data were not included in the training set.

A network quality has been validated by means of:

- Absolute error between real values and values predicted by the model.
- Standard deviation, which shows the distribution of a tested value against a mean value.
- Pearson's correlation between the real value and values calculated with the use of the model. The closer to 1 the value is, the better the model reflects a tested process. Pearson linear correlation coefficient is a measure of the strength and direction of correlation. Correlation coefficient is calculated based on the formula:

$$r = \frac{cov(x,y)}{Sd_x Sd_y} \qquad (1)$$

$$cov(x,y) = \frac{\Sigma(x_i - \bar{x})(y_i - \bar{y})}{n} \qquad (2)$$

Table 2.
Input parameters

Parameters				
Skip sinter	Sinter screenings	Sinter 2	Pellets	Pellet screenings
Manganese ore	Lump ore	Fe concentrate	BOF slag	Fe-Si-Mn slag
Limestone	Quartzite	Dolomite	Coke 1	Coke 2
Coke 3	Coke 4	PCI	Pea coke	Coke 5
Coke breeze	Anthracite	IO/Coke load	Number of charges	Hot blast volume
Gas for intensification	Hot blast pressure	Hot blast temperature	Oxygen amount	Oxygen %
Top pressure	Top temperature	CO_2	CO	H_2
Gas calorific value	Hot metal temperature	Fe content in sinter		

5. Results of modeling

MLP networks have been used for the model development. In the process of programming the results, which significantly deviated from the mean and made only a few percent of the total, have been rejected. In the next stage an optimum number of input neurons and hidden neurons have been selected. Many network architectures with different numbers of hidden neurons and input variables have been tested. Table 3 presents the architecture of six sample neural networks. The best of them consisted of 38 input neurons and 18 neurons in a hidden layer with a hyperbolic tangent activation function and an identity function for an output neuron. For the identity function an activation level is transmitted directly to the output, whereas tangent hyperbolic function presents better results than other networks, owing to its symmetric character.

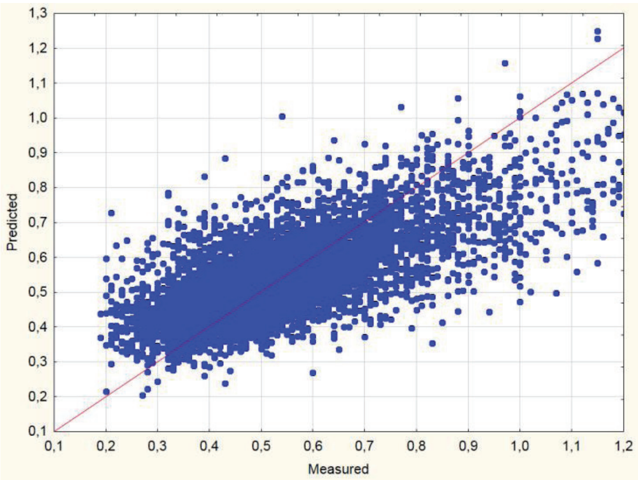

Fig. 4. Comparison between a real value and predicted value for the network MLP 38-18-1

The best Pearson correlation coefficients have been satisfactory for training, testing and validation sets and they oscillate at a level of 0.7. The above shows that the phenomenon has been well described by means of a black box model.

Figures 4 and 5 present a comparison between a predicted and real values for the best network. The graphs show that the prediction of the results by the models is problematic, if the Si level is high. This may be caused by the irregular BF operation and comparatively few results of this type in a whole data set.

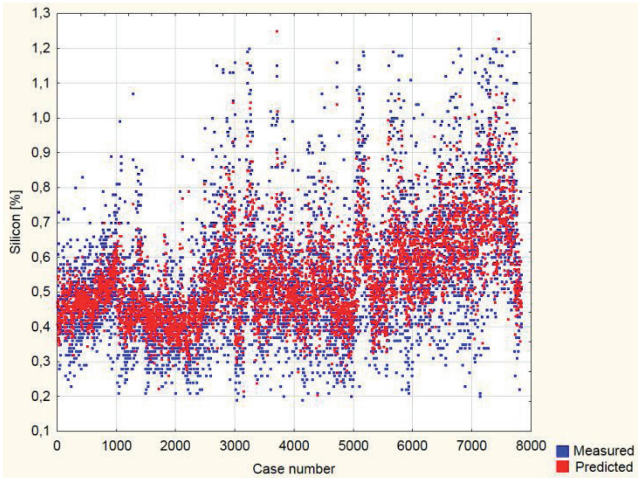

Fig. 5. Comparison between a real value and a value predicted for the network MLP 38-18-1

Figures 6 to 8 present an output datum dependence upon two chosen input parameters.

Table 3.
Output parameters

Network architecture	Training set			Testing set			Validation set		
	Average absolute error	Standard deviation ratio	Pearson correlation	Average absolute error	Standard deviation ratio	Pearson correlation	Average absolute error	Standard deviation ratio	Pearson correlation
MLP 38-11-1	0.0951	0.0086	0.6873	0.1021	0.0094	0.6370	0.1064	0.0109	0.6144
MLP 38-6-1	0.0997	0.0094	0.6512	0.1046	0.0100	0.6087	0.1058	0.0105	0.6282
MLP 38-18-1	0.0926	0.0081	0.7100	0.1034	0.0096	0.6333	0.1080	0.0109	0.6154
MLP 38-16-1	0.0936	0.0083	0.7021	0.1024	0.0095	0.6369	0.1043	0.0104	0.6359
MLP 38-19-1	0.0935	0.0083	0.7012	0.1006	0.0092	0.6459	0.1047	0.0105	0.6306
MLP 38-25-1	0.0972	0.0090	0.6690	0.1008	0.0091	0.6516	0.1049	0.0103	0.6376

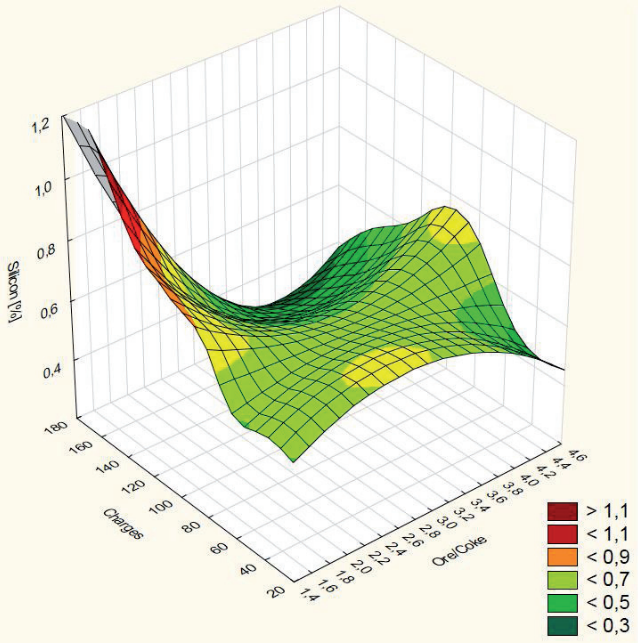

Fig. 6. Impact of IO/ Coke load and number of charges on the Si content

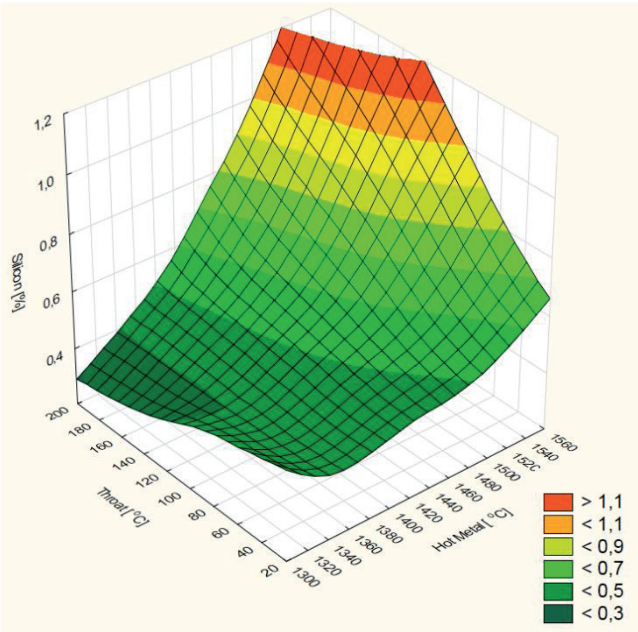

Fig. 7. Impact of hot metal temperature and top temperature on the Si content

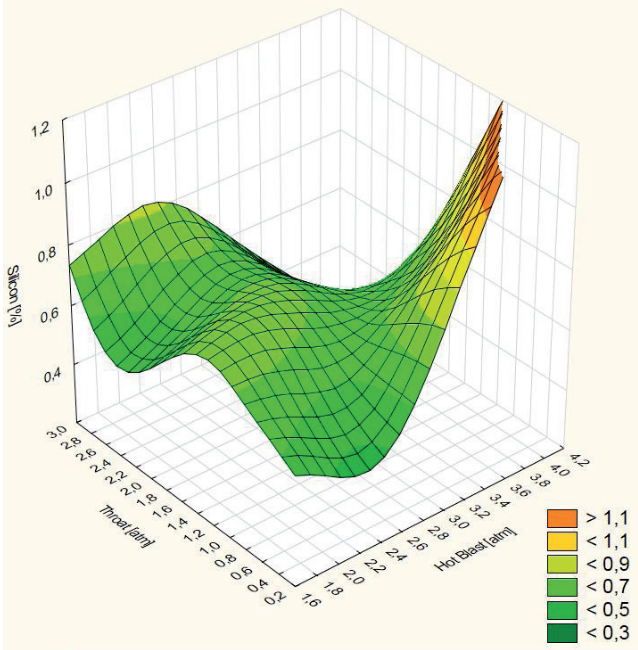

Fig. 8. Impact of hot blast pressure and top pressure on the SI content

6. Conclusions

Artificial neural networks are a very good tool for the modeling of various dependences. The paper presents the properties of artificial neural networks used for the blast furnace process modeling. The output parameter for the network was the Si content in hot metal and the input parameters were the variables, which describe the BF process. The results of the BF process modeling have been satisfactory and more network improvements are still possible. During the process modeling operation a correct selection of input data is of a primary importance.

Neural networks can be used as a tool for modeling many different complicated processes.

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