APPLICATION OF NEURAL NETWORKS AT PREDICTION OF HOT METAL COMPOSITION

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Abstract

Use of the control-steering systems in blast furnace technology contributes to the improvement of the quality of hot metal, which can be expressed by desirable and stable chemical composition and required temperature of hot metal at the tap. The paper presents the possibility of using artificial neural network as part of BF technology supporting system, and in particular its use to predict silicon, sulfur and phosphorus containing in hot metal. The models of neural networks have been created on the industrial operation basis of blast furnace No. 5 Arcelor Mittal Poland Krakow.

Keywords: Blast furnace, neural networks, prediction of hot metal composition

1. INTRODUCTION

Increasing demands on the hot metal quality and minimizing of the costs associated with the blast furnace process are forcing engineers to develop new solutions [1-3]. Introduction of new measuring devices and using of mathematical models greatly simplifies the control of the process. Whereas introducing of the digital monitoring expanded control capabilities of the blast furnace process through direct presentation of data. However, operation and control of blast furnace is still a challenge because of the difficulty of making some measurements, especially at the high temperature parts like hearth and bosh. Desire to the new solutions of improving and stabilizing the blast furnace process has led to the introduction of a new science technology which is artificial intelligence [4-6]. Application of neural networks at prediction with little advance of the abnormal conditions in blast furnace has made a new opportunities and consequently the considerable stir at modeling of such a difficult process [7-9].

The present paper shows an examples of using artificial intelligence at prediction of hot metal composition, particularly silicon, sulfur and phosphorus containing at the next tap. Obtained results were compared with real parameters of hot metal and also with calculations performed by linear regression method. The compared differences between methods are graphically presented.

2. CHARACTERISTIC OF THE BEST NEURAL NETWORKS CHOSEN FOR ANALYSIS OF HOT METAL QUALITY

During the research and observations in Arcelor Mittal - Krakow Branch, collected an enormous amount of data sets, which consisted of parameters classified as having an influence on the content of silicon, sulfur and phosphorus in hot metal. **Table 1** shows characteristics of the best selected networks for prediction of silicon, sulfur and phosphorus in hot metal respectively

For silicon containing in hot metal prediction was chosen network of type MLP (Multi-Layered Perceptron) with using of 11 input data. The network with minimal error possessed 8 neurons in first hidden layer and 5 neurons in second hidden layer. The quality of ANN was 0.598.

For sulfur prediction the nest network was also ANN of type MLP with using of 11 input data. Minimal error was obtained for 23 neurons in first layer and 1 in second one. The quality of ANN was 0.574.

However, for phosphorus prediction the best ANN was of type RBF (Radial Basic Functions) with using of 9 input data and 12 neurons at first layer only.

Table 1 Characteristics of the best selected neural networks used for prediction containing of Si, S and P

Element	Type of ANN	Number of data input	Number of neurons in the first hidden layer	Number of neurons in the second hidden layer	Average ANN error	Quality of ANN
Silicon	MLP	11	8	5	0.123	0.598
Sulfur	MLP	11	23	1	0.005	0.574
Phosphorus	RBF	9	12	-	0.002	0.385

The values of the ANN quality parameters may raise objections, if compare them to the results obtained for the network describing other processes [1]. But it should be noted, that blast furnace due to the nature of work, size, and difficulty of measuring conditions is a challenge for mathematical modeling. To clarify the view on the practical value of obtained networks it should be analyzed their histogram, showed in **Table 2**.

Thus, for silicon prediction an acceptable range of errors should be at least 0-0.1. An accuracy of Si prediction is about 70 %, so it should be admitted that this result is not high. For instance the ANN developed in Lulea Steelworks was obtained result about 85 % at range of error 0-0.05 [7]. This fact can be explained by absence of averaging storage of raw materials in Krakow Steelworks, which surely badly influences on inaccuracy of SiO_2 containing probes [10]. However, prediction results of sulfur and phosphorus containing in hot metal are much rewarding.

Table 2 Dependence of prediction accuracy on range of elements containing errors

	Range of silicon content errors						
	0 - 0.05	0 - 0.1	0 - 0.15	0 - 0.2	0 - 0.25	0 - 0.3	0 - 0.35
Accuracy of Si predictions	45.8 %	69.8 %	84.3 %	93.2 %	99 %	100 %	-

	Range of sulfur content errors				
	0 -0.004	0 - 0.01	0- 0.014	0 - 0.02	0 - 0.024
Accuracy of S predictions	56.6 %	92.2 %	98.8 %	99.6 %	100 %

	Range of phosphorus content errors					
	0-0.002	0-0.004	0-0.006	0-0.008	0-0.01	0-0.011
Accuracy of P predictions	76.3 %	89.6 %	96.7 %	99.6 %	99.6 %	100 %

3. AN EFFECTIVENESS COMPARISON OF OBTAINED NETWORKS WITH REGRESSION METHOD

In order to compare the performance of artificial neural network model it has been compared with linear regression method. Regression relationship was obtained basing on the same input variable data as for ANN. **Figure 1** shows the comparison.

$$Si=(a_1 \cdot W_1)+(b_1 \cdot W_2)+(c_1 \cdot W_3)+(d_1 \cdot W_4)+(e_1 \cdot W_5)+(f_1 \cdot W_6)+(g_1 \cdot W_7)+(h_1 \cdot W_8)+(i_1 \cdot W_9)+(j_1 \cdot W_{10})+(k_1 \cdot W_{11})+w \quad (1)$$

where:

Si - predicted silicon containing,%,

W_1 - hot blast volume m^3/h $\quad a_1 = 7.311$

W_2 - hot blast moisture, g/m^3 $\quad b_1 = 0.003$

W_3 - hot blast temperature, ^{0}C — $c_1 = 0.0003$
W_4 - Si containing in HM at previous tap, % — $d_1 = 0.698$
W_5 - SiO_2 containing in top dust, % — $e_1 = 14.173$
W_6 - C containing in top dust, % — $f_1 = -3.404$
W_7 - share of pellets, % — $g_1 = 0.015$
W_8 - Ore/Coke — $h_1 = -0.004$
W_9 - slag mass, kg/tHM — $i_1 = -0.000031$
W_{10} - slag basicity, - — $j_1 = 0.199$
W_{11} - burden basicity, - — $k_1 = 0.018$
$w = -1.7$

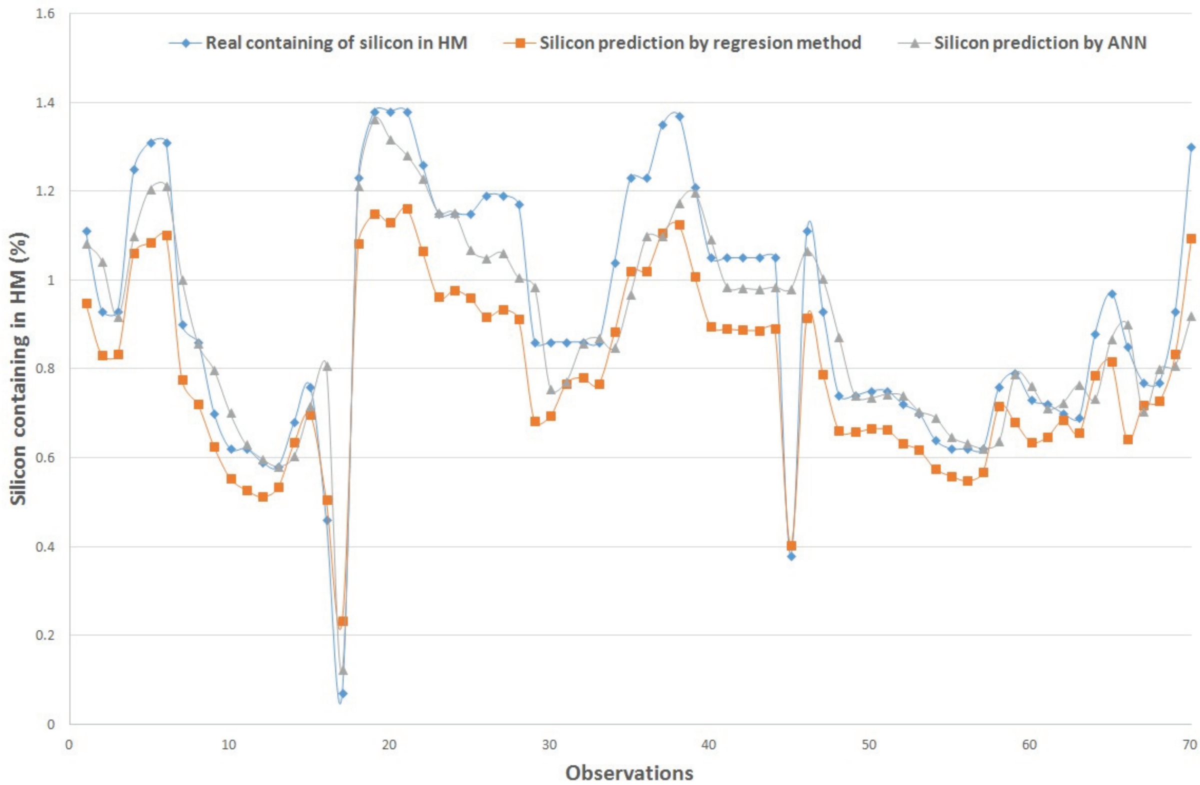

Figure 1 Comparison of silicon prediction by different models with real measurement

For sulfur prediction was obtained equation (2) and comparison of methods shows **Figure 2**.

$$S=(a_2 \cdot V_1)+(b_2 \cdot V_2)+(c_2 \cdot V_3)+(d_2 \cdot V_4)+(e_2 \cdot V_5)+(f_2 \cdot V_6)+(g_2 \cdot V_7)+(h_2 \cdot V_8)+(i_2 \cdot V_9)+(j_2 \cdot V_{10})+(k_2 \cdot V_{11})+v \quad (2)$$

where:

S - predicted sulfur containing, %
V_1 - burden bacicity, - — $a_2 = -5.4 \cdot 10^{-5}$
V_2 - slag bacicity, - — $b_2 = -\ 0.05387$
V_3 - hot blast temperature, ^{0}C — $c_2 = -8.1 \cdot 10^{-6}$
V_4- hot blast moisture, g/m^3 — $d_2 = -0.00016$
V_5 - hot blast volume, m^3/h — $e_2 = 5.41 \cdot 10^{-8}$
V_6 - Ore/Coke,- — $f_2 = -0.00131$

V_7 - slag mass, kg/tHM
V_8 - S containing in top dust, %
V_9 - S containing in slag, %
V_{10} - S containing in HM at previous tap, %
V_{11} - S input with the burden, kg/tHM

$g_2 = 0.000216$
$h_2 = 0.641174$
$i_2 = -0.01148$
$j_2 = 0.452605$
$k_2 = -0.0131$
$v = -0.13$

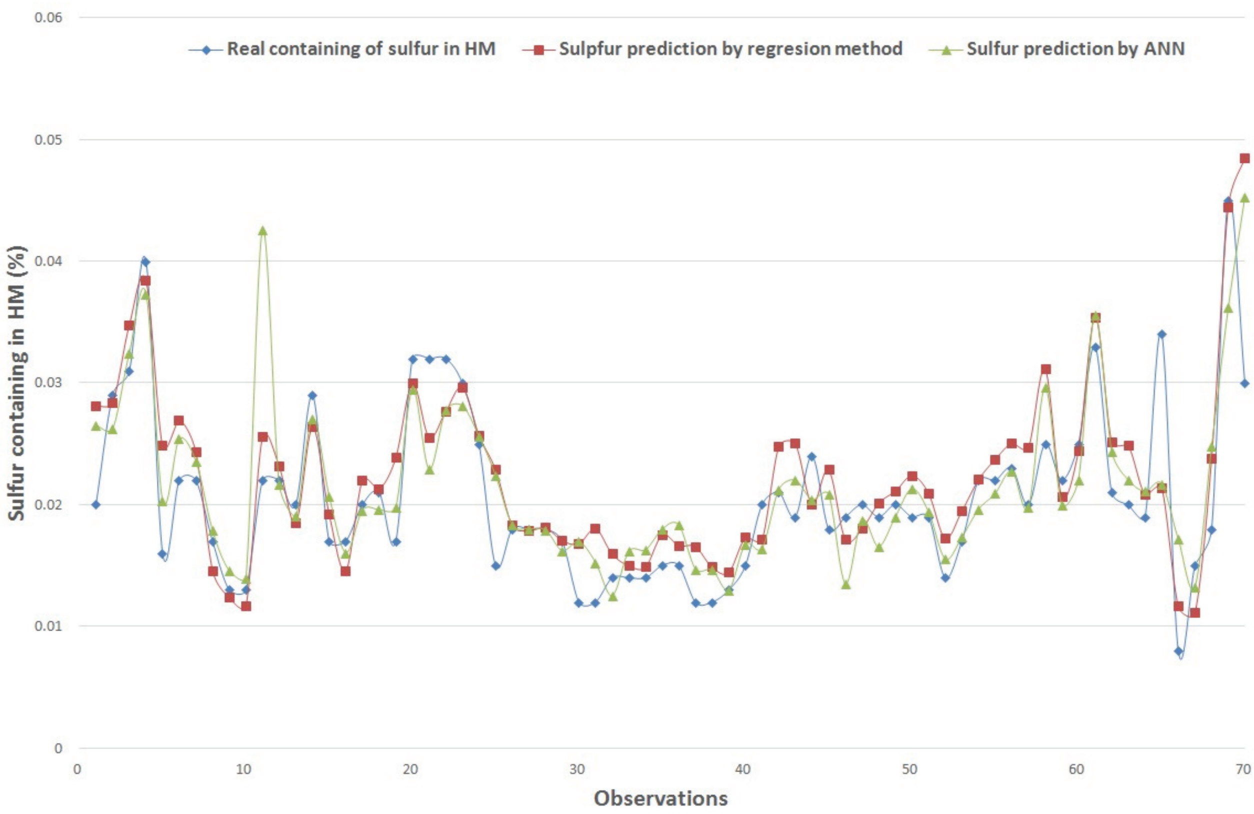

Figure 2 Comparison of sulfur prediction by different models with real measurement

For phosphorus prediction was obtained equation (3) and comparison of methods shows **Figure 3**.

$$P=(a_3 \cdot Y_1)+(b_3 \cdot Y_2)+(c_3 \cdot Y_3)+(d_3 \cdot Y_4)+(e_3 \cdot Y_5)+(f_3 \cdot Y_6)+(g_3 \cdot Y_7)+(h_3 \cdot Y_8)+(i_3 \cdot Y_9)+y \quad (3)$$

P- - predicted phosphorus containing, %
Y_1 - burden basicity, -
Y_2 - slag basicity, -
Y_3 - hot blast temperature, ^{0}C
Y_4 - hot blast moisture, g/m^3
Y_5 - P_2O_5 containing in top dust, %
Y_6 - slag mass, kg/tHM
Y_7 - P_2O_5 containing in HM at previous tap, %
Y_8 - P_2O_5 input with the burden, kg/tHM
Y_9 - P_2O_5 containing in coke ash, %

$a_3 = -0.003700066$
$b_3 = -0.000651258$
$c_3 = 3.2731 \cdot 10^{-6}$
$d_3 = 7.8128 \cdot 10^{-6}$
$e_3 = -0.030535552$
$f_3 = -4.83466 \cdot 10^{-11}$
$g_3 = 0.317267771$
$h_3 = 0.132052768$
$i_3 = 0.291710723$
$y_3 = -0.28$

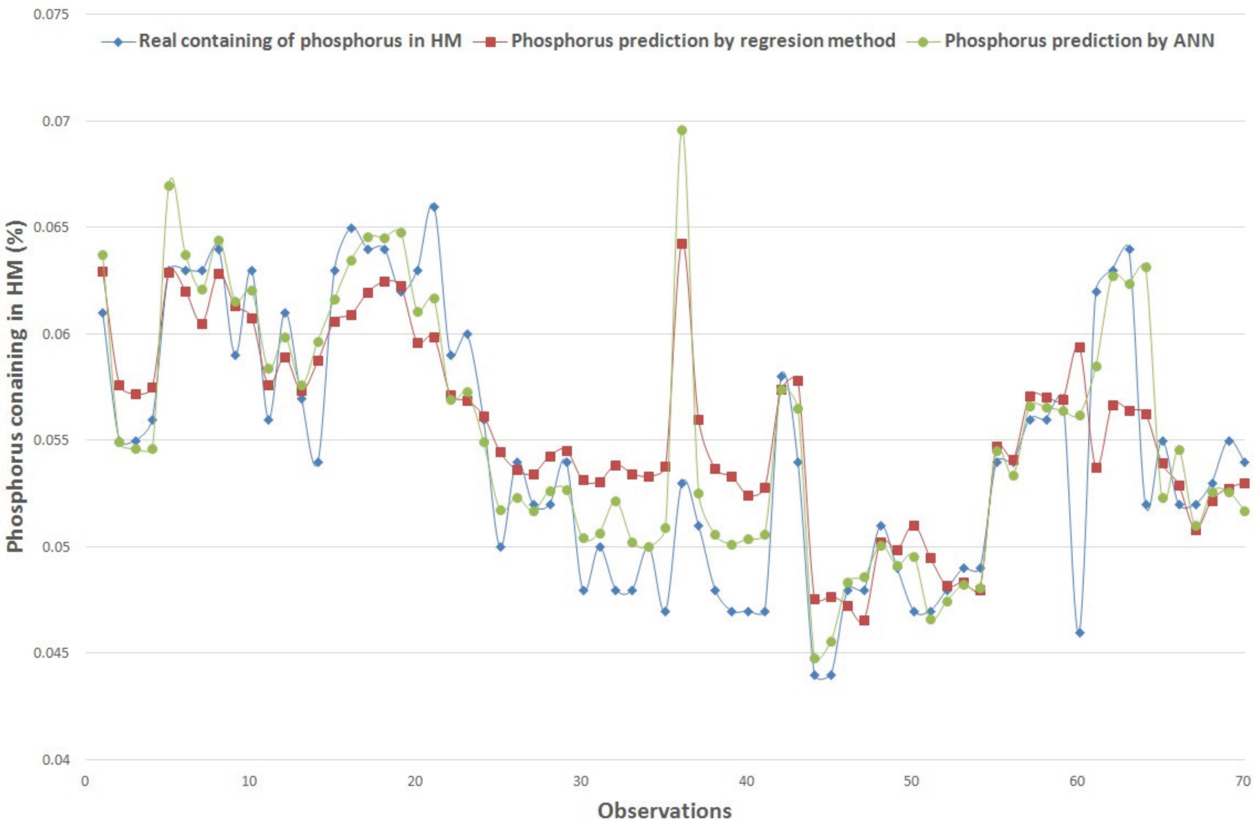

Figure 3 Comparison of phosphorus prediction by different models with real measurement

From **Figures 1 - 3** can be concluded that predicted by ANN values are closer to real parameters of hot metal, so at prediction of Si, S and P containing neural networks are more effective than linear regression method.

4. CONCLUSION

Intelligent systems, imitating action of biological systems, allow for efficient and effective problem solving, which were previously seen as problems typically "human", such as image recognition and speech recognition trends. Their capabilities can also be used to solve a completely different kind of problems, such as modeling, control systems in real time, signal filtering, noise reduction, image analysis or classification.

Participation of models using artificial intelligence, particularly in systems of supporting the work and blast furnaces control is very justified. These models can work independently, it can also be a way to duplicate a solution based on the description of physical phenomena and confirm it or deny. However, this requires a lot of work in the future, analysis, modeling and experience to be able to describe in detail so complicated working unit as a blast furnace by neural networks.

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