INVESTIGATION ON FUZZY LOGIC AND NEURAL NETWORKS TO FORECAST HOT METAL TEMPERATURE IN A BLAST FURNACE: FANCIM EXPERIENCES

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ABSTRACT

The main objective of the FANCIM project was the development of a blast furnace model, using Neural Networks (NN) and Fuzzy Logic techniques. These models would be used to simulate the hot metal temperature, and allows to plant operators see the trend of above mentioned variable, and to optimise blast furnace performance.

During the project next tasks have been accomplished:

- Evaluation of data collecting software.
- Data pre-treatment.
- Selection of system architecture.
- Selection of variables for NN system.
- Training and validation of NN.
- Selection of variables for Fuzzy Logic system.
- Training and validation of Fuzzy Logic.
- Simulation of the models based on Fuzzy Logic and NN techniques.

KEYWORDS: Blast furnace, Fuzzy Logic, Neural Networks, Forecasting, Simulation, ANFIS, Subtractive Clustering, Hot Metal Temperature, Multilayer Perceptron.

INTRODUCTION

The FANCIM project was designed to improve the blast furnace control. The main objective was to accomplish a HMT model, in order to forecast its trend. This advisory system would be able to help the plant operators, and therefore to reduce coke consumption. Another objectives of the project were to investigate the use of NN and Fuzzy Logic techniques in metallurgical processes.

ACTIVITIES CARRIED OUT

DATA COLLECTION

Total amount of variables obtained was eight. They can be classified in three main categories:

- Shaft Parameters: Ore / Coke rate.
- Tuyere Inputs: Blast Temperature, Volume, Oxygen, Pressure, Moisture, and Pulverised Coal Injection (PCI) rate.
- Hot Metal properties: Hot Metal Temperature (HMT).

Four data sets were collected. Two sets with a sample period of two minutes, and two data sets of ten minutes.

DATA PRE-TREATMENT

Two methods to study the of data behaviour were carried out:

Cross Correlation

The calculation of cross correlation provides the linear dependence between two variables. In our case (a highly non-linear system), it has just been a guide for the trend of the system.

Cross correlation between Hot Metal Temperature (HMT) and operating input variables were calculated. Positive and negative correlations were found between HMT and moisture with some lags. The positive correlation could be due to control actions of the plant operator.

Histograms

A histogram analysis was carried out with all the variables used in the models, for determining the working range of them. Large peaks were found in almost all the variables, except the moisture. The moisture is the main variable used for controlling; thus their values spread on a wider area.

ARCHITECTURE SELECTION

For developing the model, it has been used the system identification theory (1). It was used a collection of past outputs and past inputs from the blast furnace, to forecast the output under study.

It is possible to consider the following blast furnace model structure:

$$\hat{y}(t) = g(\varphi(t))$$

$$\varphi(t) = [y(t-1), \ldots, y(t-n), u(t-1), \ldots u(t-n)]$$

Where:
$\hat{y}$ (t): output prediction.
$\varphi(t)$: regression vector.
y(t): model output.
u(t): model input.

The regression vector is a collection of past inputs and outputs of the system, so it was very important to select this vector correctly in order to obtain feasible results.

It is possible to use neural networks to estimate the relationships between variables (2). The neural network used in system identification is the typical multilayer perceptron (MLP). The MLP used has three layers, and it was trained with a particular case of the back-propagation algorithm: the Levenberg- Marquardt method.

NN FORECASTING

A network was achieved to predict HMT. It was trained with 4000 data, and validated with 1000 data. The regressor used is the following:

$$\hat{y}(t) = f(y(t - \tau_1), \overline{u}_i(t), \tau_i)$$

$$\overline{u}_i = \frac{\sum_{t=t_a-2\tau}^{t_a} e^{-2\left(\frac{[\tau-(t_a-t))]}{\tau}\right)^2} \cdot u_i(t)}{\sum_{t=t_a-2\tau}^{t_a} e^{-2\left(\frac{[\tau-(t_a-t))]}{\tau}\right)^2}}$$

Where:
τ_1 = elapsed time since previous measurement.
τ = estimated delay for input variables (depends on the variable).
τ_i = elapsed times previously described.
t_a = time without delay.

The variables used in the model are deployed in Table I.

τ_i	**OUTPUT ($\hat{y}$)**
Time between taps	
Time since the tap beginning	
Time since the last measurement	
INPUTS (U_i)	
Blast Volume	HMT prediction
Blast Temperature	
Moisture	
Oxygen	
PCI	
Ore/Coke rate	
HMT delayed	

Table I:. Variables in NN

Some results obtained are represented in Figure 1 and Figure 2.

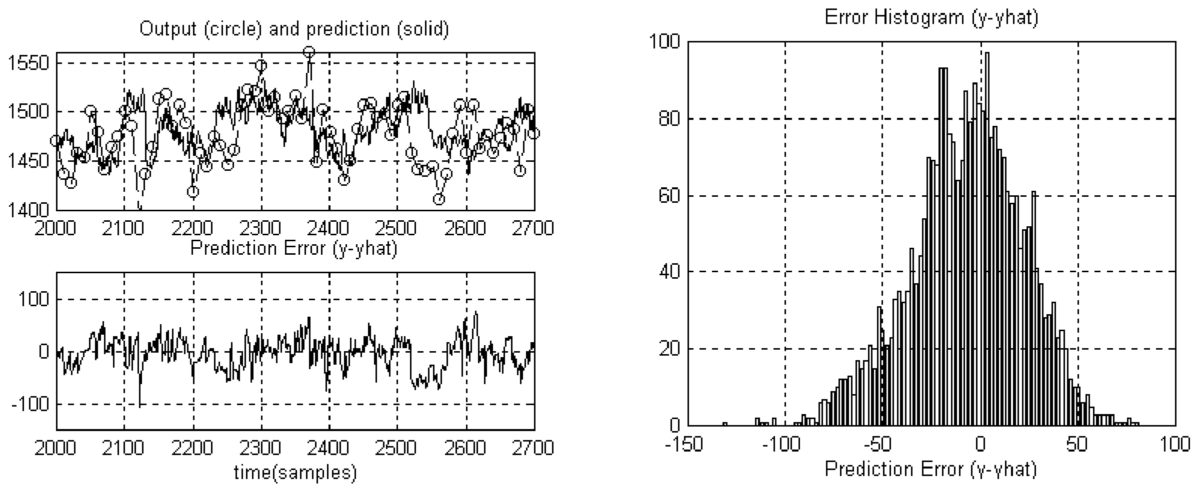


Figure 1: Error in autopredictive HMT.

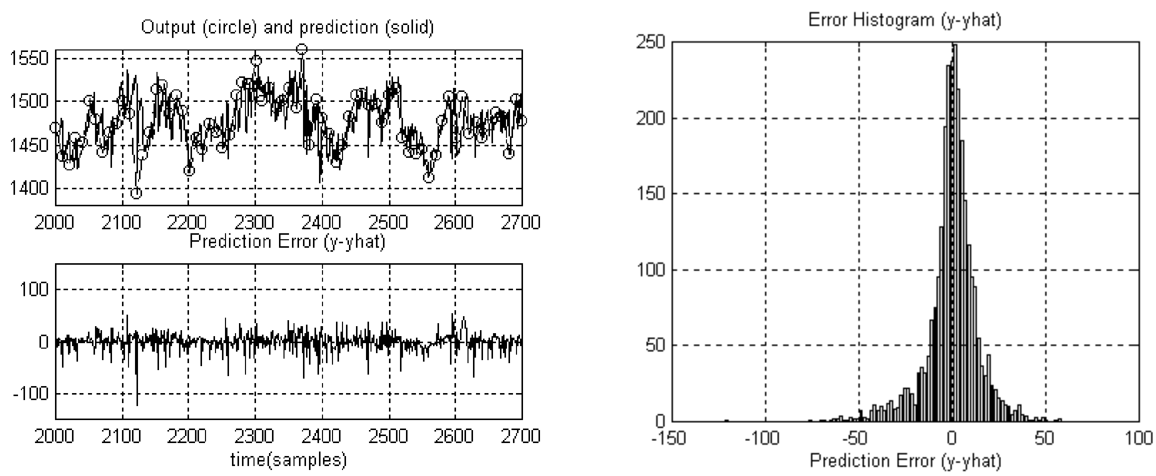


Figure 2: Error in predicted HMT.

FUZZY FORECASTING

A Fuzzy Logic System was achieved for predicting HMT. It was trained with 12000 data and validated with 3000 data. The regressor used is the following:

$$\hat{y}(t+1)=f\,(y(t-\tau_1),y(t-\tau_1-10),y(t-\tau_1-20),...$$
$$...u_i(t-\tau_2),u_i(t-\tau_2-10),u_i(t-\tau_2-20))$$

$$i=1\,,\,...\,,\,6.$$

Where:

τ_1 = 40 minutes.

τ_2 = 120 minutes (Blast Moisture, PCI, Blast Volume, Oxygen).

τ_2 = 240 minutes (Blast Temperature).

τ_2 = 480 minutes (Ore / Coke rate).

The variables used in the model are deployed in Table II.

INPUTS (U_i)	**OUTPUT ($\hat{y}$)**
Blast Volume	HMT prediction
Blast Temperature	
Moisture	
Oxygen	
PCI	
Ore/Coke rate	
HMT delayed	

Table II:. Variables in Fuzzy Logic System.

One result obtained is represented in Figure 3.

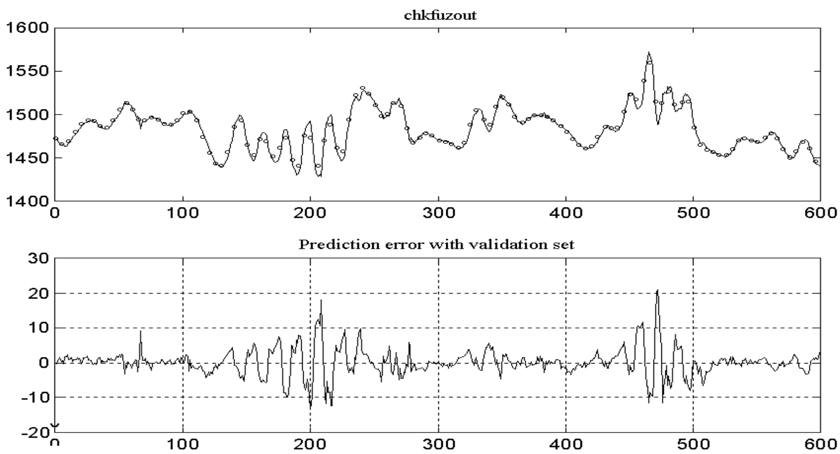


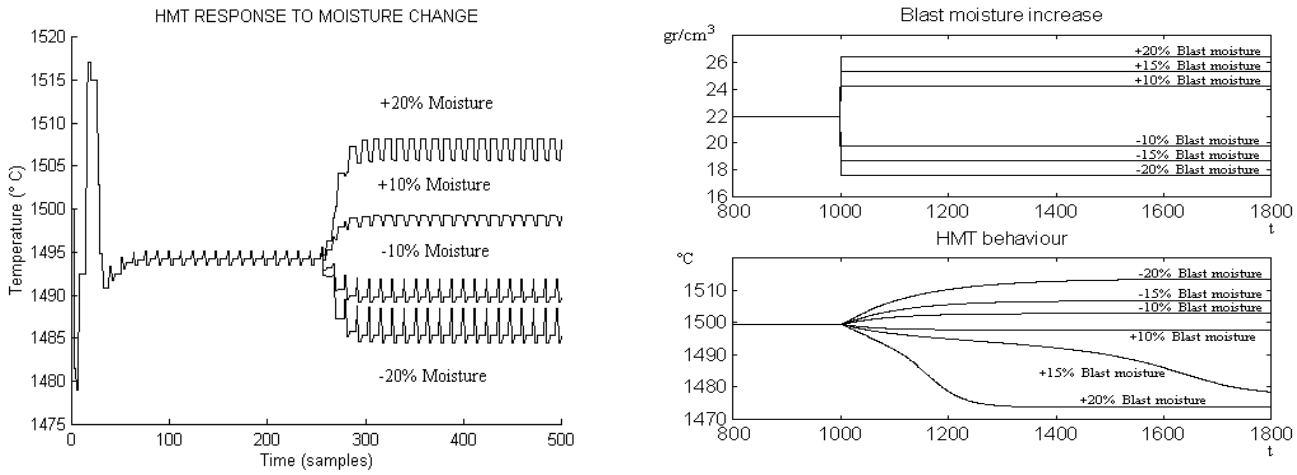
Figure 3: Predicted output in HMT

Where:
o: HMT real values.
-: HMT predicted values.

RESULTS AND DISCUSSION

Once obtained a network and a Fuzzy model able to validate the system, two simulators were accomplished in MATLAB SIMULINK in order to see HMT behaviour (3). This simulator provides a guide for plant operators enable to advice them the HMT trend (4). They are able to modify input variables, in order to see HMT change.

Simulators plot HMT trend in different moisture changes. The results appear in Figure 4.



A B

Figure 4: HMT responses to different moisture changes with (A) NN, and (B) Fuzzy Logic.

It is possible to see the correct HMT trend: it increases when moisture decreases. The NN response of PCI and Ore / Coke rate changes is completely wrong. The Fuzzy response is correct for all the variables, although in some periods are unstable.

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