Above Burden Temperature Data Probes Interpretation to Prevent Malfunction of Blast Furnaces - Part 2: Factory Applications

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The application of neural networks to the interpretation of a large amount of data from blast furnaces is still very innovative in the steel and metallurgical industry. Contrary to the deterministic research which is based on mass and energy balances, as well as on chemical kinetics, the development of simulation in "black box" processes has strongly appeared as a consequence of the stochastic origin of the variables used. Specifically, this paper shows the application of neural networks to the processing of thermal information provided by the temperature measuring probes located at the furnace top, above the level of the ferric and reductant charge. As a result of this work, a computer tool as a user-friendly aid to the person in charge of the process was developed with the following information: (i) A tool that supplies a real time thermal distribution of the blast furnace gases which are properly classified (Operational Thermal Standards). (ii) It provides the system with alarms which prevent potential incidents (collapses/slippages) over an hour in advance of any incident. (iii) It guides the person in charge as to how to regulate the blast parameters in order to control the situation.

Keywords: Blast furnace; operating control; simulation; neural network; loading thermal standards

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Introduction

Scientific and technological progress is built on three pillars: experimentation, theoretical models and simulation. During the last century, experimentation and theoretical speculation have provided knowledge but nowadays scientists are giving impetus on obtaining knowledge from process simulation.

Specifically, knowledge by means of simulation can be differentiated into deterministic models and stochastic models. Recently, in the steel and metallurgic field, scientists have been interested in developing research based on Neural Network (NN) [1,2]. These considerations give us a chance to state that steel industry is a modern science and technology which is able to take advantage of the most avant-garde knowledge, rather than a group of obsolete practices.

Over the last few years, there has been an exponential growth in the number of control parameters in the steelmaking process. It has passed from only a few data to a large amount of variables in the process. Precisely, nowadays, there is a paradox with the number of variables as the person in charge of the installation often gets confused, rather than frequently informed. Modern computer systems, together with NN, however, help us to build data bases which supply us with the information about the evolution of the most important variables in the process [3-5].

Inside the blast-furnace stack, the aim is to manage a uniform drop in the charge. In this part of the blast furnace, the softening of the ferric charge takes place (with the corresponding loss of porosity), while the high quality reductant coke layers let the reductant gases flow (coke slits). It would thus be interesting to know the temperatures inside the charge in that zone of the blast furnace. However, in real time, it is impossible to obtain experimental thermal data in that zone. The only alternative is to use gas temperatures at the blast-furnace top by means of probes located above the charging level, in order to acquire an indirect knowledge about the materials in the cohesive zone [6].

In this paper, it is attempted to use the temperatures provided by the above burden probes in order to obtain information by means of an appropriate neural network as to optimize the conditions for the drop in the blast furnace temperature [7-10].

The speed rate in the drop is the reason for the scaffolding where a large quantity of material is hanging thus totally or partially blocking the uniform drop of the material loaded at the blast furnace top. Indirectly, this drawback can be detected thanks to the corresponding computer alarms which have been installed as a result of the NN analysis of the thermal data from the blast furnace top, and the development of the corresponding loading thermal standards for the blast furnace which have been studied [11,12].

In this paper, a neural system has been prepared so that, when it is installed in a blast furnace, it can alert the person in charge of the process to the potential risk of a load collapse more than one hour in advance.

Classification using Neural Networks

The above mentioned temperature profiles can be classified according to their particular shape. A neural

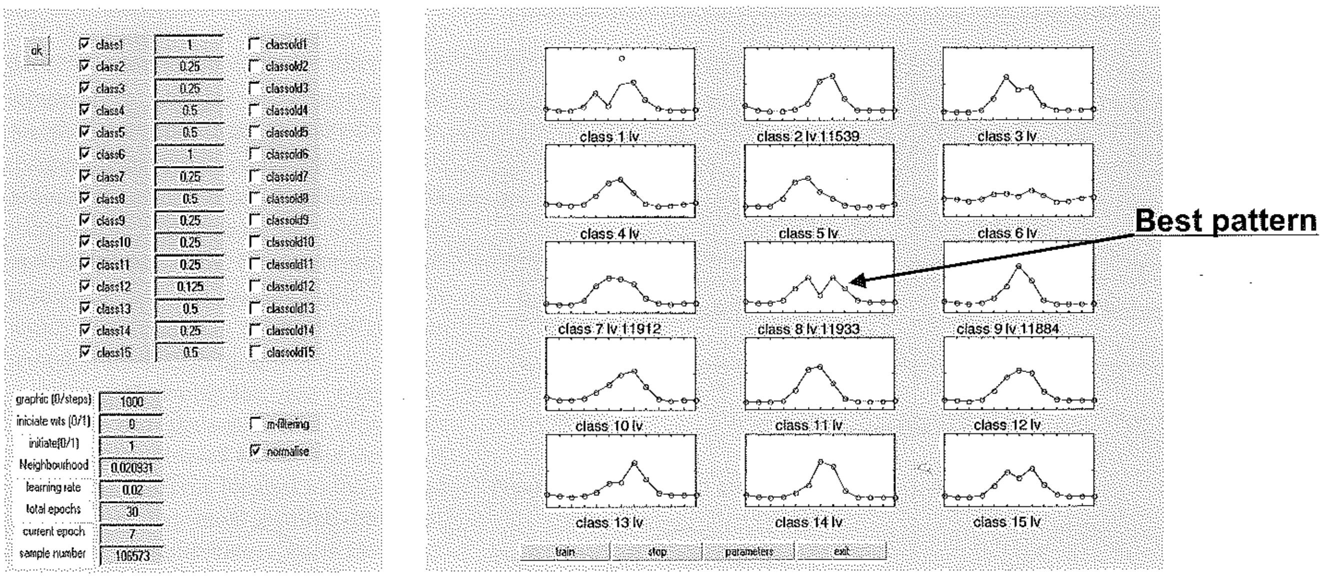

Figure 1. Neural network training program's user interface.

network is a useful tool to classify the signals from above burden probe temperatures; each class being represented by a pattern, which is a profile created by the neural network during the training process [13].

Measurements from the thermocouples of above burden probes were arranged in a 13-D array, one for each thermocouple installed in the above burden probes, that is, one coordinate for each temperature sample. These arrays, $\vec{P}$ = (T01, T02, T03, T04, T05, T06, T07, T08, T09, T10, T11, T12, T13), were employed during the neural network training and validation, after standardisation.

Offline and online training. The neural network training program was designed specifically for above burden temperature profiles, keeping in mind the results achieved during the study of the variables described above. Two additional signals were employed as program control signals, an on/off signal and the stock-rod signals, allowing the program to accept or reject temperature profiles for training. The profiles are only accepted if the blast furnace is working and if the burden level is between 0.5 to 1.0 meters (from the nominal stock line level). The reason for these limitations is derived from the effect of burden descent on temperatures profiles. Temperatures related to stoppages are of no interest.

The left side of **Figure 1** shows the training parameters selected by the user during the training period and the factors that modify the learning rate for the corresponding neuron. Each neuron can be trained at a different learning rate. This prevents oscillations when the classes are reaching their final solutions.

The right side of Figure 1 shows the evolution of the patterns obtained during the training so that they can be inspected by the user. The windows can be refreshed every time a new sample is put in the program, and the best pattern is presented in red (in this case class 8 – column 2 - row 3) and below each pattern the time expended on it.

Analysis of Patterns obtained

The previously described program was employed extensively to obtain final shapes and representative patterns in order to decide the total number of patterns to be employed for training and validation purposes. To that end, a large number of trials, with the number of patterns varying from 6 to 30 were performed. After examining the results, a set of fifteen patterns were selected as these yielded the best results (**Figure 2**).

A study of these patterns shows that several of them have a very similar shape. As far as the neural network is based on Self Organising Maps (SOM), patterns of temperature profiles that have a similar shape but a shifted position are classified as different.

To obtain a clearer image of these, it is useful to perform some kind of interpolation among the temperatures obtained for the patterns. In this case a cubic spline interpolation was used. This allows estimating us the position of maximum temperature. **Figure 3** shows an example of cubic spline interpolation for classes 1, 5, 3 and 6. The straight lines represent the results of the interpolation showing the actual position of the temperature peaks.

After performing the interpolation, the patterns can be easily compared. Some of them are very similar and the main difference is the asymmetric position of the maximum temperature. This effect should be related to an asymmetric gas flow. Slight asymmetries are detected by the neural network and classified in different patterns but it is necessary to preserve this number of patterns because a lower number of them leads to errors in temperature classification.

Furthermore, it is necessary to regroup the classes obtained in order to relate them to the blast furnace state. From the obtained results, the previous fifteen classes can be regrouped in five major classes.

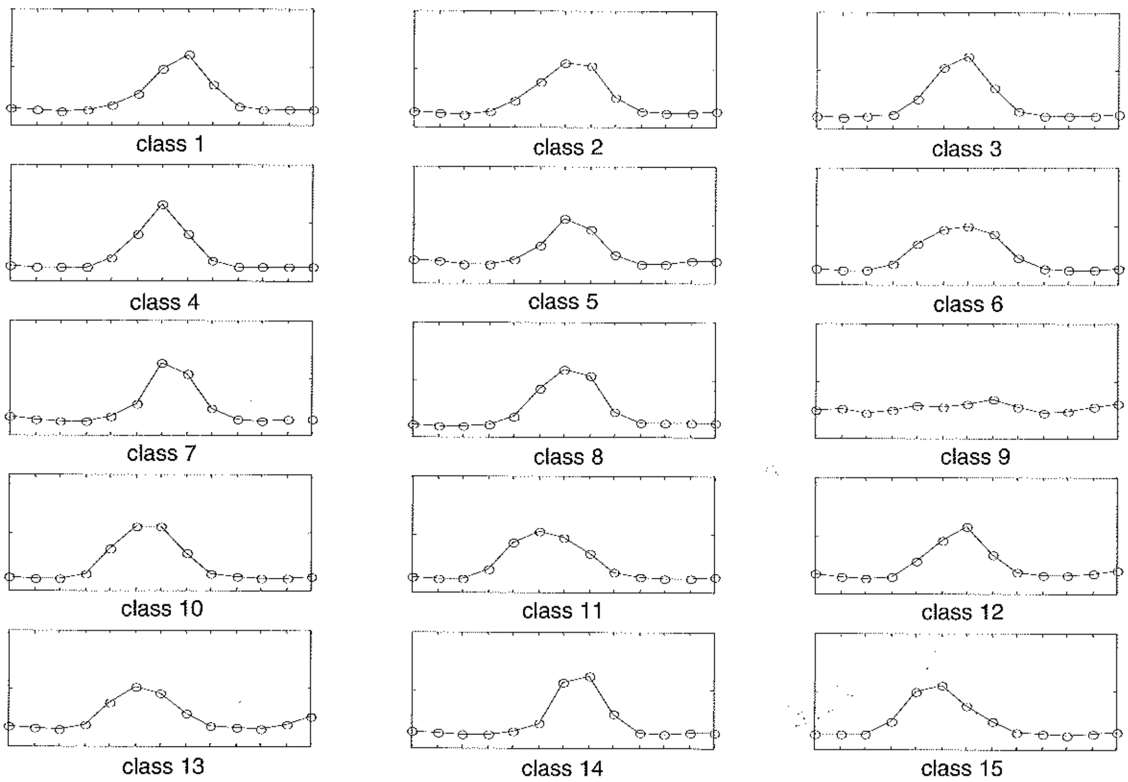

Figure 2. Patterns obtained by self organizing maps (SOM) training.

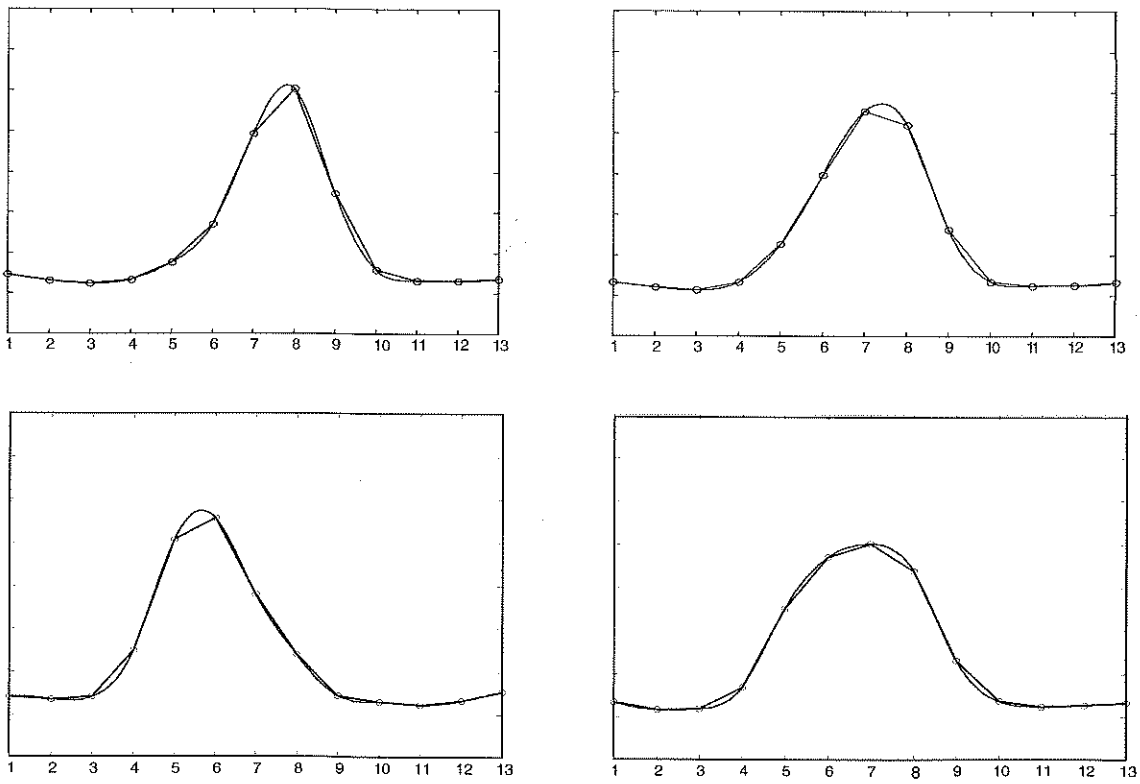

Figure 3. Example of cubic spline interpolation for classes 1, 5, 3 and 6; numbers 1 to 13 indicate thermocouples.

Table 1 shows these five major classes in addition to the previous classes. **Figure 4** shows the first of these major classes. All the now regrouped patterns are put in relation to stable blast furnace performance with high productivity and a strong central gas flow. This result was expected because the blast furnace used for the present work is usually operated with a high amount of central coke due to a high PCI rate, the current state of blast furnace walls and the low alkali content in ores employed in the burden that avoid scaffold formation.

It is important to highlight that the patterns were obtained after the temperature profiles were normalised. As the gas flow may be asymmetric, temperatures measured by the probes are projections of the three dimensional gas temperature distributions over the probes' plane. Thus, the most important feature is not the peak height but its width thus reflecting a larger or smaller temperature distribution.

After performing the new classification, the old patterns were reordered, with similar classes being put together (**Figure 5**). Patterns located in the central column are the most centred patterns; their highest temperature is located very close to the thermocouple no.7. Patterns located in the right column have their highest temperature shifted to the right and patterns located in the left column have their highest temperature shifted to the left, except for the last one representing the class related to stoppages, put in this position arbitrarily.

Therefore, the patterns related to a central flow and a stable situation have been located in the upper part of Figure 5. Moving downwards, the patterns represent situations with less central gas and, in general, a less stable state. This new distribution allows the operators to follow the transition and easily check the blast furnace state via the use of intuitive traffic light-like colours.

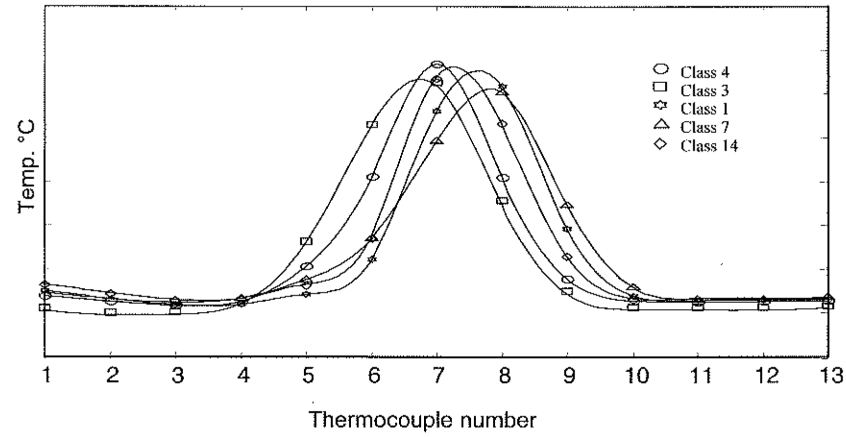

Figure 4. Major class 1 grouping classes 1, 3, 4, 7 and 14.

Table 1. The five major classes.

Class number	Previous classes
1	1 – 3 – 4 – 7 - 14
2	8 – 10 - 2
3	6 – 11
4	5 – 12 – 13 - 15
5	9

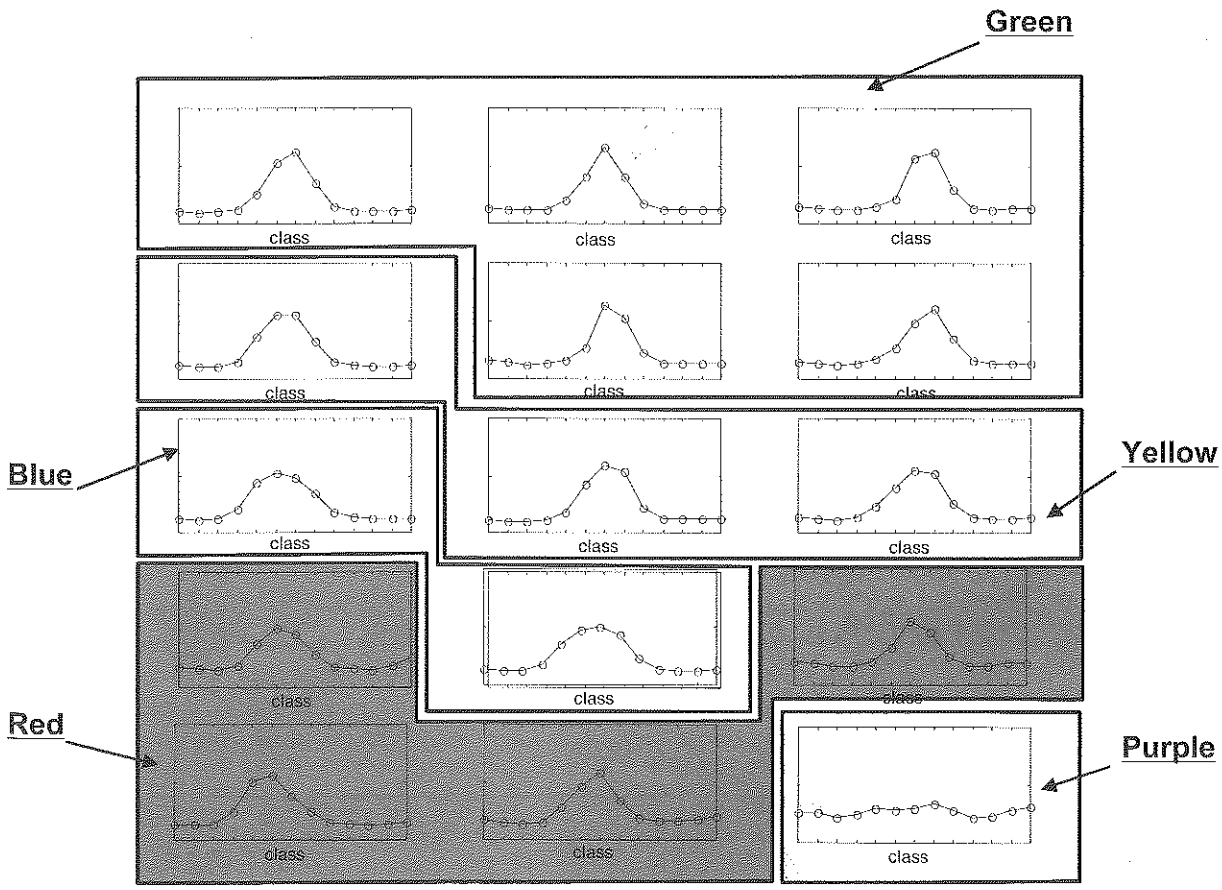

Figure 5. Classes reordered by similar shape, according to their major class. (Green: major class 1, yellow: major class 2, blue: major class 3, red: major class 4 and purple: major class 5)

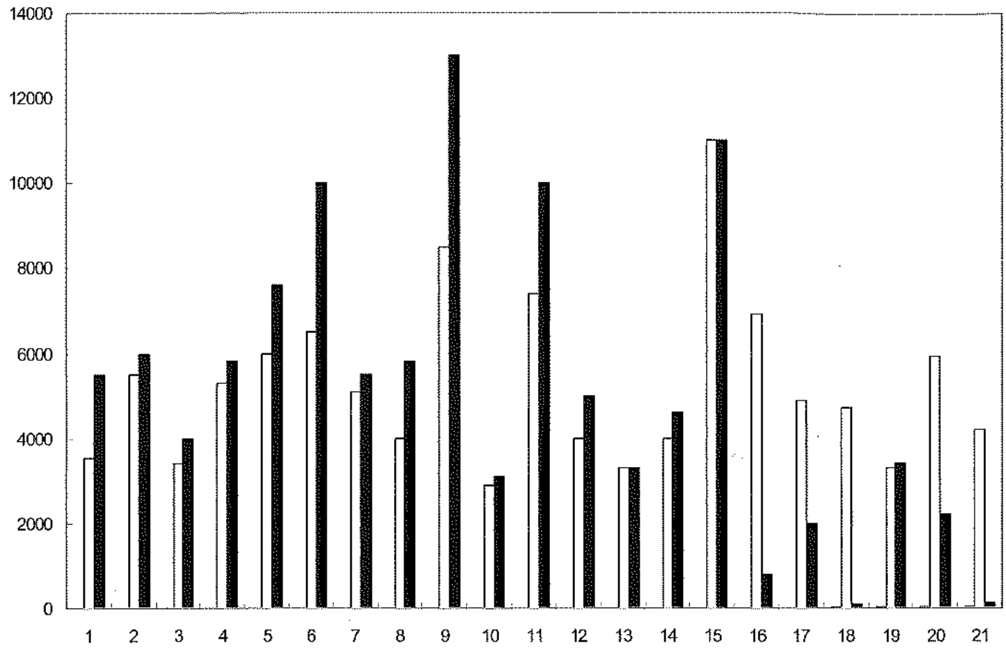

Figure 6. Statistical distribution of temperature profiles according to patterns; white: original signals; black: signals after rebuilt M-shaped patterns.

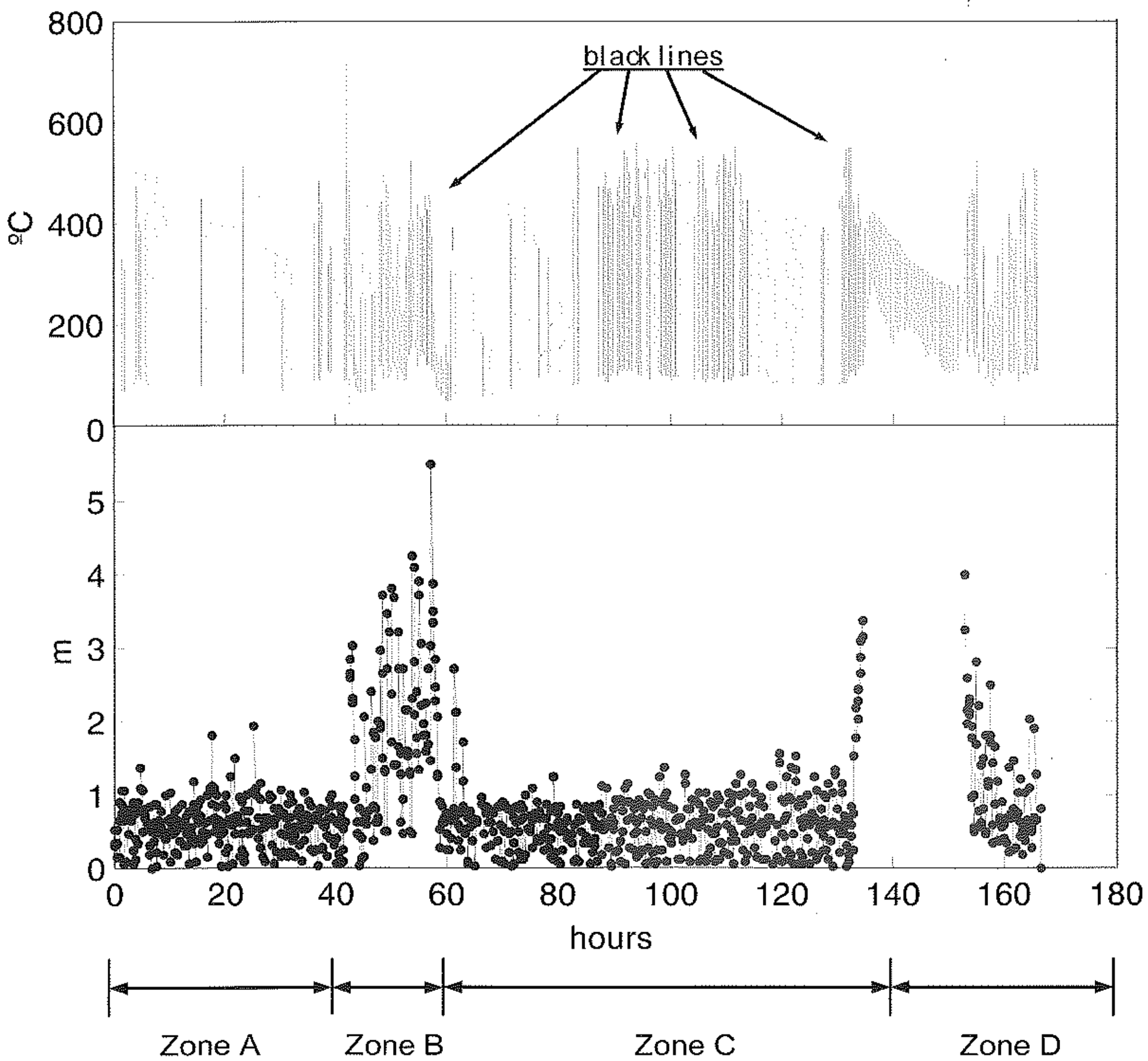

Figure 7. Classification of above burden probe temperatures for a long period of blast furnace performance. Comparison with stock rod signals.

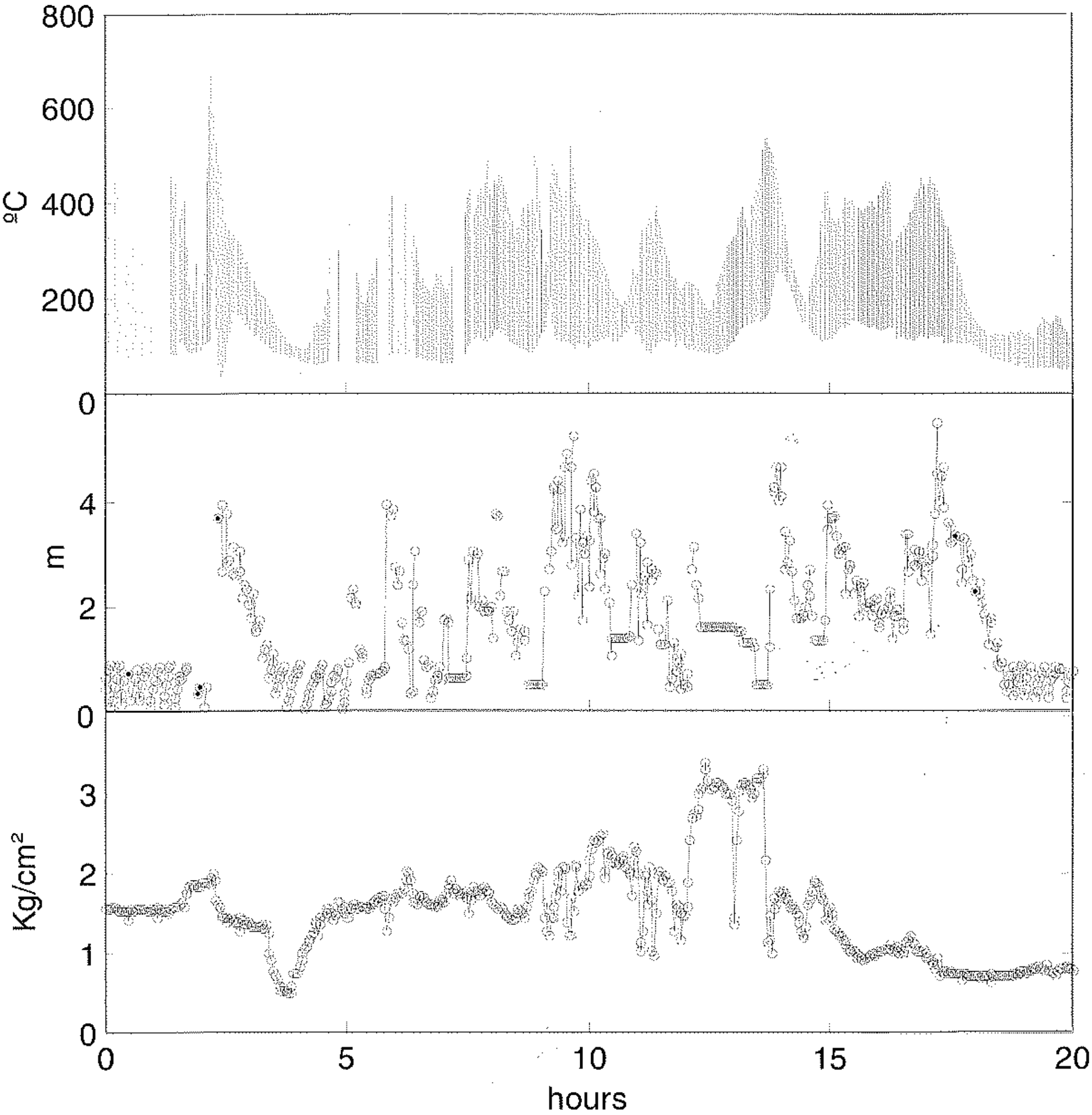

Figure 8. Classification of above burden probe temperatures in Zone B. Comparison with stock rod signals and pressure drop between tuyeres and throat.

Model Validation

Once the classes' final form was established, a program to analyse the available data was developed and used extensively. A systematic analysis allowed the definition of the relationship between the patterns and blast furnace state. As a summary of the results obtained, **Figure 6** shows a bar diagram with the classification performed by the neural network for a period longer than one year. The bright bars (left bars) represent the classification performed for the original signals by the Self-Organising Map. The black ones (right bars) represent the classification performed for the same signals after rebuilding those profiles affected by the cooling system. (This process was explained in the first part of this work, [16]). Classes 16 to 21 are special classes for M-shaped profiles. The number of remaining M-shaped profiles was reduced dramatically after the signals were rebuilt.

The statistic shows how the patterns related to normal blast furnace performance are more frequently obtained.

The above performed description generally fits well with the present blast furnace performance and the temperature classification made by the neural network allows for description of the blast furnace state and, in some cases, the forecasting of hangings and collapses. As an example to illustrate this, a period of irregular blast furnace performance has been selected and the obtained temperature profiles have been classified employing the developed model. The upper part of **Figure 7** shows the temporal evolution of above burden probe temperature profiles during the selected period. A single vertical line represents each temperature profile, covering a period of 180 hours. Each one is coloured according to the pattern to which it belongs. The black lines represent temperature profiles altered due to the probe cooling and are useless because the information has been destroyed (M-shape profiles).

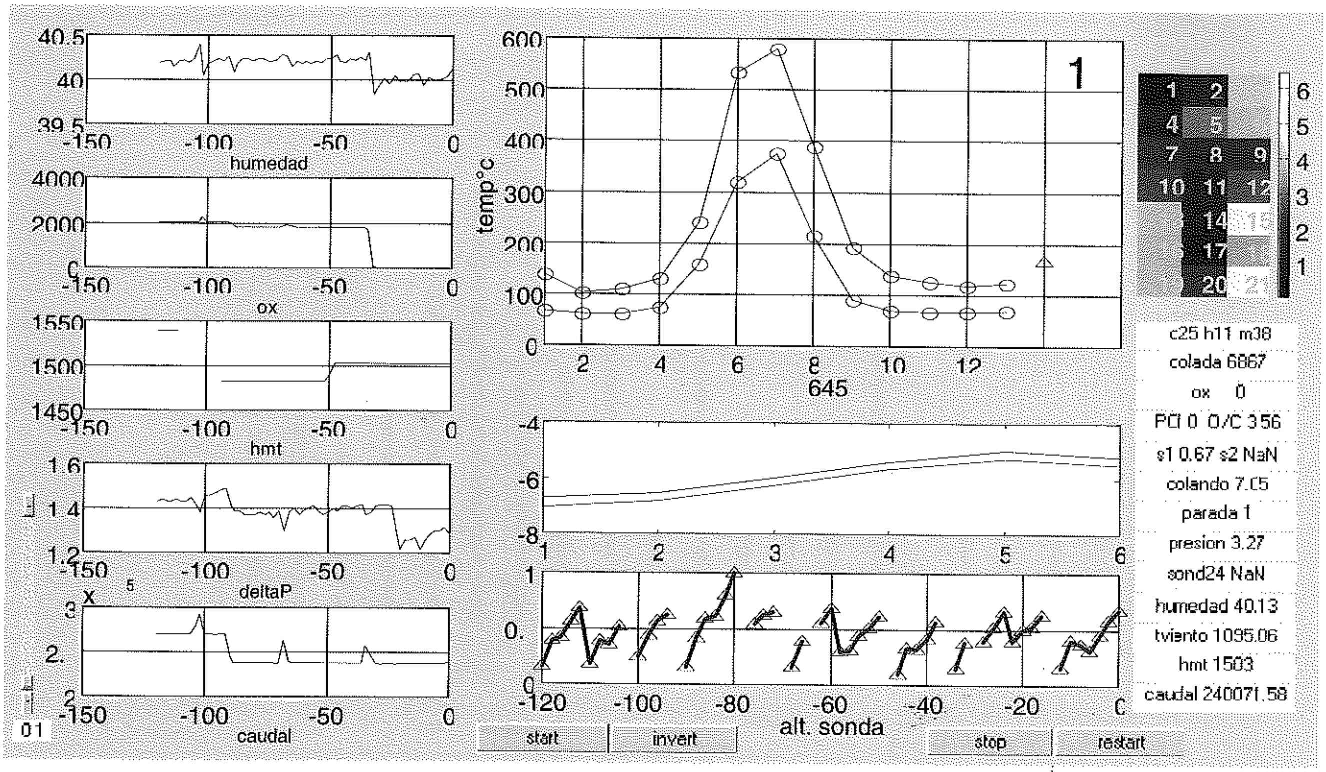

Figure 9. User's interface of validation program.

In the lower part of Figure 7 the stock rods are represented in order to compare them with above burden probe signals. There is a stock rod change employed at 90 hours where a slight shift in the burden level can be observed. This height difference could be the reason for the slight asymmetry shown for the above burden temperature profile.

It is possible to divide the represented period into four different zones.

Zone A (0 – 40 hours): The zone begins with a stable situation. After that, a less stable period takes place which is also reflected in the stock rod signal showing some slight slips.

Zone B (40 – 60 hours): A zone with high instability. Major hangings and slippage take place during the entire period, which must be studied in more detail.

Zone C (60 – 140 hours): A stable zone. The descent of the burden is regular, as can be seen in the lower part of the figure.

Zone D (140 – 180 hours): indicates a programmed blast furnace stop with the subsequent start. After the blast furnace re-start, the profiles indicate that the blast furnace has not reached its normal performance yet.

In **Figure 8** Zone B has been expanded. In the lower part of the figure a new plot representing the pressure drop between tuyeres and throat has been added. This period begins with two hours of normal blast furnace behaviour. After that, the burden suffers a slip. The stock rod shows that something abnormal is also taking place. In particular, the last stock rod signal appears to be stopped just before the slip. The pressure drop undergoes a sudden rise before the slip and goes down after it.

Note that the lines representing classes turn up almost one hour before the first major slip takes place, providing an early warning about the abnormal blast furnace behaviour which will take place shortly. After approximately seventeen hours, the last slip takes place and the blast furnace begins to slowly recover.

The characteristic gas temperature pattern after a slip is a sudden jump of the top gas temperature followed by a gradual decrease caused by the frequent charging needed to recover the stock level [14]. During this period, the burden distribution control is lost (due to the longer trajectories of the falling burden) with a flat temperature probe profile as a result [15].

Tool for On-line Probes Interpretation

As a complementary part of the present work, a software platform was implemented to classify temperature profiles and to analyse the other blast furnace parameters. It was designed to work in both on-line and off-line mode, taking data from either the blast furnace process computer or from a data file respectively (**Figure 9**).

A complete set of blast furnace parameters are presented on the screen in order to compare and study their evolution. Furthermore, other information such as blast moisture evolution over time, oxygen enrichment, hot metal temperature, pressure drop between tuyeres and throat and stock-rod during the two previous hours are graphically shown. Some other data are presented in numerical format, such as time, number of tapping, PCI and ore/coke rate. Working on-line, the program refreshes data on the screen every two minutes, and in the off-line case, reads new data from a data file.

Conclusions

The study carried out on the above burden probe signals has allowed us to gain 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 not of significant interest to plant operators.

In this work it is put forward that every time a new temperature profile is obtained from the above burden probes, it is classified and, subsequently, a valid diagnosis --which is useful to the plant operators- on the blast furnace performance is made, using a traffic light-like method. At the same time it is possible to forecast hangings and burden collapses more than one hour in advance.

A new user-friendly tool for above burden probe interpretations, based on the above mentioned research and allowing the plant operator to obtain not only the bare probe signals but also an initial interpretation of their meaning, was also developed.

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