International Journal of Science and Research (IJSR)
ISSN: 2319-7064
ResearchGate Impact Factor (2018): 0.28 | SJIF (2018): 7.426

Artificial Neural Network-Based Committee Machine for Predicting Fuel Rate and Sulfur Contents of a Coke Blast Furnace

P. Assis[1], L. Carvalho[2], A. Irgaliyev[3]

[1]Escola de Minas, Universidade Federal de Ouro Preto, Brazil
Invited Prof at TarSU- Taraz, Kazakhstan
Assis[at]ufop.edu.br

[2]Escola de Minas, Universidade Federal de Ouro Preto, REDEMAT
Universidade Federal de Ouro Preto- Ouro Preto, MG - Brazil
leonard.de.carvalho[at]gmail.com

[3]Under Grad Student at M. Kh. Dulaty Taraz State University
ansarbay127[at]gmail.com

Abstract: ***Being developed over the centuries, it currently occupies a prominent role in the world production scenario, being the stage of the process related to the obtaining of hot metal an element of great importance to establish the competitiveness of national steel. From this perspective, the control of the process of obtaining hot metal is relevant to ensure competitive prices and a sustainable process. Considering the presented situation, this research developed a committee machine, being three networks to predict each of the study variables, namely: i) fuel rate; ii) sulfur content in hot metal. The committee machine was developed to model the hot metal during the operation of a coke blast furnace, according to the input parameters provided. The results obtained by the committee machine were lower than those of the neural networks acting alone, and the following RMSE values were verified: i) fuel rate: 4.88 (network 1), 4.74 (network 2), 6.14 (network 3) and 4.67 (committee); ii) sulfur content: 0.00915 (network 1), 0.00917 (network 2), 0.00974 (network 3) and 0.00726 (committee). Considering the results obtained, the model can be used to provide important support in monitoring and decision making during the operation.***

Keywords: modeling, blast furnace, artificial neural networks, committee machines

1. Introduction

Iron reduction process is ancient, has been developed over the centuries, occupies currently leading role in the global production scenario. By viewing the data from the hot metal production, the blast furnace is responsible nowadays for 96% of that production [1]. Yagi [2] point out that this is the stage responsible for the consumption of 69.4% of total energy and 73.4% of CO_2 emission from the steel production process, highlighting the importance of the search for a process each more efficient, with impacts on industry and environmental, which indicates the relevance of studies on the blast furnace operation with regard to better outcomes for the production of hot metal.

According to the World Steel Association, more than 65% of primary energy in steel production comes from coke, which in Brazil represents 76% of the energy matrix, according to the 2018 Sustainability Report of the Instituto Aço Brasil, the steel industry is responsible for approximately 5% of world energy consumption.

About complex process controls, there is a growing use of artificial neural networks for process modeling due to its application versatility and increased response reliability, as the neural network receives new data in the training process.

The use of multiple artificial neural networks with distinct characteristics for the simulation of a process has the possibility of reducing the margin of error of the results, when compared with those acting in isolation; this arrangement is called committee machines.

The objective of such a model is to provide information to support decision making during production to obtain better stability/optimization of the operation.

2. Materials and Methods

2.1 Description of the database

The data used come from the blast furnace operation of a Brazilian steel industry. Twenty-three input variables were selected, as shown in Table 1, which also presents information on the model output variables.

Table 1: Model Input Variables

Variable	unity	Mean
O_2 Flow	nm^3/h	7904
Blow Flow	nm^3/min	2773
O_2 Enrichment	%	3.74
Blow pressure	kg/cm^2	3.06
Wind Humidity	g/nm^3	26.05
Breath Temperature	ºC	1099
Flame Temperature	ºC	2172
Vent Air Speed	m/s	223.2
Permeability (k)	-	6.93
Sinter	kg/t	1388
Ore	kg/t	224
Pellet	kg/t	16
Quartz	kg/t	17.56
Coke Moisture	%	3.46
Small Coke Moisture	%	11.44
Coke Gray	%	7.89
Steam Flow	t/h	1.35

H_2 in coal (pci)	%	3.98
The $_2$ in the coal (pci)	%	2.68
N_2 in coal (pci)	%	1.71
C charcoal (pci)	%	80.62
Coal Moisture (pci)	%	1.51
S Coal (pci)	%	0.5771

2.2 Data Preprocessing

The data used to develop the model were previously treated to adjust the vector to be used for each of the inputs (adjust the delay time or residence time), identify the outliers, blank values and standardize the data.

2.3 Setting data delay time

From this perspective, [3] performed the analysis of the delay time between each of the input variables through their correlation with an output variable, using the highest correlation value between the input and output variables to determine the delay time of that variable. It was considered in the study cited a variation of 0 to 5 hours in the determination of the delays for the development of a model of pig's silicon prediction.

This procedure was used in developing the model, comparing each of the input variables to the output variable fuel rate, applying a range of 0 to 8 hours.

2.4 Data Standardization

Considering the variety of characteristics of the data to be obtained, and there may be data to be used by time, binary or of different magnitudes, the data was standardized, which also contributes to a convergence of the model with a smaller number of epochs.

2.5 Definition of the number of neurons in the intermediate layer

Thus, tests were performed with variation in the number of neurons in the intermediate layer from 13 to 25 to compare the results obtained and determine the number of neurons in the intermediate layer of each network to be used in the model.

2.6 Cross - Validation

To perform the k- fold cross-validation (k = 10), the sample was divided into ten parts, nine for training and one for testing. The process was repeated ten times, so that each part was used as a test after the training of the other nine.

2.7 Committee Machine Components

To obtain the committee members, that is, each of the neural networks that make up the final model was used the variation of weights in which each network begins its training.

3. Results and Discussion

3.1 Delay time

Briefly, the following are the residence times applied to each of the input variables to obtain each of the vectors with the input and output data sets to be used for model development, as shown in Table 2:

Table 2: Delay time of model input variables.

	Delay
x_1	t-8
x_2	t
x_3	t-3
x_4	t
x_5	t
x_6	t
x_7	t-8
x_8	t
x_9	t-5
x_{10}	t-7
x_{11}	t-7
x_{12}	t-7
x_{13}	t-7
x_{14}	t-7
x_{15}	t-7
x_{16}	t-8
x_{17}	t-8
x_{18}	t-8
x_{19}	t-8
x_{20}	t-8

3.3 Definition of the number of neurons in the intermediate layers

Tests to determine the number of neurons for input layer were performed individually for each network. Based on the best values found, the number of neurons in the middle layer of each neural network was defined, as shown in Table 3.

Table 3: Number of neurons in the middle layer for each of the models

Network	Number of Neurons	Average MSE
Sulfur	16	0.01336
Fuel Rate	21	5, 2119

3.4 - Training of committee machine members

The members of the committee machine were obtained, that is, each of the models was performed from different weights. This procedure was performed by configuring the beginning of weights in three ways, namely: i) all weights beginning with a value of zero; ii) all values starting at one; and iii) all weights starting at twenty.

3.5 - Overall Results

Among the results, presented in Table 4, it is verified that the one obtained with the committee machine is better than the ones obtained individually by the models, but still, the models acting in isolation can present good and convergent results for the prediction of silicon content in hot metal.

Observing the mean values found for RMSE between training and testing, using cross-validation, no differences were observed that could indicate the presence of overfitting, which is when the model has low error during training in relation to the error observed in the test group.

The results also do not indicate the presence of underfitting, which is when the model cannot adequately generalize the problem, presenting high values RMSE in training and tests or difficulty in convergence during the model training.

Table 4: Summary of results (RMSE average) obtained by models 1, 2 and 3 and committee machine.

Variable	Test1	Test2	Test3	Committee
Sulfur (%)	9.2E-03	9, 20E-03	9.7E-03	7, 25E-03
Fuel Rate (kg)	4.88	4.75	6.14	4.67

Finally, a comparison was made between the values obtained by the model in relation to those found in the literature, as presented in Tables 5 and6, and it was possible to verify that the proposed model obtained better results, confirming the potential of its use to obtain better monitoring and control of the process.

Table 5: Comparison of results between the fuel machine and models reported in the literature.

	[4]	[5]	Committee
%error	8.6%	1.58%	0.9640%

Table 6: Comparison of results between the committee machine (sulfur) and models reported in the literature.

	[6]	[7]	Committee
RMSE	0.005	0.0009	5.26E-05

4. Conclusions

It is noteworthy that only variables related to process input data were used, so that the prediction is performed without dependence on process output variable measurements, such as top gas composition and slag basicity.

Regarding the final model adopted, the theoretical advantage in using the committee machine is that each of its component acts in a distinct solution region and obtaining a valid answer to the problem, with the committee machine being the final answer. The combination of each component permits a minor error of separate one.

It is noted that the use of this modeling technique enabled the construction of models with greater accuracy and can be used as a tool to aid in decision-making and planning of the operation, as well as contribute to improving the supervision and stability of the process.

Considering the results obtained, the model can be used to provide important support in monitoring and decision making during the operation.

References

[1] SAMPAIO, R. S. (2008). NT Uso de Carvão Vegetal em Mini Altos-Fornos. Estudo Prospectivo do Setor Siderúrgico.

[2] YAGI, J., NOGAMI, H., e YU, A. (2006). Multi-dimensional mathematical model of blast furnace based on multi-fluid theory and its application to develop super-high efficiency operations. Fifth International Conference on CFD in the Minerals and Process Industries. Melbourne: CSIRO

[3] HAN, Y., LI, J., YANG, X., LIU, W., e ZHANG, Y. (15 de 10 de 2018). Dynamic Prediction Research of Silicon Content in Hot Metal Driven by Big Data in Blast Furnace Smelting Process under Hadoop Cloud Platform. Wiley Hindawi.

[4] RASUL, M. G., TANTY, B. S., e MOHANTY, B. (2007). Modelling and Analysis of Blast Furnace Performance for Efficient Utilization of Energy. Applied Thermal Engineering, 27, pp. 78-88.

[5] WANG, Y., ZHANG, H., JIANG, Z., e ZHAO, G. (2013). Research of Coke Rate Prediction of Blast Furnace Based on Operative Characteristics of Auxiliary Resources. Advanced Materials Research, 605-607, pp. 1792-1797.

[6] WANG, W., CHEN, W., YE, Y., XU, Z., e JIA, B. (2006). Application of Neural Netwwork to Predict Sulphur Content in Hot Metal. Iron and Steel, 41(10).

[7] DOBRZANSKI, L. A., TRZASKA, J., GAWRON, M., e BERLINSKI, M. (junho de 2015). The Use of Artificial Neural Networks for the Prediction of Sulfur Content in Hot Metal Produced in Blast Furnace. Journal of Achievements in Materials annd Manufacturing Engineering, 70(2), pp. 86-92

Acknowledgements

The authors would express their gratitude to Federal University of OuroPreto, REDEMAT, M. Kh. Dulaty Taraz State University for helping us to publish this paper.

Authors Profiles

P. S. Assis, Metallurgical Engineer at UFMG, Brazil, 1975. M.Sc.at UFMG, Brazil, 1978. Dr-Ing at RWTH, Germany, 1991. He worked as Collaborator at Acesita (now APERAM) and Mannesmann (now Vallourec) during almost 19 years. Then turned to University as Professor at UFOP (Federal University of OuroPreto, Brazil).Visiting Prof at UFF, Niterói, Brazil. From 2000, Honorary Prof at Hebei University, China. Full Prof at Federal University of OuroPreto, Brazil & Invited Prof. at Taraz State University named M. Kh. Dulaty, Kazakhstan. E-mail: assis[at]ufop.edu.br
https://orcid.org/0000-0003-0874-4162

L. de A. Carvalho, Graduated in Metallurgical Engineering from UFMG (2005), having received the "Alcindo Vieira" awards from the UFMG School of Engineering and "Fábio Décourt Homem de Melo" from the Brazilian Association

of Metallurgy, both for their good academic performance during graduation, in addition to the 2005 Class gold medal (best graduate).Master's degree at CEFET / MG (2014) and PhD in Materials Engineering at REDEMAT/UFOP (2019), whose work was the use of artificial neural networks for the modeling of blast furnaces. E-mail: leonardaraujo[at]yahoo.com.br

A. Irgaliyev, was born in Taraz, Kazakhstan. He has finished Nazarbayev Intellectual School of Physics and Mathematics in Taraz with good results. After that he was entered in M. Kh. Dulaty Taraz State University in the Information System and Technologies, where he is under-Grad Student. E-mail: ansarbay127[at]gmail.com