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Engineering

# ARTIFICIAL NEURAL NETWORKS TO PREDICTION FUEL RATE IN THE BLAST FURNACE OPERATION

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**ABSTRACT** This paper proposes the use of artificial neural networks for the prediction of fuel consumption in the blast furnace. For this purpose, a dataset of 270 records, with 19 input variables were considered, based on the historical data of operation from the years 2014 to 2017 of a blast furnace of a Brazilian steel mill, and it was verified that model presented good results with correlation coefficient of 0.837, consisting of an input layer with 19 neurons, intermediate layer with 19 neurons and output layer with 1 neuron.

**KEYWORDS :** artificial neural network, blast furnace, fuel rate, modelling.

## INTRODUCTION

The iron reduction process is millenarian, started in an artisan and empirical way, today it is consolidated in a strong steel industry, with an economic role and annual steel production of more than 1.5 million tons in 2017, being one of the main the blast furnace route reduction process.

In the technological and modeling field, in order to improve the production conditions, in addition to predicting the effects of changes in production parameters, several models were proposed for simulation of the blast furnaces, including bi and three-dimensional models that enabled advances and information detailed information about the flow of fluids and mass and thermal balances inside the blast furnace.[1]

The modeling of a blast furnace is performed as a function of the process-related "n" variables and their respective behaviors and / or interactions during the process, and one of the main difficulties is to adequately describe the interactions between particle-particle and particle-fluid. [2]

In the field of simulation of complex processes, the application of solutions based on neural networks has gained space due to its versatility of application and possibility of development and increase the trustworthiness of responses, as the neural network receives new data in the process of operation / training.

A neural network is a machine designed to model the way the brain performed a particular task; the network is usually simulated by programming, being able to recognize patterns and perform learning.[3]

The fundamental unit of an artificial neural network is the neuron, which can be expressed mathematically as:

$$y = \varphi \left(\sum_{i}^{n} (x_i w_i) + b\right)$$

where:
xí: input;
ωí: synaptic weight;
b: bias;
φ: activation function;
y: output.

## OBJECTIVES OF STUDY

The objective of the present work was the development of a model based on artificial neural networks that can reliably predict the blast furnace operation results related to total fuel consumption.

## CASE STUDY

For the development of the model, the data of operation of a blast furnace of a Brazilian company were used.

The database is composed of 270 records with 19 variables, referring to the measurements performed from January 2014 to June 2017.

The relation of variables considered in the study, mean values and respective standard deviation are listed in chart 1.

**Chart 1: Relation of input variables of the model**

| Input | Unit | Mean value | Standard deviation |
|---|---|---|---|
| Hot metal production (planned) | t/day | 7014 | 248 |
| Sinter | kg/t | 1256 | 65 |
| Iron Ore | kg/t | 205 | 69 |
| Pellet | kg/t | 155 | 84 |
| Dolomite | kg/t | 6,8 | 4,7 |
| Slag Basicity | % | 1,23 | 0,05 |
| Coke ash | % | 9,1 | 0,88 |
| Humidity of Coke | % | 4,28 | 0,7 |
| Humidity of Small Coke | % | 11,3 | 1,49 |
| Nitrogen | $Nm^3/t$ | 17,1 | 11,3 |
| Oxygen Flow | $Nm^3/h$ | 14489 | 3624 |
| Enrichment Oxygen | % | 4,06 | 0,96 |
| Flame Temperature | ºC | 2196 | 36 |
| Hot Blast | Rate | $Nm^3/min$ | 4618 |
| | Temperature | ºC | 1169 |
| | Humidity | $g/Nm^3$ | 21 |
| | Pressure | $kg/cm^2$ | 3,49 |
| Air Speed Tuyeres | m/s | 217 | 13 |
| Permeability | | 4,07 | 0,28 |

The choice of characteristics of the neural network, such as architecture and type of learning, will depend on the problem to be solved. In a variety of problems the neural networks called MLP (MultiLayer Perceptron) have been used, due to their versatility and wide possibility of solving linear and non-linear problems. [4]

The model was developed using MultiLayer Perceptron (MLP), because it is a versatile arrangement that allows the solution of linear and non-linear problems by artificial neural networks. [5]

The activation function is logistic and supervised learning, using the backpropagation algorithm.

The number of neurons in the intermediate layer depends on the complexity of the problem to be modeled, with no an exact solution for determining the number of neurons in the middle layer [6-7].

In the present case a performance analysis was performed considering a set of data set for an intermediate layer with 16, 17, 18, 19 and 20 neurons, obtaining better results with 19 neurons in the intermediate layer.

The training was conducted using the Levenberg-Marquard algorithm, which has often superior to other training algorithms with fast and stable convergence [8].

Thus, the artificial neural network was composed of 19 neurons in the input layer, one for each input, 19 in the intermediate layer and 1 in the output layer.

## RESULTS AND DISCUSSION

Analyzing the dispersion diagram between the actual values and those estimated, a strong correlation between the variables is verified, confirmed by the correlation coefficient obtained in the value of

R2 =0.837. (see figure 1)

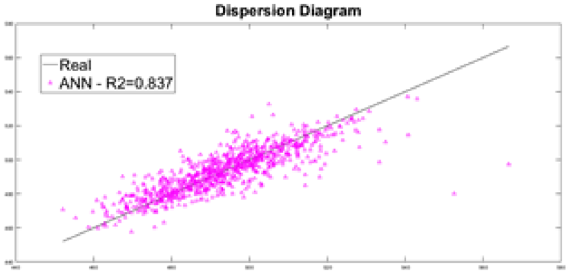


**Figure 1: Dispersion Diagram.**

It obtained a Mean Square Error (MSE) of 67.0 and Root Mean Square Error (RMSE) of 8.2, reinforcing the good quality of the obtained model.

In order to test the proposed model, we conducted a fuel consumption simulation for 40 day of the blast furnace, from june/2017 to middle of july/2017, for comparison of model results compared to those observed in practice.

Figure 2 shows the comparison between the result of the artificial neural networks and the real measurements.

It was found that in 85% of the predictions the margin of error was less than 2.5%, as indicated in figure 2.

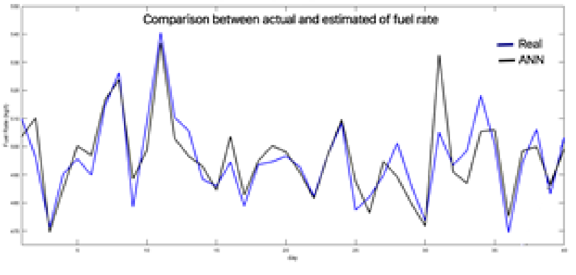


**Figure 2: Comparison between actual and estimated of fuel rate.**

Considering the results and margin of error obtained, it can be seen that such a model can be used as a tool to aid decision-making during the operation.

## CONCLUSIONS

The results found for the correlation coefficient (R2), MSE and RMSE indicate that the model can be used to predict fuel rate efficiently.

The proposed model can be used as a tool to aid in decision making of variable changes and the respective results in blast furnace operation.

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