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# The use of artificial neural networks for the prediction of sulphur content in hot metal produced in blast furnace

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**ABSTRACT**

**Purpose:** The paper presents the possibilities of using artificial intelligence for the prediction of sulphur content in 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:** : Materials research performed with the use of data mining and neural networks is consistent with the results obtained during the real research in a real laboratory. The obtained results show that the construction of such neural networks is practical. There is a strong correlation between predicted value and real value.

**Practical implications:** The presented model can be used in the industrial practice as an additional tool for blast furnace and steel plant operators.

**Originality/value:** Prediction of sulphur content in hot metal at the stage of adjusting hot metal process parameters.

**Keywords:** Artificial intelligence methods; Blast furnace; Sulphur; Data mining

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**METHODOLOGY OF RESEARCH**

## 1. Introduction

The use of Artificial Intelligence in environmental modelling has increased, together with recognition of its potential. Prediction of materials properties is extremely useful. Different models are being applied in a real world and industrial problems, from functional prediction and system modelling to pattern recognition engines and robust classifiers. Computer simulations became more effective and they started to assist in experiments or manufacturing. The escalating cost of materials testing in terms of money and time for critical components in some industry fields increases the need for an effective, fast, and cheap research method [1-4].

Models help engineers build better products and improve their understanding of the process. They clear the way for predicting the mechanical and physical properties of materials. They could be a tool for systematic parameter studies in the optimum design of composite materials for specific applications. Such a solution can also be used for building the adaptive systems. Smart home systems are another example of using artificial neural network. They are aimed at reducing the power wastage [5-7].

These days a demand for steel is higher than ever. Fast technological progress stimulates a demand for steel in an automotive and building industries. Customer expectations are continuously increasing, they motivate the steel industry to follow the line of a constant development and innovation, implementation of a new or significantly improved production or delivery method [8].

Blast furnace process includes numerous complicated mechanical, thermal and chemical 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 [9].

Neural networks is a tool, thanks to which modelling of processes – whose correlations have not been completely examined so far – is possible. The ability of artificial neural networks to learn and approximate relationships between input and output are decoupled from the size and complexity of the problem. Actually, as relationships based on inputs and outputs are enriched, approximation capability improves [4, 10, 11].

## 2. Material

The purpose of blast furnace is to chemically reduce and physically convert iron oxides into liquid iron called hot metal. Hot metal makes an input charge for the Basic Oxide Furnace (BOF). 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 a subject to mechanical working. Hot metal chemistry has been shown in Table 1. Sulphur is usually considered to be very impurious that must be eliminated from the blast furnace process. It is a common practice to control the sulphur content with a slag basicity and also with a carbon content, because the correlation is so strong. Most of the sulphur comes to the blast furnace from coke, where it is bound as organic sulphur and as FeS. Sulphur circulation has been shown in a Table 2 [9, 12].

In a blast furnace charging process batches of charge material are typically loaded in a cyclical sequence into the furnace from the top hoppers, using a top charging system. A top charging system currently used in modern BFs consists of two hoppers 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. It is connected with processes, which take place inside the BF (Fig. 1) [9, 13].

Modern blast furnaces are the refinement of traditional furnaces, but equipped with instruments and control architecture. The most important parts of the production process are the operation and control of blast furnace in terms of controlling the internal temperature at various segments and monitoring the impurity levels online [12].

BF charge materials (mix of sinter, iron ore, coke and fluxes) are charged into the top of the shaft. Incorrect charge distribution disturbs a BF operation and reduces hot metal output. A blast of heated air and also, in most instances, a gaseous, liquid or powdered fuel are introduced through openings at the bottom of the shaft just above the hearth crucible. The heated air burns the injected fuel and much of the coke is charged in from the top to produce the heat required by the process and to provide reducing gas, which removes oxygen from the ore. The reduced iron melts and runs down to the bottom of the hearth. The flux combines with the impurities in the ore to produce slag, which also melts and accumulates on top of the liquid iron in the hearth [9, 12].

The blast furnace process starts when hot blast is blown into blast furnace via tuyeres at a temperature up to 1200°C. Hot blast burns the fuel, which is accumulated in front of the tuyeres. That burning generates a very hot flame and is visible through the peepholes as the raceway [13, 14].

Coke is the main source of heat (Eq. 1, 2) in the blast furnace and is burned in the raceways, in a BF hearth.

$$C + O_2 = CO_2 \tag{1}$$

$$CO_2 + C = 2CO \tag{2}$$

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 a 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 [9, 15-17].

Table. 1.
Hot metal chemistry

| | Chemistry [%] | | | |
|---|---|---|---|---|
| | Si | Mn | P | S |
| Min | 0.250000 | 0.110000 | 0.070000 | 0.008000 |
| Max | 1.000000 | 0.470000 | 0.126000 | 0.027000 |
| Mean absolute error | 0.524298 | 0.246741 | 0.096668 | 0.016340 |
| Median | 0.510000 | 0.250000 | 0.098000 | 0.016000 |
| Standard deviation | 0.122081 | 0.055533 | 0.008787 | 0.004027 |
| Kurtosis | -0.110987 | 0.072629 | 0.232914 | -0.328165 |

Table 2.
A typical sulphur balance in blast furnace

| Sulphur in [kg/tHM] | | Sulphur out [kg/tHM] | |
|---|---|---|---|
| Pellets | 0.14 | Hot metal | 0.56 |
| Slag formers | 0.52 | Slag | 3.74 |
| Coke | 2.31 | BF dust | 0.35 |
| Oil | 1.92 | Balance | 0.24 |
| Total | 4.89 | Total | 4.89 |

Sulphur enters the blast furnace mainly as the coke content and is released into a blast furnace gas stream as $H_2S$ or a gaseous compound of carbon monoxide and sulphur (COS), when the coke is burned (Eq. 3) [12].

$$FeO + COS = FeS + CO_2 \qquad (3)$$

Sulphur which combines with iron must be removed at a very high temperature that exists in the hearth. It is done by reduction of iron sulphide in the presence of a basic flux, such as lime (Eq. 4) [12].

$$FeS + CaO + C = CaS + Fe + CO \qquad (4)$$

The amount of removed sulphur depends on the temperature in a hearth and the slag volume [12].

## 3. Artificial neural networks (ANNs)

Artificial neural networks have been applied to predict many complex problems. They have been inspired by brain modelling studies. Implementations in a number of application fields have been presented and brought ample rewards in terms of efficiency and ability to solve complex problems [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 [9, 11].

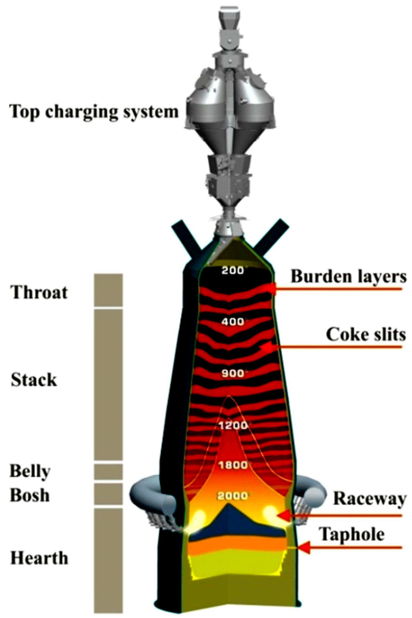


Fig. 1. Blast furnace (BF)

The most commonly used neural network configurations are known as multilayer perceptrons. In the structure each neuron output is connected to every neuron in subsequent layers connected in a cascade, with no connections between neurons in the same layer.

Neurons are most often arranged in layers. A neural network has at least two physical components, namely, the processing elements and the connections between them. The processing elements are called neurons, and the connections between the neurons are links. Every link has a weight parameter associated with it. Those connections make the links, along with information, which is transferred in a network. Each neuron receives a stimulus from the neighboring neurons connected to it, processes the information, and produces an output. Neurons that receive stimuli from outside of the network are called input neurons (input layer). Neurons whose outputs are used externally are called output neurons (output layer). Also there may be hidden layers between the layers mentioned above [9, 19, 20].

Every neuron model consists of a processing element with synaptic input connections and a single output. The signal flow of neuron inputs, $x_n$, is considered to be unidirectional. The neuron output signal is given by the relationship F, which is illustrated in Figure 2. 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 [21].

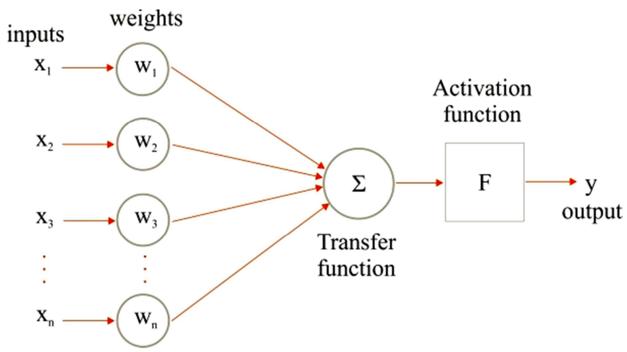


Fig. 2. Artificial neuron model

In order to use an artificial neural network for solving a given problem it is required to set the weights of interneuronal connections for neurons in the adjacent layers. The weights setting consists in a multiple presentation of a simulated phenomenon set of patterns to the network. The neural network is controlled by setting and adjusting weights between links.

Initial weights are usually a set at some random numbers and they are adjusted during neural network training [9].

## 4. Methodology of modelling

For the purpose of simulation the data including 2961 rows have been collected. Initially in the structure of the analysed networks 25 input neurons were established, 24 out of which referred to the blast furnace process and one referring to the hot metal chemistry data. Parameters have been shown in Table 3. A set of data has been selected in the period from January 1, 2001 to December 31, 2013. It represents all three blast furnaces in ArcelorMittal Poland, Unit in Dabrowa Gornicza. The models of artificial neural networks have been used to predict the S content in hot metal.

The input data were randomly divided into three sets. The first group, making 50% of the whole, has been used for network training. The remaining two groups, 25% each, have been used for the network validation and testing. The training set was used for development of the neural network model, The validating set was used for checking the model during establishing the values of weights, and the testing set was used for verifying the model when the network training was completed. For data analysis for neural networks models` multilayer perceptron MLP, back propagation, conjugate gradient as a learning method were used [22].

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.
- Quotient of deviations is a measure which always takes non-negative values. In a very good model the measure reaches the value from 0 to 0.1. If the measure is greater than one, then the use of the constructed model is not warrantable.
- 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:

## 5. Results of modelling

MLP networks have been used for the model development. In the process of programming the results, which significantly deviated from the mean have been rejected. In the next stage an optimum number of input

Table 3. Input parameters

| Range | Parameters | | | | |
|---|---|---|---|---|---|
| | Skip sinter [Mg] | Sinter screenings [Mg] | Pellets [Mg] | Pellet screenings [Mg] | Manganese ore [Mg] |
| Min | 1206 | 0 | 0 | 0 | 0 |
| Max | 12474 | 937 | 3712 | 814 | 1272 |
| | Fe concentrate [Mg] | BOF slag [Mg] | Fluxes [Mg] | PCI [Mg] | Coke 1 [Mg] |
| Min | 0 | 0 | 0 | 0 | 301 |
| Max | 435 | 382 | 232 | 679 | 3499 |
| | Coke 2 [Mg] | Coke 3 [Mg] | Coke 4 [Mg] | IO/Coke load | Fe content in sinter [%] |
| Min | 0 | 0 | 0 | 0.678 | 52.05 |
| Max | 790 | 837 | 665 | 4.47 | 60.02 |
| | Gas for intensification [$m^3 \cdot 10^3$] | Hot blast pressure [kPa] | Oxygen [%] | Top temperature [°C] | $CO_2$ [%] |
| Min | 0 | 2.20 | 21.00 | 23.00 | 16.10 |
| Max | 755 | 4.00 | 27.00 | 180 | 23.9 |
| | CO [%] | $H_2$ [%] | Gas calorific value [kJ] | Hot metal temperature [°C] | S content in hot metal [%] |
| Min | 19.50 | 0.50 | 2848.00 | 1327.00 | 0.008 |
| Max | 28.5 | 8.2 | 4722 | 1513 | 0.03 |

neurons and hidden neurons have been selected and many network architectures with different numbers of hidden neurons have been tested. Figures 3 to 6 present an output datum dependence upon two chosen input parameters. Figure 7 presents a comparison between predicted and real values for the best network. A mean error value, a quotient of standard deviations and a correlation have been presented in Table 4. The selected network is characterized by the lowest average absolute error and by the highest Pearson correlation coefficients.

Table 4.
Quality assessment coefficients of the MLP 24-5-1 neural network

| Assessment coefficient | Training | Validating | Testing |
|---|---|---|---|
| Average absolute error | 0.0009 | 0.0010 | 0.0009 |
| Quotient of standard deviations | 0.2795 | 0.2733 | 0.2604 |
| Pearson correlation coefficient | 0.9601 | 0.9620 | 0.9656 |

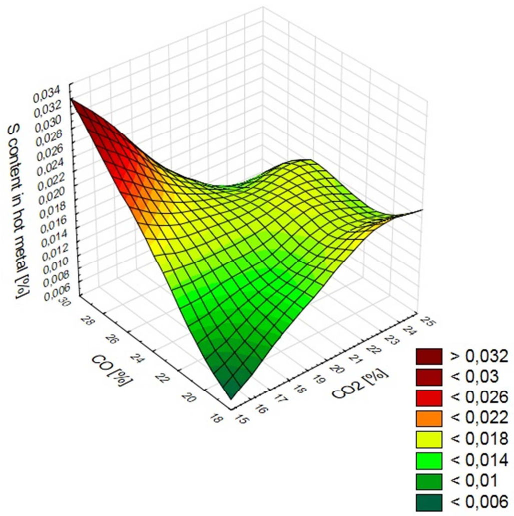


Fig. 3. Impact of CO and $CO_2$ on the S content (Skip sinter 9375 Mg, Sinter screenings 0 Mg, Pellets 0 Mg, Pellets screenings 0 Mg, Manganese ore 0 Mg, Fe concentrate 0 Mg, BOF slag 118 Mg, Fluxes 36 Mg, PCI 0 Mg, Coke 1 2704 Mg, Coke 2 0 Mg, Coke 3 0 Mg, Coke 4 103 Mg, IO/Coke load 3.34, F content in sinter 5.98%, Gas for intensification $250 \cdot 10^3$ $m^3$, Hot blast pressure 3.44 kPa, Oxygen 23%, Top temperature 89°C, $H_2$ 2.4%, Gas calorific value 3377 kJ, Hot metal temperature 1411°C)

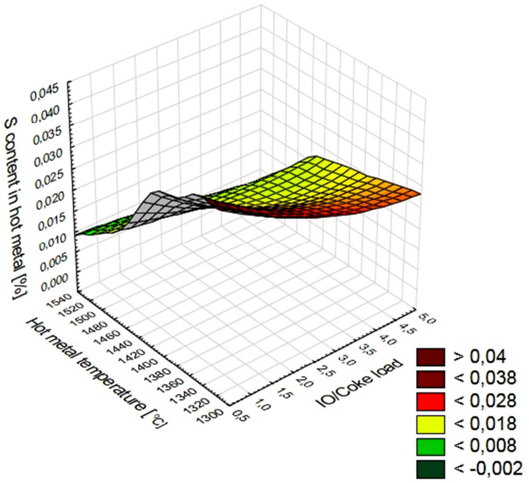


Fig. 4. Impact of hot metal temperature and IO/Coke load on the S content ((Skip sinter 9375 Mg, Sinter screenings 0 Mg, Pellets 0 Mg, Pellets screenings 0 Mg, Manganese ore 0 Mg, Fe concentrate 0 Mg, BOF slag 118 Mg, Fluxes 36 Mg, PCI 0 Mg, Coke 1 2704 Mg, Coke 2 0 Mg, Coke 3 0 Mg, Coke 4 103 Mg, F content in sinter 5.98%, Gas for intensification $250{\cdot}10^3$ $m^3$, Hot blast pressure 3.44 kPa, Oxygen 23%, Top temperature 89°C, $CO_2$ 22.3%, CO 21,7%, $H_2$ 2.4%, Gas calorific value 3377 kJ)

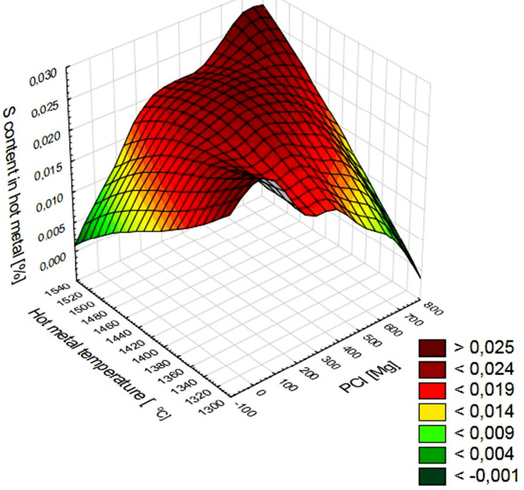


Fig. 5. Impact of hot metal temperature and PCI on the S content (Skip sinter 9375 Mg, Sinter screenings 0 Mg, Pellets 0 Mg, Pellets screenings 0 Mg, Manganese ore 0 Mg, Fe concentrate 0 Mg, BOF slag 118 Mg, Fluxes 36 Mg, Coke 1 2704 Mg, Coke 2 0 Mg, Coke 3 0 Mg, Coke 4 103 Mg, IO/Coke load 3,34, F content in sinter 5.98%, Gas for intensification $250{\cdot}10^3$ $m^3$, Hot blast pressure 3,44 kPa, Oxygen 23%, Top temperature 89°C, $CO_2$ 22.3%, CO 21.7%, $H_2$ 2.4%, Gas calorific value 3377 kJ)

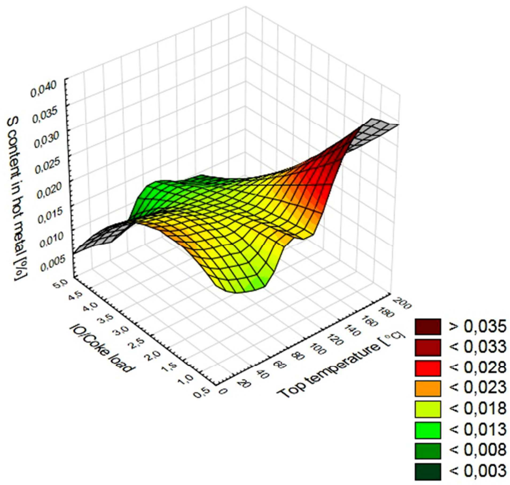


Fig. 6. Impact of IO/Coke load and top temperature on the S content (Skip sinter 9375 Mg, Sinter screenings 0 Mg, Pellets 0 Mg, Pellets screenings 0 Mg, Manganese ore 0 Mg, Fe concentrate 0 Mg, BOF slag 118 Mg, Fluxes 36 Mg, PCI 0 Mg, Coke 1 2704 Mg, Coke 2 0 Mg, Coke 3 0 Mg, Coke 4 103 Mg, F content in sinter 5.98%, Gas for intensification $250{\cdot}10^3$ $m^3$, Hot blast pressure 3.44 kPa, Oxygen 23%, $CO_2$ 22.3%, CO 21,7%, $H_2$ 2.4%, Gas calorific value 3377 kJ, Hot metal temperature 1411°C)

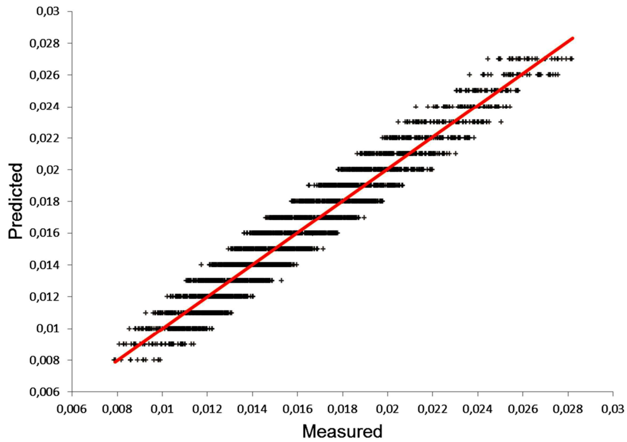


Fig. 7. Comparison between a real value and predicted value for the network MLP 24-5-1

## 6. Conclusions

Artificial neural networks are a very good tool for the modelling of various dependences. The neural network model developed from experimental data can be used to predict a sulphur content in hot metal. The overall prediction error is about 0.1% for a predicted value of S content in hot metal as compared with the measured value. The output parameter for the network was the S content in hot metal and the input parameters were the variables, which describe the BF process. The results show the effectiveness of the method and more network improvements are still possible. During the process modelling operation a correct selection of input data is of a primary importance.

## Additinal information

Selected issues related to this paper are planned to be presented at the 22nd Winter International Scientific Conference on Achievements in Mechanical and Materials Engineering Winter-AMME'2015 in the framework of the Bidisciplinary Occasional Scientific Session BOSS'2015 celebrating the 10th anniversary of the foundation of the Association of Computational Materials Science and Surface Engineering and the World Academy of Materials and Manufacturing Engineering and of the foundation of the Worldwide Journal of Achievements in Materials and Manufacturing Engineering.

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