Above Burden Temperature Data Probes Interpretation to Prevent Malfunction of Blast Furnaces - Part 1: Intelligent Information Preprocessing

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In the last few years, the use of computers has made it possible to achieve a better image of blast furnace performance, allowing the establishment of models, the comparison of variables and the construction of powerful databases to store the variables and their evolution during the process. Nevertheless, part of the investment made in blast furnace equipment is not properly utilized and a considerable part of the information collected could be put to much better use. The application of modern data mining techniques has overcome these problems. This work shows ways to apply these techniques to data from probes located in the throat or shaft of the blast furnace, as well as how to extract useful information by defining and classifying a set of patterns in classes from temperature profiles that have been linked to the stability of the process in steelworks with blast furnaces.

Keywords: Blast furnace; above burden probes; stock rod; in burden probes; correlations analysis; neural network

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Introduction

In recent years, computers have made it possible to achieve a better image of blast furnace performance, allowing not only the display of variables but also the establishment of establish models, the comparison of different variables and the construction of powerful databases to store the variables and their evolution during the process [1,2].

As unfortunately it is not possible for a human being to analyse all the information from the sensing devices and computers in real time, part of the investment in blast furnace equipment cannot exploit all options and a considerable part of the information collected remains unused.

It is possible to overcome these problems using the modern techniques of data mining. They comprise a broad set of methods such as classical statistical analysis, principal component analysis, signal processing and other more advanced ones like neural networks or fuzzy logic.

In modern factories there are huge databases that store large collections of process variables from which it is possible to extract useful information buried in the signals and to obtain relationships among different parameters of the blast furnace operation [3,4]. This would take too much time to be done during daily blast furnace operation, but by treating these stored data, it is possible to obtain results that can be re-transferred to the process computer in a way that allows the plant operator to obtain a more comprehensive view of the current variables significance.

This work shows ways to apply the above mentioned techniques to some of the probes located in the throat or shaft of the blast furnace and also how the results obtained can help the plant operators to make correct decisions.

The behaviour of the upper part of the blast furnace plays a decisive role in the performance of the whole furnace. Gas and burden distributions control the rate of ore reduction, determine the shape and height of the cohesive zone and, as a consequence, have a strong influence on the stable performance of the blast furnace [5-7]. This work presents the first part of a large project studying how to extract useful information by defining and classifying a set of patterns in classes from temperature profiles that have been linked with the stability of the process. Thermocouple signals from above burden probes were analysed and employed to establish their relationships with the stability of the whole process. The tool selected was a neural network [8] (SOM - Self Organising Maps).

Every time a new temperature profile is obtained from the above burden probes, it is classified [9,10] as belonging to one of the classes represented by the patterns and subsequently a valid diagnosis of the blast furnace performance is made. At the same time, by looking at the results achieved by the neural networks [11], it is possible –for the plant operators- to forecast hangings and burden collapses more than one hour in advance.

The work will be completed with the development of a new user-friendly tool, currently in use in some European blast furnaces, for above burden probe interpretations, based on the above mentioned research and allowing the plant operator to obtain not only the probe signals but also an initial interpretation of their meaning. This development is explained in the second part of this series of papers [16].

Device Description

The study was undertaken for European steelworks with blast furnaces equipped with above burden temperature probes and a total of thirteen thermocouples, but the

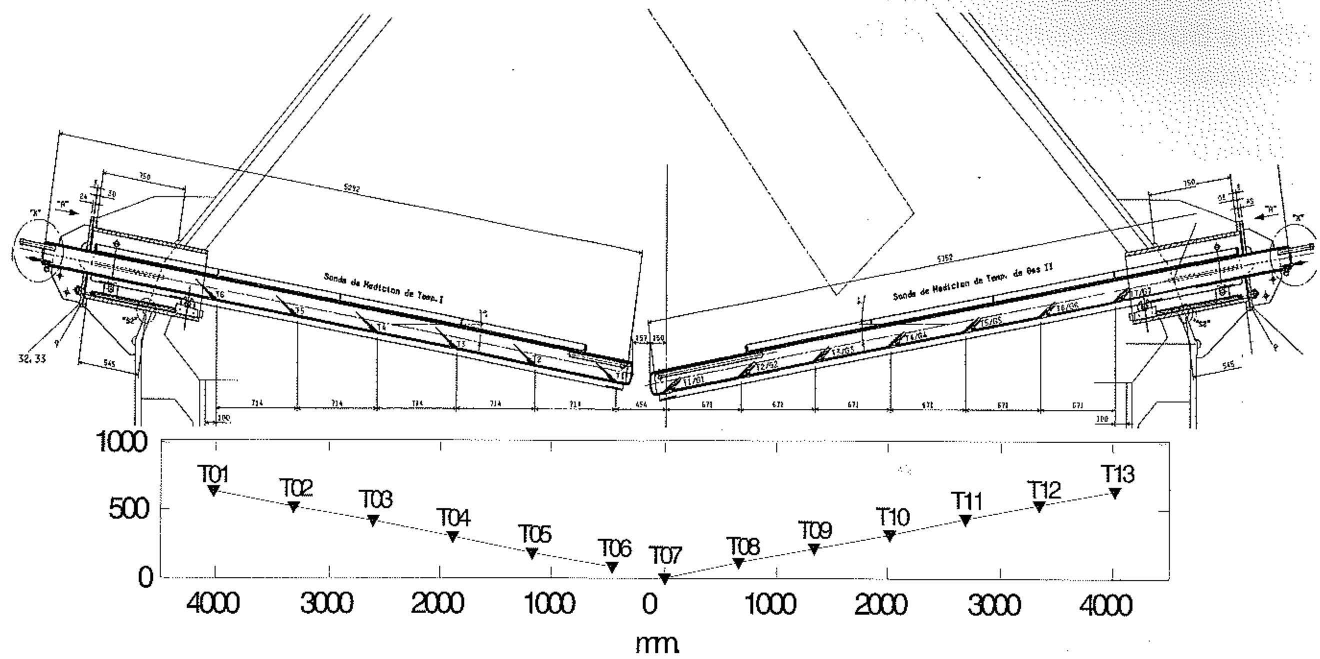

Figure 1. Illustration of above burden probe temperatures in a European blast furnace.

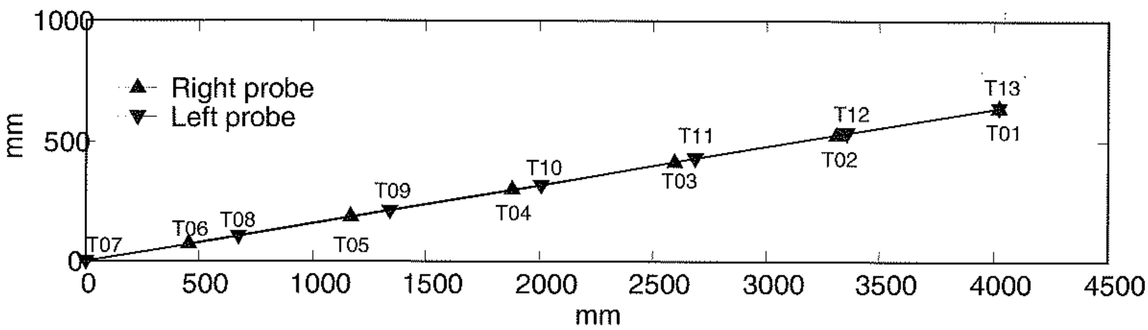

Figure 2. Relative position of thermocouples with respect to central blast furnace axis.

system (software/hardware configuration) can be easily adapted to work with more thermocouples and systems with different burden charging devices.

Figure 1 illustrates the above burden temperature probes located in a blast furnace. There were two probes located at the same vertical levels, covering a diameter of the blast furnace throat. According to this figure, the right-hand probe has seven thermocouples equidistantly distributed along it - the distance between two consecutive thermocouples is equal to 671 mm - locating the first one 100 mm from the wall and the seventh one in the blast furnace central axis. The left-hand probe has only six thermocouples, also equidistantly distributed along the probe but with a different distance between consecutive ones. In this case, the distance between two consecutive thermocouples is 710 mm. The first measurement point is located 100 mm from the wall, too, and the last one is only 454 mm from the seventh of the right-hand probe. It is important to take into account these geometrical features, because they affect the interpretation of the signals. In this paper the notation T01, T02,..., T13, will be used to identify the thermocouples.

Both probes are set with a 9°-tilt angle with respect to the horizontal in order to compensate for the slope of the burden, trying to place the probes as parallel as possible to the burden surface. This means that the difference in height between the central thermocouple and those located nearest to the wall is around 650 mm.

At the beginning of the work both probes were equipped with a nitrogen cooling system to prevent deformation, or bending upwards, of the probe structure. Not only the damage to the probes must be taken into account because there is also a serious risk that the charging system chute, located closely above, crashes down onto them. This cooling system, operative during this entire project, has been replaced by another one which employs water as the cooling agent, because the new system yields more feasible temperature signals, avoiding "M-shaped" temperature profiles.

Figure 2 shows the relative position of each thermocouple with respect to the blast furnace centre. As can be seen, the difference is greater between the thermocouples located at both sides of the central one (T07) and tends to reduce toward the wall, so that thermocouples T01 and T13 are located in an almost symmetrical position.

Data Collection

During the present work, and as a requirement for project development, a huge database was created, collecting data from the blast furnace over a period of two years. These data came from different sensor devices located in the blast furnace with a sampling rate of two minutes per sensor. If a variable changed more slowly than that, the last value was repeated until the sensing device read a new one.

The variables included in the data set are listed in **Table 1**. These variables were analysed to study their influence on the above burden probe temperature signals. In some cases, these relationships were observed by a simple data inspection, while in other cases, it was necessary to employ some signal analysis techniques as will be described below.

Basic statistical analyses were performed using a total amount of 106 737 data for each variable, covering a period of 148 successive days of blast furnace performance. This analysis, applied in the first place to above burden temperatures, consists of the calculation of different statistical values for temperatures cast by each thermocouple of both above burden probes (see **Table 2**).

Data Analysis

Basic Analysis. Basically, the minimum temperatures are room temperature and correspond to long stoppages of the blast furnace.

In general, the maximum temperatures are affected by the cooling system and they cannot be considered as the actual maximum temperatures reached by the gas. This effect is stronger for thermocouples located in the central part of the probes (T06, T07 and T08), because they trigger the nitrogen cooling stream if the temperature is higher than 500°C.

As expected, the analysis of the mean and median values reveals other interesting signal features; the maximum value for means is obtained for the central thermocouple T07. However, because of the thermocouples' relative position, it is to be expected that the mean value for T06 would be closer than the mean value for T08.

In fact, there is some asymmetric behaviour that is clearly visible if all mean temperatures are represented together (see **Figure 3**). The gas appears to be hotter on the right side than on the left one; at least, this would be the "mean" behaviour of this blast furnace.

The strong effect of the cooling system is also observed when comparing the values of mean and median for the different thermocouples. For the outer thermocouples (T01-T05 and T09-T13) the mean value is always greater than the median and for the inner thermocouples (T06-T08) the mean is less than the median. This is associated with the hard and fast fall in temperature promoted by the

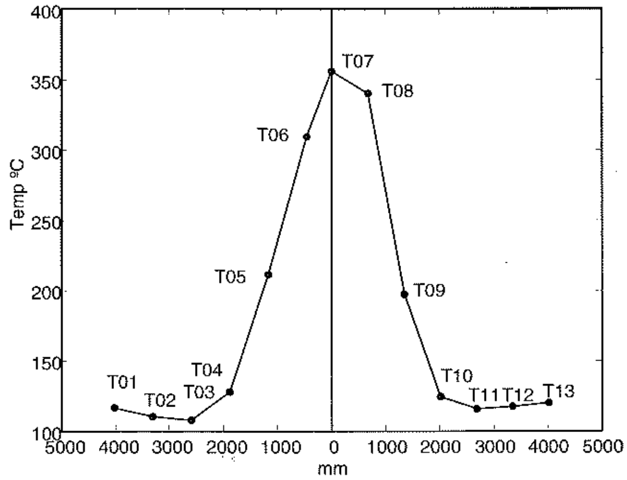

Figure 3. Mean values of above burden temperatures.

Table 1. Variables included in the data set.

Group	Variables
A. Blast furnace temperatures	Above burden probes (13 measurements)
	Wall temperatures (11 levels, 4 to 8 measurements depending on level)
B. Burden parameters	Stock rod signals (two 6 m and one 16 m long)
	Burden charging pattern
	Ore to coke ratio
	Charging rate
C. Blast Parameters	Blast volume
	Blast temperature
	Blast moisture
	O_2 enrichment
	Blast pressure
	PCI
D. Exhaust gas composition	% CO
	% CO_2
	% H_2
E. Hot metal properties	Hot metal temperature
	Silicon content
	Beginning and end of tapings

Table 2. Calculation results of different statistical values for temperatures cast by each thermocouple of both above burden probes.

Thermocouple no.	Min	Max	Mean	Median	Std
T01	27	495	116.4	103.5	55.0
T02	28	550	109.9	94.8	62.4
T03	26	595	107.1	92.0	63.6
T04	26	554	127.7	112.1	66.7
T05	24	550	210.9	197.3	96.0
T06	21	548	309.4	313.1	120.1
T07	23	624	355.5	371.5	111.7
T08	24	684	339.9	347.8	117.6
T09	26	735	197.3	176.8	92.2
T10	28	683	124.2	109.5	64.1
T11	30	569	114.9	103.5	60.7
T12	30	489	117.3	105.5	60.8
T13	29	415	120.1	112.8	51.1

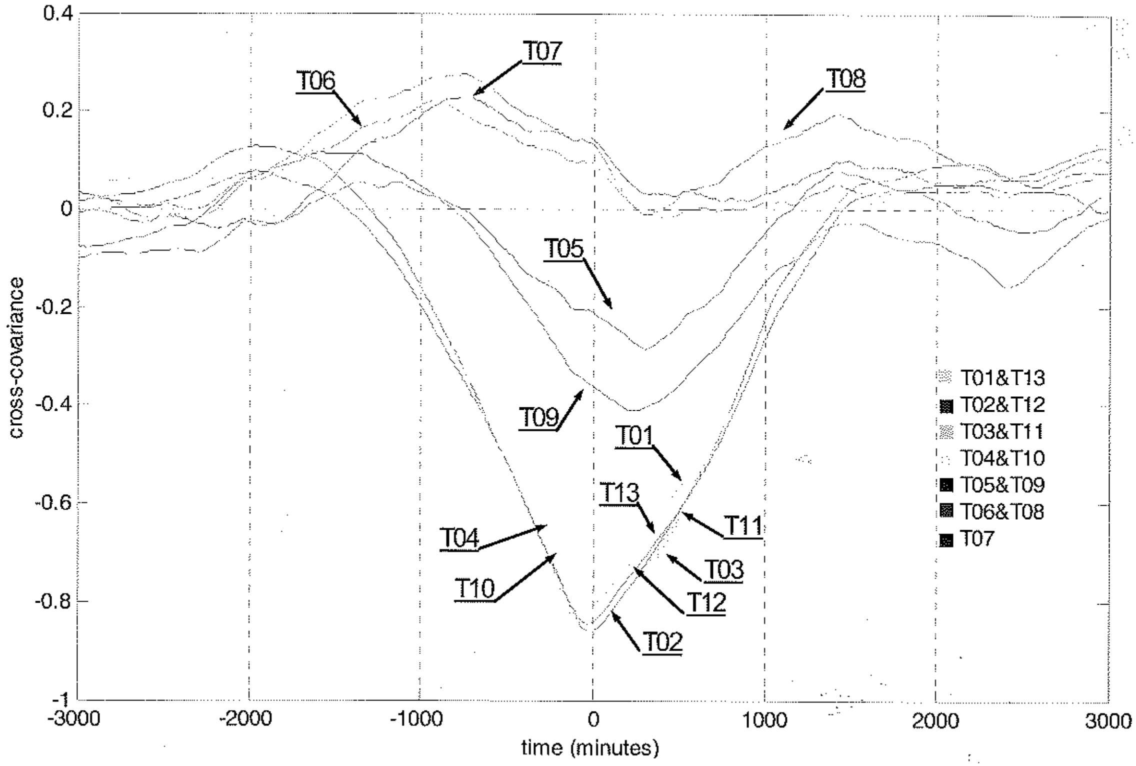

Figure 4. Cross-correlation between blast volume and above burden probe temperatures.

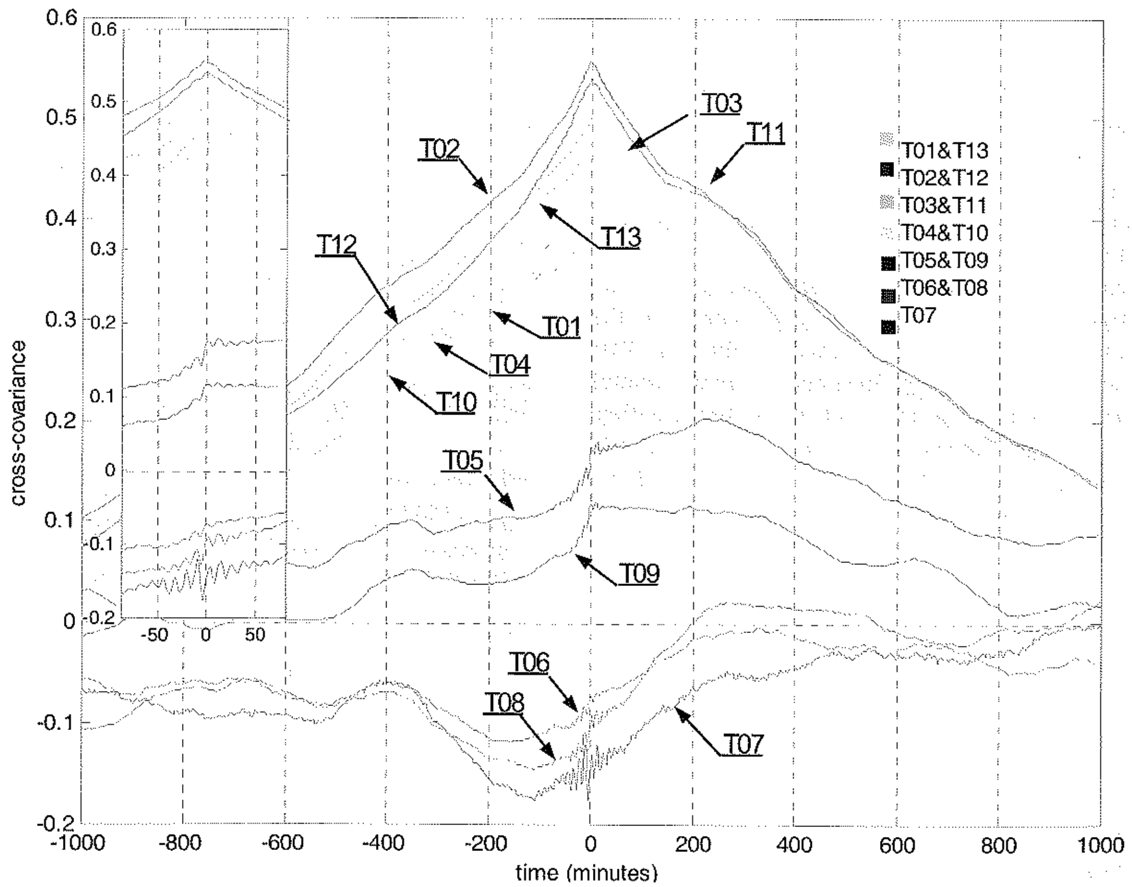

Figure 5. Cross-correlation between burden level and above burden probe temperatures.

cooling system that affects mainly these thermocouples. On the other hand, the mean value for central thermocouples is far lower than expected, near 500°C during normal operation.

Analysis of correlations and its meaning for the blast furnace operation. After this preliminary study, the collected data were also employed to analyse the correlation between the above burden probe temperatures and other relevant variables, obtaining, in such a way, useful information for the plant operator. For this purpose, the cross covariance for each thermocouple and the variables included in Table 1, groups B, C and E was calculated. In some cases, the results obtained yielded a poor correlation (e.g., the variables included in group E) and will not be presented here.

The cross correlation between two data sets $x(n)$ and $y(n)$, with M data each, is specified by the equation

$$r_{xy} = \frac{1}{M}\sum_{n=0}^{M-1} x(n)y(n-l) \quad l = 0,\pm1,\pm2,....$$

Therefore, if there are two signals with a cross correlation but with time lag, the maximum value of the cross correlation must be reached at l (lag between both signals).

So, the values at the y-axis can be positive or negative considering that the maximum of the cross correlation must be reached by a negative value provided that first the variables that are a cause and later the predictable effects are correlated, bearing in mind that the negative time is equal to the delay with which the cause works.

Cross covariance among temperatures for the thirteen thermocouples and the blast volume **(Figure 4)**. The thermo-couples located in the centre of the blast furnace throat show a weaker correlation than those located closer to the wall. Thus, the thermocouples T01-T13, T02-T12 and T03-T11 present a strong negative correlation with the blast volume. The delays of the thermocouple responses to changes in the blast volume vary between 20 and 50 min, according to the position of the minima. Although the correlations are poor, they present a maximum with a delay of around 30 hours.

Thermocouples T05 and T09 show a minimum in the non-causal part of the graphic. It is a broad peak and the reason for these results could be that the blast volume is increased after periods of abnormal blast furnace performance. Usually, during these periods, the blast and temperatures inside the furnace are reduced. After these periods the blast is again increased to be up to its set point. This means that these thermocouples located one meter and more from the blast furnace centre contain sensitive information on the thermal state of the blast furnace. These thermocouples, T05 and T09, present also a weak correlation maximum with a lag of 20 hours.

Finally, the three central thermocouples, T06, T07 and T08 show a rather poor correlation. This result was expected for several reasons:

a) These thermocouples are strongly affected by the cooling system
b) The blast furnace centre is more sensitive to changes than the periphery
c) The blast furnace centre is usually going during normal operation

These central thermocouples show a maximum with a lag comprised between 12 and 16 hours.

Taking all these results together, it is possible to conclude that the blast volume has two effects. For short periods, it tends to cool the blast furnace and, after a longer period, it heats the blast furnace, beginning in the centre and finishing at the periphery. One possible explanation is the smaller specific heat losses at higher production rates, so more energy has to leave the process with the gas.

Cross covariance among burden level measured by the stock rods* [12] *and probes temperatures. **Figure 5** shows the results, similar to the previous case. Again the results are clustered around three cases:

Thermocouples T01 and T04 and their symmetrical partners, T13 and T10, show a similar behaviour. They have a rather strong correlation with the stock rod signal and, as can be expected, their correlation is positive. This indicates that the gas arrives to the probes hotter when the burden goes down. There are no appreciable lags among these signals, which means that the response of the gas temperature to the burden level is very fast.

The results are still positive for thermocouples T05 and T09 but the correlation in this case is not so clear.

Thermocouples T06 and T08 exhibit a negative and very poor correlation. The strong effect of the cooling system and the faster gas temperature change in the blast furnace centre may again explain this behaviour. Another possible explanation is the redistribution of the burden that takes place after large slips, which often leads to a loss of the central working of the furnace (i.e., causes flat temperature profiles) as described in [13].

The centre of Figure 5 has been enlarged to show oscillations with a period of around 12 minutes. This one fits well with the charging rate and suggests the possibility of filtering the probe signals to eliminate the effect of the normal burden level changes.

Cross correlation among coke consumption and above burden probe data **(Figure 6)**. This correlation is strongly related to the results shown in **Figure 7** which presents the ***correlation with PCI***. Coke consumption and PCI have an inverse relationship (usually, when the PCI rate is decreased, the coke consumption is increased). Comparing both figures this relationship is observed. As far as PCI is the governing parameter, it is more interesting for our purposes to analyse the results in Figure 7.

Although the maximum values reached for the correlation between PCI and T06 and T08 are small, they show a peak with almost no lag, and this indicates the fast heating rate produced by PCI. The results for other thermocouples are not very significant, as far as PCI is correlated with other variables of the blast; in particular, an increase in PCI rate is related to an increase in blast volume. The response as the wall is approached tends to be less and, probably, is completely buried in the global effect of the blast.

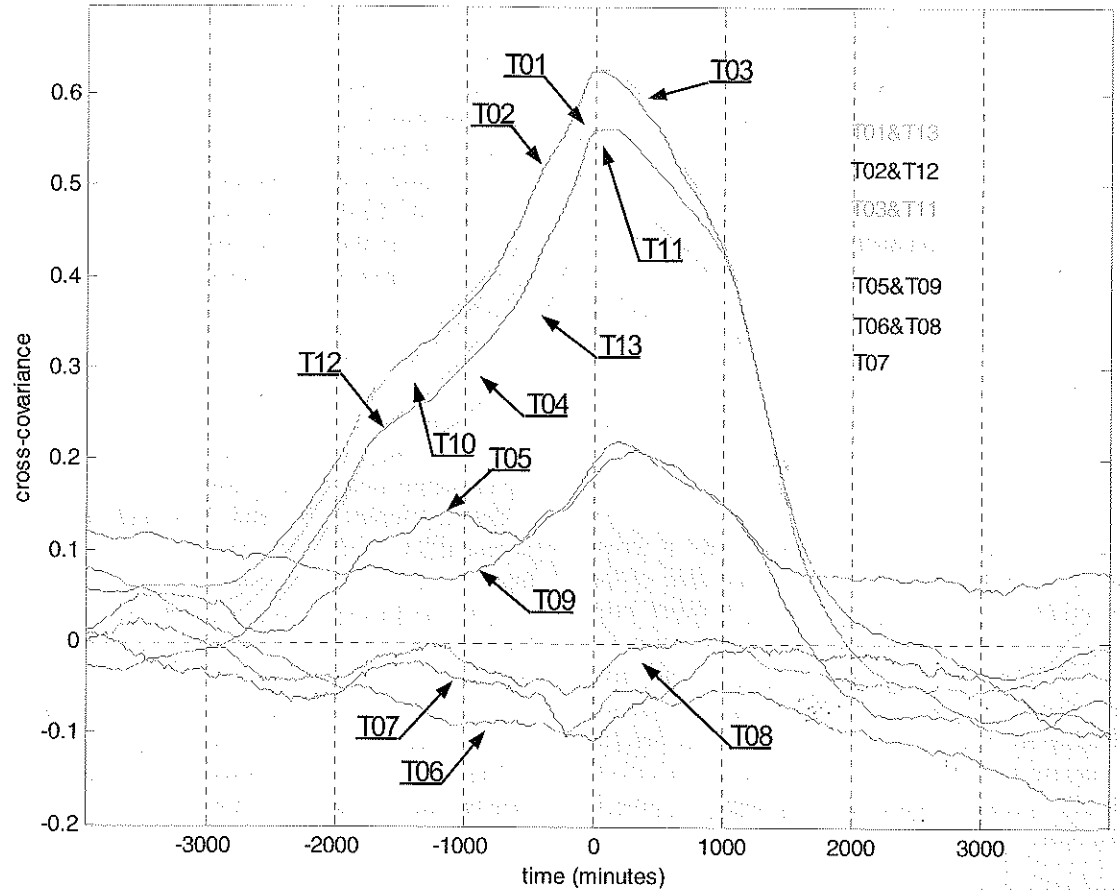

Figure 6. Cross-correlation between coke consumption and above burden probe temperatures.

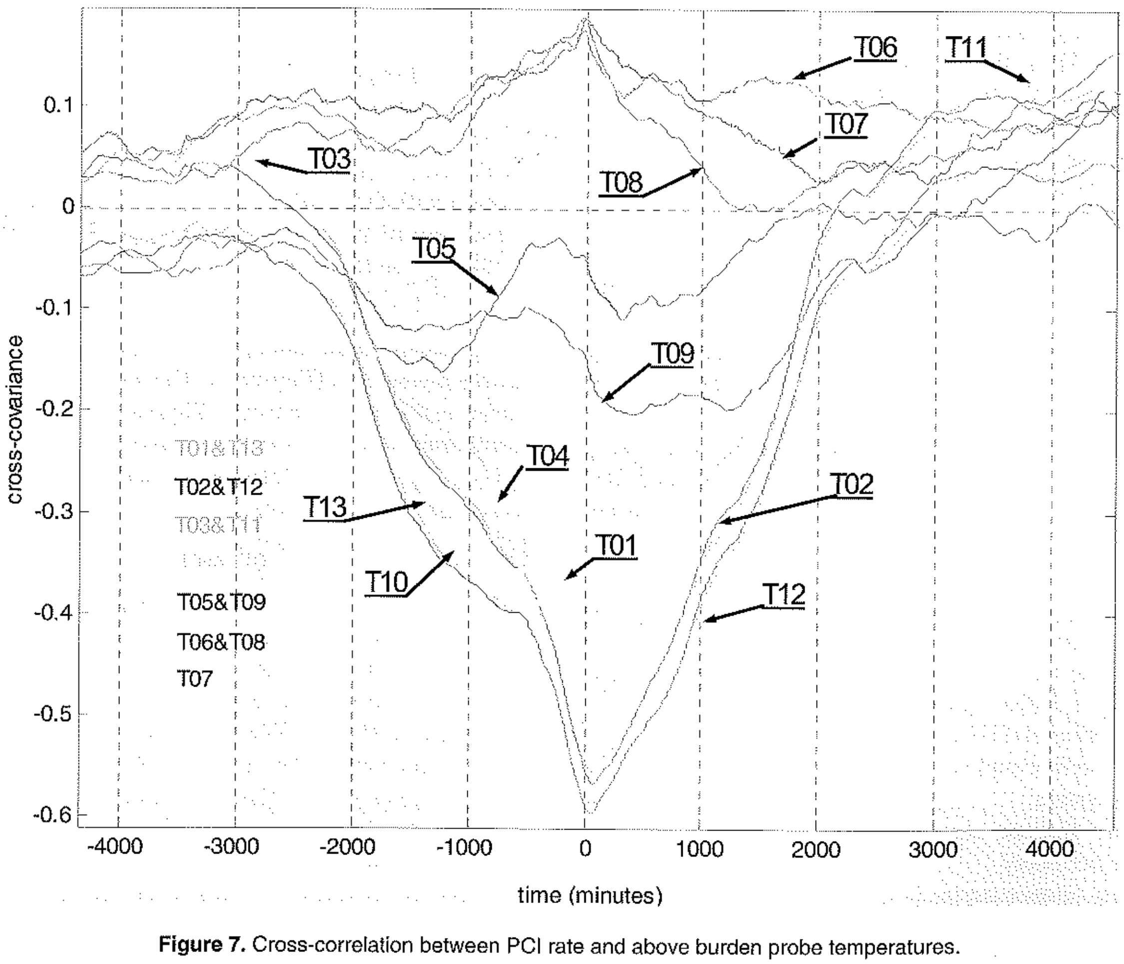

Figure 7. Cross-correlation between PCI rate and above burden probe temperatures.

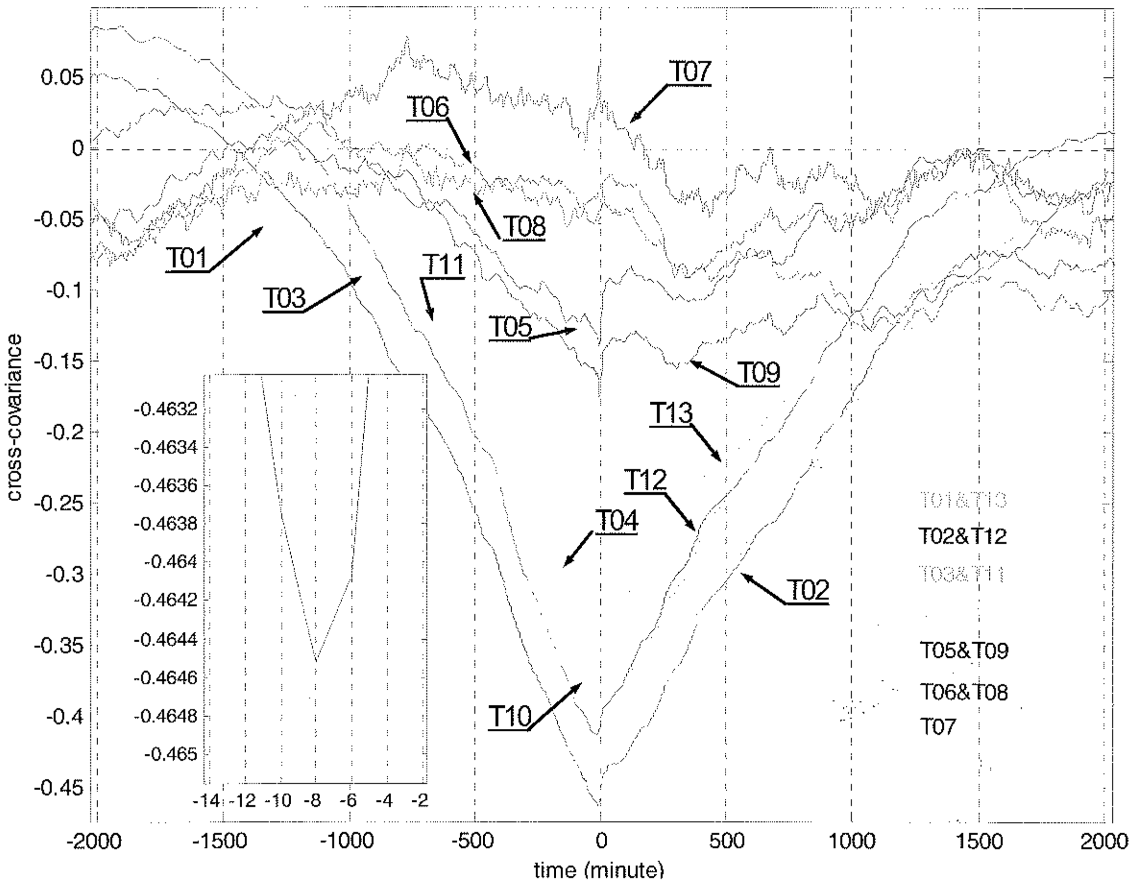

Figure 8. Cross-correlation between charging time and above burden probe temperatures.

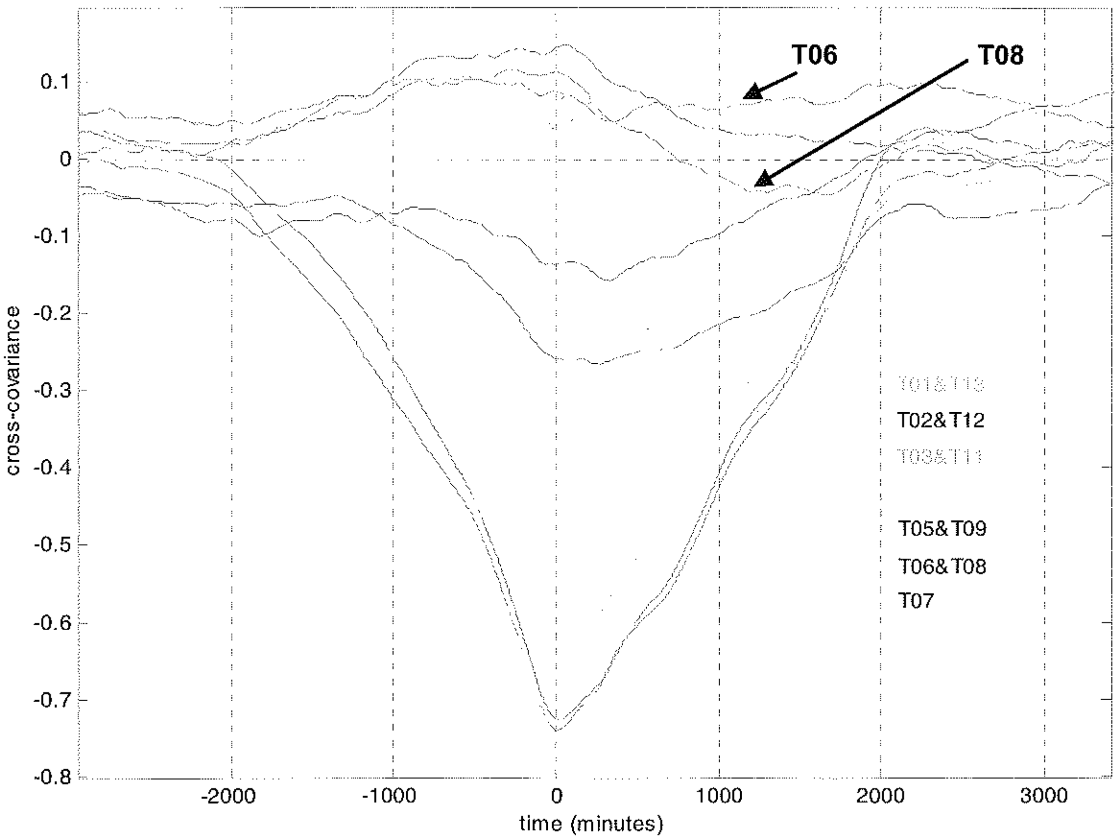

Figure 9. Cross-correlation between blast temperature and above burden probe temperatures.

Cross correlation among charging rate and above burden probe temperatures **(Figure 8).** As can be expected, the correlation is negative because the upper part of the blast furnace is cooled when the charging rate increases. This correlation presents a lag of 8 minutes, in good agreement with the minimum time to introduce a new burden. Another interesting feature is the sharp change just before the correlation peaks reflecting strong cooling promoted by the introduction of new cold burdens.

For thermocouple T07 there is a positive correlation for the same lags as mentioned above (8 minutes) [14]. Although it is an extremely weak correlation, it could be related to the local deflexion towards the centre suffered by the gas when a new burden is introduced into the blast furnace because, as far as the charging patterns employed tend to concentrate coke in the centre of the blast furnace to obtain a central coke column, the ore amount tends to be greater near the wall. This promotes a permeability decreasing near the wall and the subsequent deflexion of gas flow towards the centre.

Cross correlation among blast temperature and above burden probe temperatures **(Figure 9).** When we compare the results of this figure and those obtained for the blast volume, we see that both show similar features. In fact, blast temperature and blast volume are strongly correlated and this is the reason why a negative correlation is obtained for peripheral thermocouples. In the case of central thermocouples, T06 and T08, the raise in temperature shows a slightly faster response than in the blast volume case. However, no clear conclusion can be obtained due to the strong relationships among the blast parameters.

Concerning other relevant parameters such as moisture, hot metal temperature, silicon content, etc., no clear correlation has been obtained. Probably the reason is that there is a weak coupling between the upper part (throat and shaft) and the lower part (tuyere level and hearth) of the blast furnace. So the effects of the lower part when compared to the upper part are very slow and the correlation remains completely buried among the influence of other variables.

Neural Network for Data Reconstruction

Due to a strong effect of the cooling system on the temperature measured by the thermocouples located in the blast furnace central area [15], some information is lost. To remedy this, a multilayer perception neural network was designed and trained to rebuild the signal of this thermocouple. As inputs this neural network employs the value of the thermocouples located at both sides of T07, so the neural network has in total six inputs (T04, T05, T06, T08, T09 and T10). The single output would be the value of T07. To train the network, 'clean periods' in which the temperature profiles were not affected by the cooling system were employed.

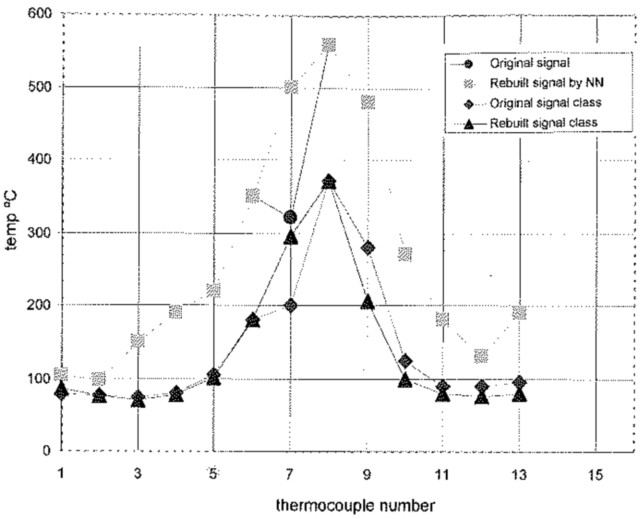

Figure 10. Rebuilding and reclassification of a profile affected by the cooling system (In the upper part of Figure the original signal and the rebuilt signal by neural network are represented. In the lower part, the lines represent the classes for the original and rebuilt signals).

Figure 10 shows the results obtained by the neural network for a particular case. As can be seen, the original profile presented a depressed temperature for thermocouple T07 due to the cooling system, decreasing the temperature value to almost 300°C, and the profile is classified in class 21 (see Part II of this series of papers). After being rebuilt by the neural network, a higher value is obtained for T07 according to the neural network training data, and the rebuilt profile is included in class 6. In the second part of this series of papers the neural network classification system will be explained.

Conclusions

The study carried out on the above burden probes signals has provided a deeper knowledge of their significance and their relationships to blast furnace performance. It has been established that observing the raw signals as they are delivered by the blast furnace probes is of little value for plant operators. Most of their information is buried in the complex relationships between them and other short-term and long-term perturbations.

The correlations involving the above burden probe temperatures and variables have a great influence on blast furnace performance. Their analysis gives the plant operator a great deal of information about the response of the blast furnace to several variable changes. This helps the operator to take subsequent decisions.

A neural network was built to successfully reconstruct the data information by the thermocouple located in the centre of the blast furnace in order to prevent loss of information caused by probe cooling.

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References

[1] S. L. Jämsä-Jounela: Current status and future trends in the automation of mineral and metal processing, Control Engineering Practice, 9 (2001), No. 9, 1021-1035

[2] H. Saxén, F. Pettersson: Nonlinear Prediction of the Hot Metal Silicon Content in the Blast Furnace, ISIJ Int. 47 (2007) 1732-1737.

[3] N. Nikus, H. Saxén: Prediction of a blast furnace burden distribution variable, ISIJ International, 36 (1996), 1142-1150.

[4] H. Saxén, N. Nikus, J. Hinnelä: Burden distribution estimation in the blast furnace from stock rod and probe signals, Steel Research, 69 (1998), 406-412.

[5] J. Hinnela, H. Saxen, F. Pettersson: Modeling of the Blast Furnace Burden Distribution by Evolving Neural Networks. Ind. Eng. Chem. Res., 42 (2003), 2314 – 2323.

[6] J. Hinnelä, H. Saxén: A neural network model of burden layer information dynamics in the blast furnace, ISIJ Int., 41 (2001), 142-150.

[7] XJ. Hao, F.M. Shen, G. Du, Y.S. Shen, Z.Xie. A blast furnace prediction model combining neural network with partial least square regression, Steel Research Int., 76 (2005), 694-699.

[8] S. Rajashekaran, G. A. Vijayalakshmi Pai: Neural Networks, Fuzzy Logic and Genetic Algorithms: Synthesis and Applications, Prentice Hall of India. (2003), pp. 1-456.

[9] A. B. Bulsari, H. Saxén: Classification of blast furnace probe temperatures using neural networks, Steel Research, 66 (1995), 231-236.

[10] F. Pettersson, J. Hinnelä, H. Saxén: Blast furnace burden distribution modelling with an evolutionary neural network, Proceedings of International Conference on Advances in Materials and Materials Processing (ICAMMP-2002), eds. Charkraborti, N. and Chatterjee, U.K., February 2002, Kharagpur, India, pp. 599-608.

[11] M. Konishi, Y. Otsuka, K. Matsuda, N. Tamura: Application of neural network to operation guidance in blast furnace, Third European Seminar on Neural Computing, London (1990).

[12] J. Hinnelä, H. Saxén: A system for interpretation of blast furnace stock rod measurements, Proc. of the 56th Ironmaking Conference, Chicago (1997), ISS, pp. 637-677.

[13] H. Saxén: Interpretation of probe temperatures in the blast furnace using polynomial approximations, Steel Research, 67 (1996), 73-78.

[14] Y. Omori (Ed.): Blast Furnace Phenomena and Modelling. The Iron and Steel Institute of Japan, Elsevier Applied Science, London, 1987, p. 376.

[15] H. Saxén: Simplified simulation of the transient behaviour of temperatures in the upper shaft of the blast furnace, Metallurgical and Materials Transactions B, 29B (1998), 691-697.

[16] R. Martín D., J. Mochón, L.F. Verdeja, R. Barea, P. Rusek, J. Jiménez: Temperature Data Probes Interpretation to Prevent Malfunction of Blast Furnaces – Part 2: Factory Applications. Steel Research Int., 80 (2009), No. 3, 194-201.