USE OF ARTIFICIAL NEURAL NETWORK FOR WALL TEMPERATURES MONITORING IN BLAST FURNACE

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ABSTRACT: The blast furnace wall monitoring, by means of wall thermocouples, plays a key role to assure stable blast furnace operating conditions and safe management of wall itself.
This paper describes the experiences in the development of an advanced intelligent temperature map analyser system. The study has shown, in simulated conditions, the capability of the Artificial Neural Network to identify the presence of process anomalies i.e. scaffolds formation and gas channelling, starting from the analysis of the wall temperature maps.

KEYWORD: Blast Furnace, Artificial Neural Network, Wall Thermal Control

INTRODUCTION

The measurement of Blast Furnace (BF) wall temperatures (Falzetti (1998)), is important for obtaining information regarding the inner state of the process. One of the most important problems concerning the analysis of the wall temperature distribution is represented by the difficulties, for the human operator, to analyse in real time all the temperature trends, and synthesise them in few simple operative indications. The advanced computational systems make it possible the improving of monitoring and controlling capabilities of BF process.

In particular, BF wall temperatures data can be utilised to obtain information about:

- the wear status and the thermal load of the wall, with the aim to support the operator in maximising the wall life time (Picard (1998), Wang (1997));
- the BF process, and so the possibility to improve the BF control (Kawahata (1998));
- the heat transfer through the wall, which is strongly related to some anomalous phenomena inside the BF, i.e. scaffolds formation and falling, channelling etc. (Falzetti (1998)).

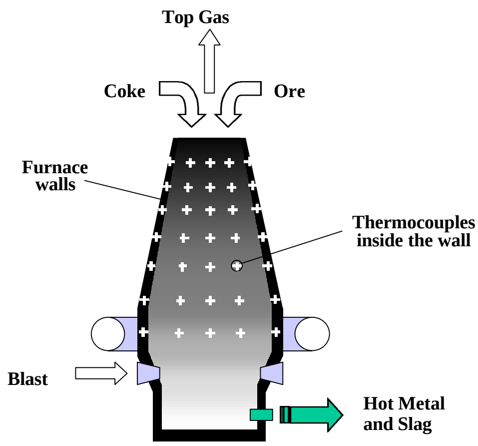

Figure 1: Scheme of thermocouples net

CSM is carrying out an activity with the aim to develop an advanced wall temperatures monitoring and analysis system.
This object is structured on two different parts:

- a basic analysis and visualisation of the wall temperature data system;
- an advanced pattern recognition system, based on Artificial Intelligence Techniques (AIT), for an 'intelligent' analysis of data, in order to recognise the distribution of scaffolds around the BF wall.

USE OF ARTIFICIAL INTELLIGENCE TO DEVELOP NEW TOOLS FOR TEMPERATURE MAPS ANALYSIS

The present research has been carried out on the BF n° 4 of Piombino Works (Lucchini S.p.A.), and an experimental version of the model is running on this plant.
The Piombino furnace is equipped with a net of thermocouples (figure 1), placed inside the furnace bricks and used to monitor the thermal state of wall. The thermocouples are organised on seven levels, from the stack top to the bosh zone, and on eight generatrix for a total of 56 thermocouples.

The AITs seem to be really attractive to solve complex problem of pattern recognition, as the scaffolds identification problem is (Crowe (1995), Falzetti (1997), Lemuet (1997), Matsuda (1994)). Furthermore, the wall temperatures data are affected by a lot of 'disturbances', that produce difficulties to find relationship between them and the BF inner process.

In the following presentation AITs are used for the identification of scaffolds and gas channelling phenomena. In particular, the present study has the objective to evaluate the feasibility to identify the scaffold and channelling distribution by Artificial Neural Network (NN) models, starting from the knowledge of the temperatures distribution at the BF wall.
Sets of virtual data, obtained by a mathematical simulation, were used to train the NN models, because it was not possible to find a large number of real scaffold distributions starting from process data.

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$$\begin{bmatrix} 1 & 1 & 1.5 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1.5 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1.5 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1.5 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1.5 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1.5 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1.5 & 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

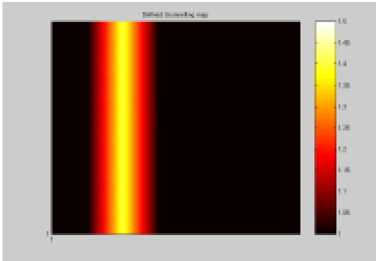

Figure 2: Channelling representation

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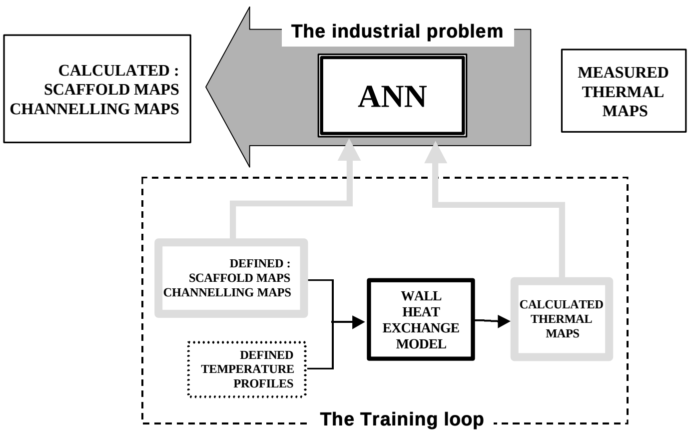

Figure 3: Logic scheme of the proposed approach

The use of AITs for the analysis of temperature maps is suggested by the problem. In fact, the large number of parameters, the two-dimensional representation of the BF temperatures, and the typical problems of pattern recognition lead to the choice of AITs.
The scaffold distribution (scaffold map) is, mathematically, represented by a two-dimensional matrix where the elements are the scaffold thickness corresponding to the net of $7\times8=56$ thermocouples placed on the wall. The channelling maps have the

same structure than scaffolds but, in this case, each element of the matrix is a number expressing the channelling local intensity factor (figure 2). Values ‘ones’ in the columns mean that the local temperature is not increased by the local channelling, ‘n’ columns, greater than ‘ones’, mean that the local temperature is increased of the ‘n’ factor by the presence of a local channelling.

Figure 3 shows the logic scheme to approach the solution. The industrial problem is to identify the presence of scaffold and/or gas channelling phenomena inside the BF, starting from the knowledge of the temperature distribution on the furnace walls. This problem is solved developing a suitable NN model trained on a large set of data.

To describe the relationship among the internal furnace phenomena and the corresponding temperature maps of the furnace wall, a proper mathematical model was developed. Such model simulates the heat exchange between the furnace burden and the external cooling system, by the relationship among: the inner furnace temperature (temperature profiles), the scaffold and channelling presence (scaffold and channelling maps) and the wall thermocouples temperatures (temperatures maps).

In principle, this model could be mathematically inverted to obtain a model able to calculate the scaffolds and channelling maps starting from the knowledge of the temperature maps. Unfortunately, among the inputs of the model (the direct model) are present the information about the temperatures inside the furnace, ‘temperature profiles’, and these information are not available in the real case, avoiding the inversion of the wall heat exchange model for the solution of the industrial problem.

A possible solution to the problem was successfully obtained by using NN to invert the wall heat exchange model (Chen (1996), Freeman (1992)).

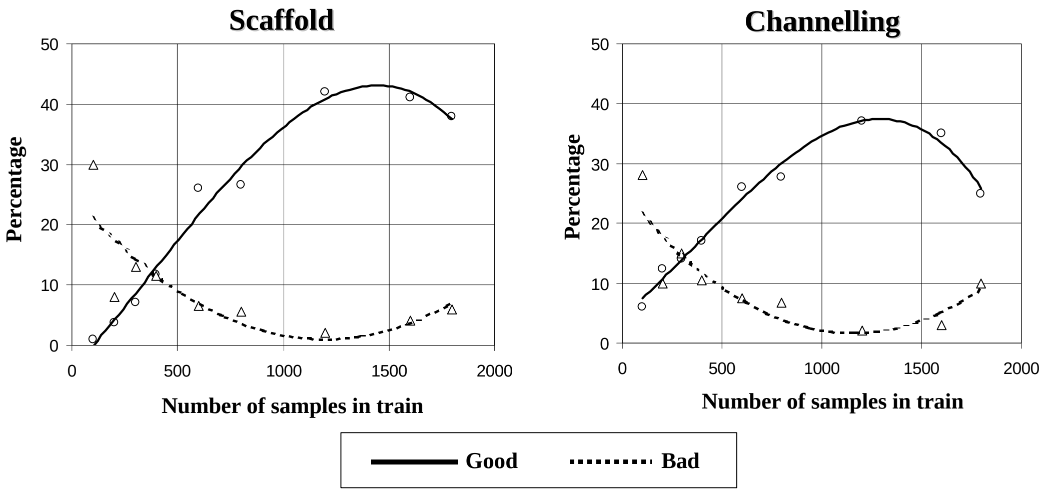

Figure 4: Quality indexes trends

Because of it is very difficult to have a large set of scaffold maps by operative source, the wall heat exchange model itself was used to generate the train and test sets of temperature maps, scaffold and channelling maps.

The Radial Basis Function (RBF) network is the NN structures used in this work. This kind of network covers application fields similar to that of the most famous Back Propagation (BP) networks, but, at the same time, the RBF results extremely faster than the BP.
However, the ‘a priori’ definition of the most suitable NN structure is not possible. According to that, other structures than RBF will be tested in the next future.

The proposed mathematical model is only one of the possible ways to generate temperature maps from scaffold maps. The model is based on several assumptions:

- the system controlling the temperature exchange at the BF wall, consists of the internal material, the scaffold thickness, the brick lining, and the external cooling system;
- the average temperatures of the inner material (gas and solid) in contact with the inner surface of the wall, along the furnace height, are known (temperature profile and channelling presence);

- the location (position and depth) of thermocouples are known, and the model computes the value of temperatures in those places;
- the local thickness of the scaffolds is known, that means to know the scaffolds map.

According to that, the model computes the temperatures of the thermocouples, when a inner temperature profile and a scaffold and channelling maps are assumed.

With reference to the results presented on this paper, a large set of random selected scaffold and channelling maps were generated and seven furnace temperature profiles families have been defined to compute, by the model, the corresponding temperature maps.
All these data were used to produce data sets available for the NN training and test. One of the most important investigation aspect was to decide the suitable dimension of the training set. Several tests were done to define the optimal number of sample for the training phase. Figure 4 shows the results of the analysis. The graphs show the evolution, in terms of percentage, of two of the three classes of merit, the Good and Bad classes (see next paragraph), versus the number of samples used during the training phase. The first graph concerns the quality of scaffolds maps calculation, while the second is for the channelling maps.

EXPERIENCE DETAILS

A performance index has been defined to evaluate the capability of the NN program to correctly recognise both scaffold and channelling maps by the temperature map.

The performance index is a measure of the agreement between the random selected maps (defined scaffold or channelling maps) and the relative scaffold or channelling maps calculated by the NN, starting from the input temperature map. The index is evaluated (figure 5) computing the average value, ($\boldsymbol{X_A}$) and ($\boldsymbol{X_C}$) of the, respectively, defined map **[X_A]** and the calculated map **[X_C]**; than the calculated map is translated of a ***D*** quantity, and this new map is subtracted from the calculated map, obtaining a corrected calculated map **[X_C]***.
At this point, the error map **[E]** is calculated and the error index is evaluated by the following:

$$\boldsymbol{e} = \frac{1}{N}\sum_{i=1}^{N}\left|E_i\right|$$

Where:

- E_i is the generic map element of the differences between the generic selected map and the translated NN calculated map
- N is the number of thermocouples
- ε is the performance index.

On the basis of this index, three merit classes: Good, Acceptable and Bad have been defined. These classes correspond

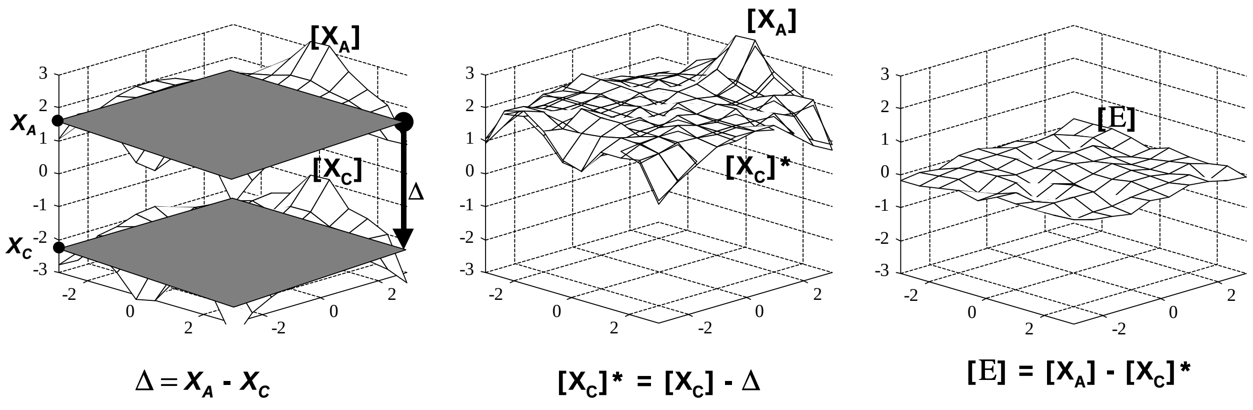

Figure 5: Error index calculation

to the performance index values shown in table 1:

	For SCAFFOLD	For CHANNELLING
Good	$e_s \le 0.05$ (cm)	$e_s \le 0.05$ (-)
Acceptable	$0.05 < e_s \le 0.15$ (cm)	$0.05 < e_s \le 0.15$ (-)
Bad	$e_s > 0.30$ (cm)	$e_s > 0.30$ (-)

Table 1: Merit classes definition

The range values have been established by the observation of a wide number of output scaffold and channelling maps.

A lot of tests have been carried out to analyse the NN capability to solve the scaffold and channelling recognition problem.
In particular, a large set of data was produced by a random selection of both temperature profiles, scaffold and channelling maps. The corresponding temperature maps were computed by using these data sets and the proposed mathematical model,.
A percentage of the whole selection of scaffold, channelling and temperature maps were successively used for the training of the NN model.
Note that the temperature profile is not present among the inputs of the network (figure 6). Previous tests, using also the temperature profile show the same quality of the results [1]. A motivation can be done considering the presence of the temperature profile in the network input increase the level of the network complexity without any benefit. However, a deeper analysis of this last question is yet in progress.
The best results obtained with such a kind of model are shown in table 2.

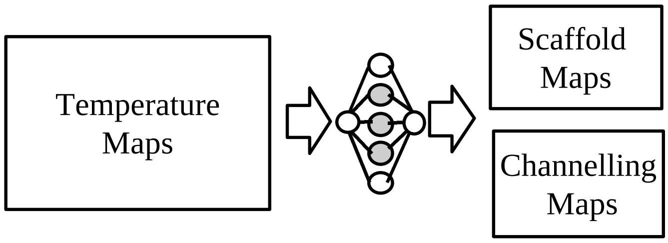

Figure 6: NN model input and output typology

	SCHAFFOLD maps Percentage distribution among the classes	CHANNELLING maps Percentage distribution among the classes
Good	43	37
Acceptable	55	60
Bad	2	3

Table 2: NN results for scaffold and channelling identification
(Results on TEST set of 400 samples. The NN was trained on set 1200 samples)

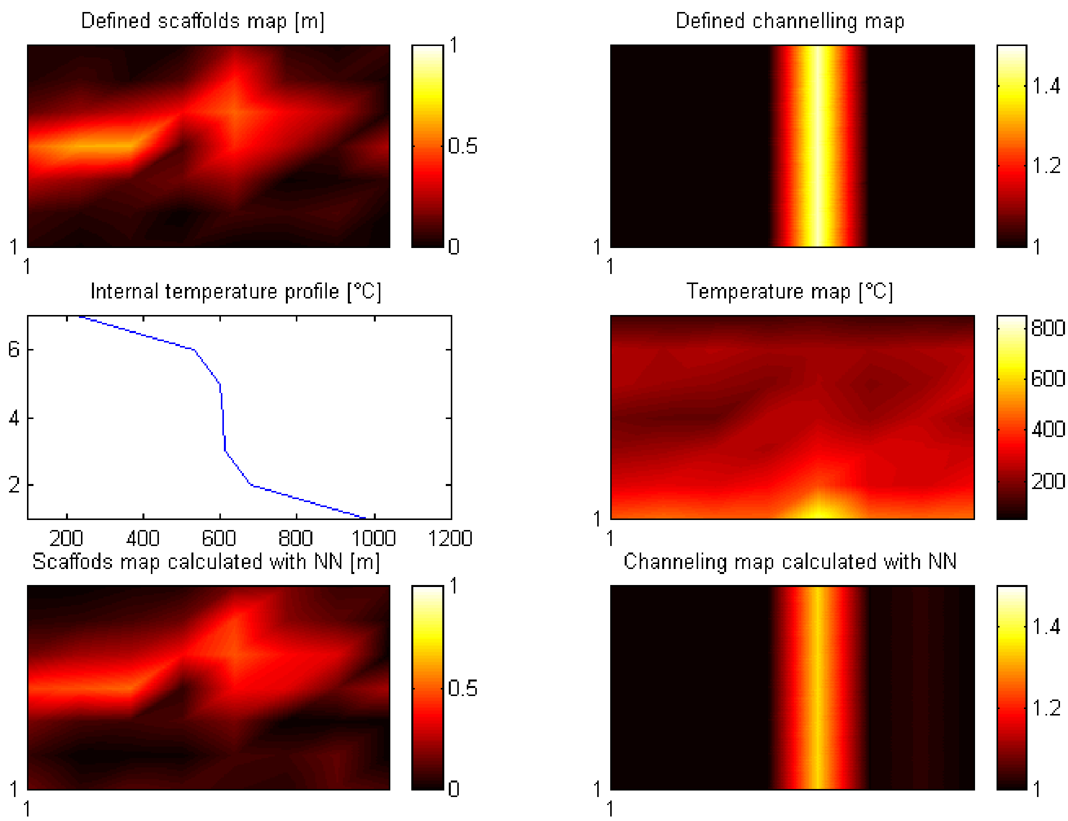

Figure 8: Example of results (ε_{Sc} = 0.047, ε_{Ch} = 0.033)

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