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A New "User-friendly" Blast Furnace Advisory Control System Using a Neural Network Temperature Profile Classifier

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The adaptation of blast furnaces to the new technologies has increased the operation information so that the sensor information can be known at every moment. However this often results in the supply of excessive data volume to the plant operators. This paper describes an industrial application for self-organized maps (SOM) in order to help them make decisions regarding blast furnace control by means of pattern recognition and the matching of temperature profiles supplied by the thermocouples placed on the above burden. The classification of patterns *via* easy color coding indicates to the operator what the blast furnace operational situation is, thus making the necessary corrections easier.

KEY WORDS: ironmaking; blast furnace; neural networks; self-organized maps (SOM); forecasting.

1. Introduction

In recent years, artificial neural networks have proved their great usefulness in solving a significant number of complex classification problems with many variables involved. However, the cost reduction of the sensors with the modernization of industrial factories has yielded a huge volume of data that has to be processed and analyzed. It seems reasonable to implement neural network-based applications where some kind of automatic classification of data is required. The neural networks are well known in computer vision and pattern matching areas. In this paper the use of neural networks as blast furnace forecasting aids using above burden temperature evolutions is proposed. Although their use in the iron industry is not new, most authors use neural networks to predict with a multilayer perceptron (MLP)[1–6] while others prefer a radial basis function (RBF).[7,8] Only a few references using neural networks to make a qualitative classification of data[9] can be found along with proposals to use them to recognize patterns in the iron making process.

This paper explains how to create a temperature classifier with a neural network which would serve as a visual aid to the plant operator while speeding up data treatment. Section 2 describes the studied variables which are used in the problem and their statistics. Next, the choice of the neural network along with its properties, training and learned patterns are detailed. Section 3 shows a graphical user interface developed using a neural network. After that, the next section presents the observed correlation between the pig iron temperature and the top gas temperature class given by the neural network, which would be useful for plant operators. Finally, the paper discusses the results and conclusions obtained in this work.

2. Problem Statement

A blast furnace is a complex industrial system where a large number of variables are monitored through hundreds of sensors placed throughout the plant. In this case, the variables in which we are interested are the above burden and the pig iron temperatures. These variables have been chosen because the obtaining of a proper profile of top gas temperature determines the quality of the pig iron and provides an efficiency indicator of how the blast furnace is working. **Figure 1** shows the statistics of the top gas tem-

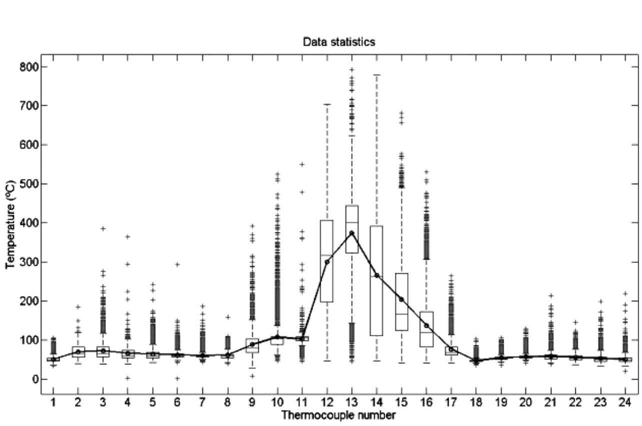

Fig. 1. Data statistics of the top gas temperature profiles in a blast furnace.

perature data. This temperature is measured each hour by means of two probes, each containing twelve thermocouples. The probes are identical and their anchorages are located in the wall, describing a diameter of the blast furnace section, so the expected behaviour would be a symmetrical temperature profile. However irregularities in the feeding processes, in the load composition and some other factors like cooling yield asymmetric profiles. Besides that, a great dispersion of the data, with many outlier samples, is confirmed. This dispersion (above all in the central thermocouples) is due to the feeding rotational movement so the load is not at the same level at every point. The cooling system acts upon the central zone of the blast furnace if the temperature exceeds 450°C, which may cause an M-profile like that of **Fig. 2** and contributes to the dispersion of the data.

Figure 3 shows the pig iron temperatures measured in the blast furnace with their mean and standard deviation. The pig iron temperature should remain over 1 450°C from the time it leaves the blast furnace until it is processed in the plant to make iron, this being due to the risk of undesirable reactions between compounds that would yield poor quality iron. This is a big problem in the industry so a lot of effort has been put into improving it.[10]

The main objective of using a neural network is to supply useful information to the plant operators. This information must be displayed quickly and in an easy to understand format because an excessive amount of information is overwhelming to plant operators, and therefore useless. In neural networks, each neuron learns a different pattern during training, even if most of them are quite similar to others. In order to avoid excessive information due to the use of a high number of neurons it is necessary consult seasoned plant operators, whose knowledge based on their experience serves to classify all these patterns into two or three classes. Three classifications can be compared: one based on the plant operators' knowledge, the neural network classification and a third, based on the criteria detailed in **Table 1**, which is purely mathematical but real and commonly used. In later sections we will demonstrate that the classification made by the neural network helped by the plant operator is the most powerful. Mathematical criteria turned out not to be a good choice due to its inflexibility; the working process of a blast furnace cannot be modelled and classified by only a couple of rules. Its ability to generalize is very limited.

These classes summarize the top gas temperature profiles in 6 common blast furnace working situations :

Optimum: The blast furnace works smoothly. The burden is well-balanced (the iron ore is located close to the wall and the coke is located in the centre) which allows the attainment of the highest temperature in the central zone of the blast furnace. Moreover, the burden has sufficient porosity to allow gases to keep zone temperatures between 300–450°C (see **Fig. 4**).

Near-optimum: The blast furnace works very well. The highest temperature is still around 300–450°C. It is not in

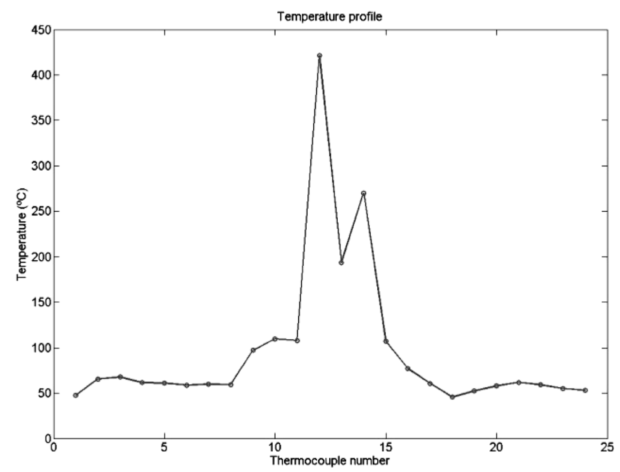

Fig. 2. M-profile caused by the cooling system.

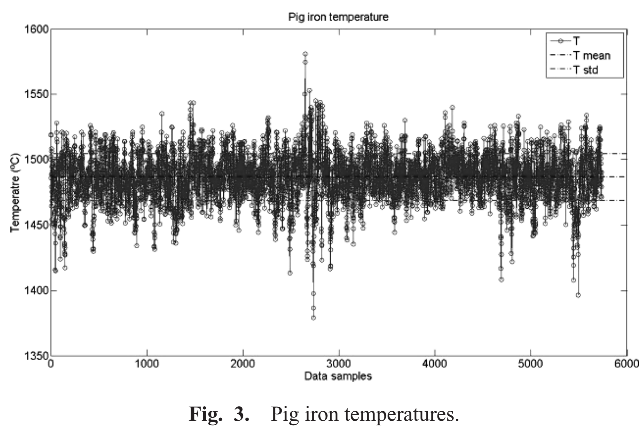

Fig. 3. Pig iron temperatures.

Table 1. Mathematical classification criteria for the learned patterns.

Profile	Temperature		
	450ºC-300ºC	300ºC-200ºC	< 200 ºC
Central	Optimum	Good	Regular
Highest Temperature: right deviated	Near-optimum	Not good	Poor
Highest Temperature: left deviated	Near-optimum	Not good	Poor
Right feeding	Near-optimum	Not good	Poor
Left feeding	Near-optimum	Not good	Poor

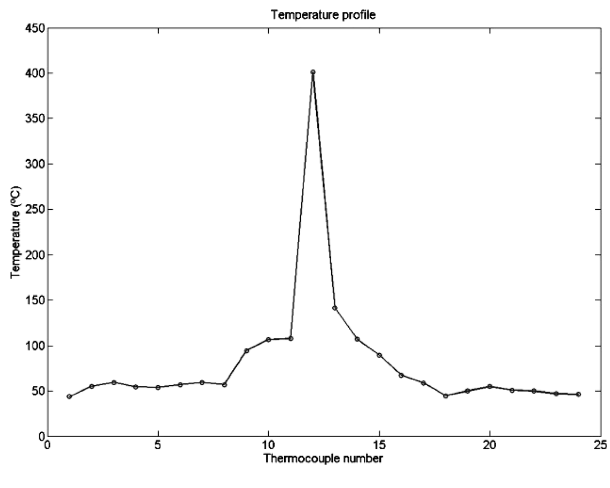

Fig. 4. Pattern of the class Optimum.

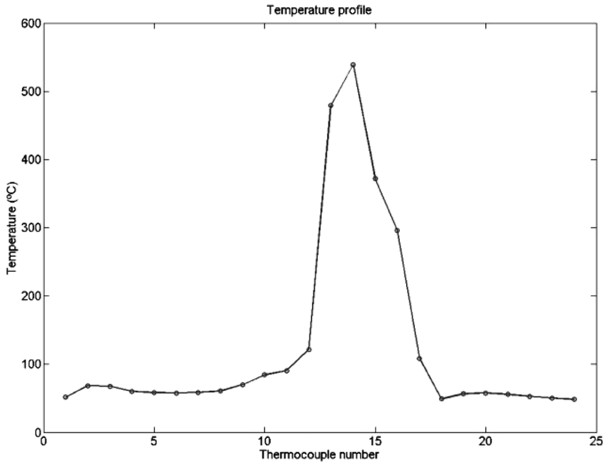

Fig. 5. Pattern of the class Near-optimum.

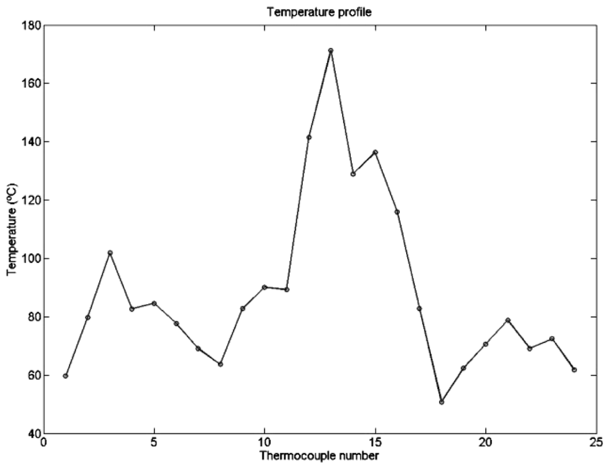

Fig. 6. Pattern of the class Regular.

the central part but deviated towards the wall. The burden feeding process has perhaps been asymmetric and abnormal heating close to the wall is taking place (see **Fig. 5**).

Good: The blast furnace works well, with the highest temperature in the central zone, although it is quite low (300–200°C).

Not good: The blast furnace doesn't work well. The burden is placed close to the wall and the temperature is lower than 300°C. It is time to set corrective actions into motion.

Regular: The blast furnace works badly. The temperature is very low (<200°C) although highest in the centre. The pig iron will have an inferior quality (see **Fig. 6**).

Poor: The blast furnace works really poorly; it is out of control. Top gas temperature is under 200°C and there are feeding problems that deviate the temperature peak. The quality of the pig iron will be poor.

In general, coke must be loaded in the centre area in order to reach a temperature around 450°C whereas the iron ore must be loaded near to the wall. If the coke is placed close to the wall, the highest temperature will be low and the measurements made by those thermocouples nearest the wall will increase.

According to this classification, the whole data histogram used is showed in **Fig. 7**. As we can see, the highest number of temperature profiles belongs to the 'Optimum' and 'Near-optimum' working situations. Only a very small quantity of samples belong to malfunction situations; due perhaps to technical problems, an incorrect feeding pattern or to a scheduled shutdown cooling. This is important because the neurons may win with data from different classes, making it possible to assign the "Optimum class neuron" label if that class of data is found among its wins. As there are many more "Optimum" than "Poor" class data, the probability of having a neuron of this class ("Poor") is small. The solution to this problem is explained in Sec. 3.2.

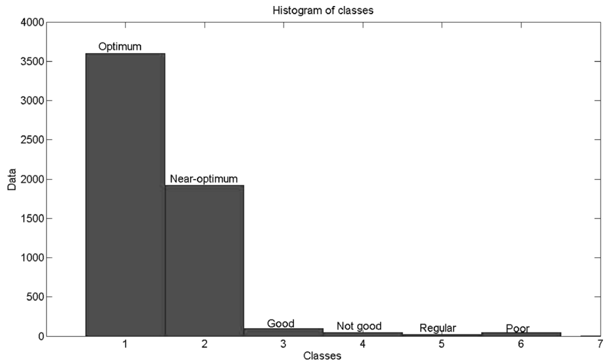

Fig. 7. Histogram of the classified temperature profiles.

3. Classification by Unsupervised Neural Network

The use of neural networks for forecasting is not new, although its use in the ironmaking industry is quite limited. On the one hand, the use of a multilayer perceptron (MLP) as the neural network, trained with an empirical model in order to forecast the values of some blast furnace variables[2,3,6] is suggested. On the other hand, Mochón *et al.*[9] propose the use of a self-organized map (SOM)[11] to classify the patterns obtained from the temperature profiles.

3.1. Choosing a Neural Network

There are many different neural networks: Dwarapudi *et al.*[1] use a MLP for the prediction, Xing *et al.*[7] and Wei *et al.*[8] use a Radial Basis Function (RBF) as the suitable neural network while Mochón *et al.*[9] prefer a SOM for this purpose.

The next step is to translate these recognized patterns into practical information for the plant operators. In this paper a SOM network has been used because the self-organized maps work fine on non-supervised problems, which is the case here. The number of patterns that can be learned is the same as the number of neurons in the network.

These patterns change with the neural network topology (a square grid in this case), the number and the order of the samples and the number of epochs used for training it. Despite that, all the tests have demonstrated that results are very similar; some common patterns are always obtained.

As seen in Fig. 7, the extremely unbalanced number of samples of each class may cause serious problems during the learning process so the training has been divided into two different parts:

One auxiliary SOM subnet of 13×13 neurons was used to extract and summarize the most important information from the samples of classes "Optimum" and "Near-optimum" by means of the 13×13 patterns they learned. Neurons change their position during the training to adapt themselves to the samples so we can consider the set of the 13×13=169 neurons as a good example of the "Optimum" and "Near-optimum" classes once the net is trained. As a result, 169 artificial samples of these classes which deliver more or less 5 500 data are obtained.

A second 10×10 neurons SOM network was used to recognize all the classes. The samples used as inputs were the weights of the previous subnet neurons for the "Optimum" and "Near-optimum" classes and the real samples for the other classes.

3.2. Brief Outline of the SOMs

A SOM network is made of mathematical entities called neurons that have two main properties: position (or weight) and neighborhood. Two neighboring neurons will be neighbors forever, even if the net is trained again or the training method is changed. In addition, each neuron has a position that is a vector of the same size as the data. In this case, the position vector is a 24-tuple long (like the number of temperature measurements in each temperature profile). Training a neural network is the most delicate stage of all. Several SOMs with different number of neurons were trained, with varying configurations and epochs in order to determine optimums. In addition, the order of the samples was randomized so the learning order determines the final result.

It was necessary to divide the samples into two subsets: test and validation. This is to avoid the risk of overfitting: the neural network can learn the introduced patterns "by heart" in which case it may be unable to generalize the results when unknown samples arrive. Training with the test subset, and comparing the results of the trained network with the validation subset, makes it possible to decide if the neural network has been overtrained.

At the beginning, the neurons have a random position in space. During training, a sample or a set of samples are shown to the neurons. As a result, the neurons change their position according to an algorithm to be near the samples. In this way, once the SOM net is trained, the neurons have been relocated to the zones with more samples, which means the neurons have learned the training data. If the samples are representative of all the data then the neurons will be too. Considering now the notion of neighborhood, two samples activating two neighbor neurons must be very similar and *vice versa*. Moreover, if we use the experience of the plant operators to label the neurons according to work situations (see Table 1), when new data arrives and activates a neuron, the data will be automatically classified with the same label as the winner neuron (the closest neuron to the data). Bhadeshia[12] contains a good introduction to the use and choice of neural networks for materials science.

3.3. Training the SOM Subnet: Balancing the Data

The data balance is made by means of the auxiliary 13×13 SOM net. Due to the properties of the SOM networks, their neurons change their positions during training, getting closer to the data in order to minimize error. That's why these neurons represent a well fitted average of the data. Thanks to this, we can use them instead of the original data, which results in a large reduction ofe data because the SOM size is only 13×13=169 neurons. In Fig. 10, the addition of the two first classes yields 169 exactly which correspond to the neurons instead of the approximately 5 500 data in Fig. 7. The distribution of the 169 neurons in these two classes can be seen in Fig. 13. **Figure 8** shows how important each neuron is in terms of learned patterns. For example, a neuron which has won 100 times during the training has learned more than others with only 7 wins. That means that there was a lot of data near the first neuron and very little data close to the second one.

The Euclidean distances between the neurons showed in **Fig. 9** measure the data dispersion as well as the relative spatial position of the patterns: if two neurons are distant from each other, they have learned two very different patterns.

3.4. Training the Final SOM Network

As explained above, the subnet to obtain a reduced subset of "Optimum" and "Near-optimum" sample classes was used. The histogram in **Fig. 10** shows the samples that will be the inputs for training the final SOM. They are still unbalanced, but the limited number of samples makes it unlikely that a perfectly balanced set of samples which yields inaccurate results could be obtained. Even with a larger number of samples in **Fig. 11** it is observed that there are four neurons which never won during training.

3.5. Pattern Recognition

Figure 12 shows the distribution of the 13×13 neurons of the SOM subnet into the two classes used during training. The colours represent the classification of each neuron according to the mathematical criteria in Table 1. As we can see, the two classes are so mixed that it is difficult to separate them by nearness criteria. In the same way, **Fig. 13** depicts this classification in the neurons of the final SOM network. It can be seen that similar patterns have different colours in **Fig. 14**, demonstrating the poor classification produced by the mathematical criteria. However, regrouping the classes from Table 1 into 3 major and colour-based

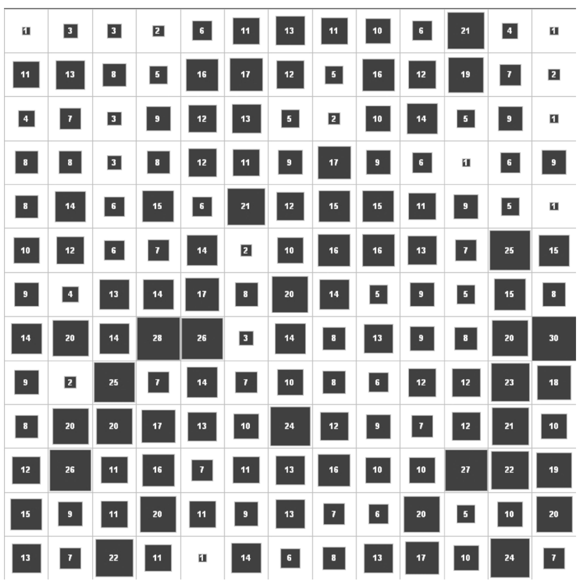

Fig. 8. Plot of the SOM subnet showing how many times each neuron has won during training.

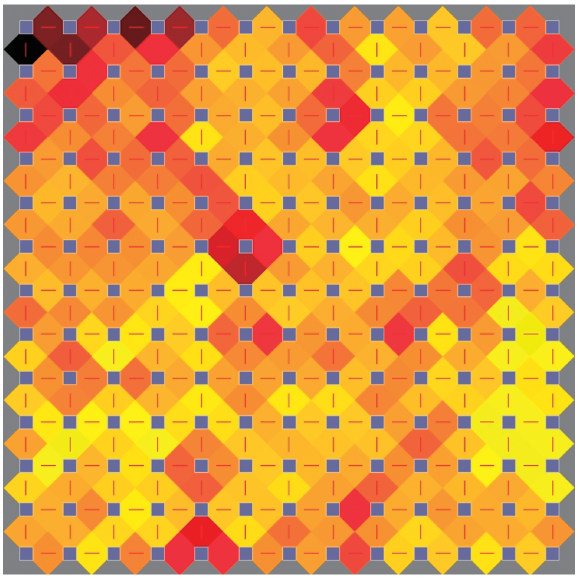

Fig. 9. Plot of the SOM subnet showing how far each neuron is placed from its neighbours after training (Black represents distant and Yellow represents near).

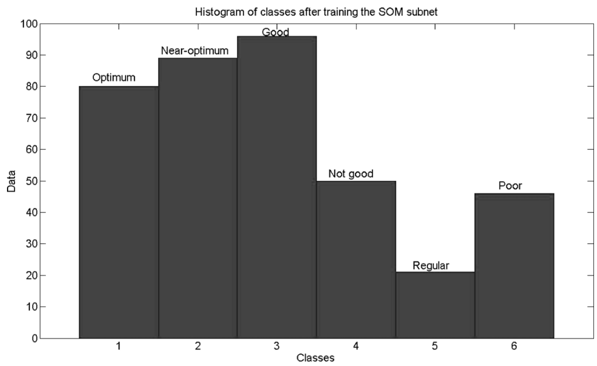

Fig. 10. Histogram of the classified temperature profiles after training the SOM subnet.

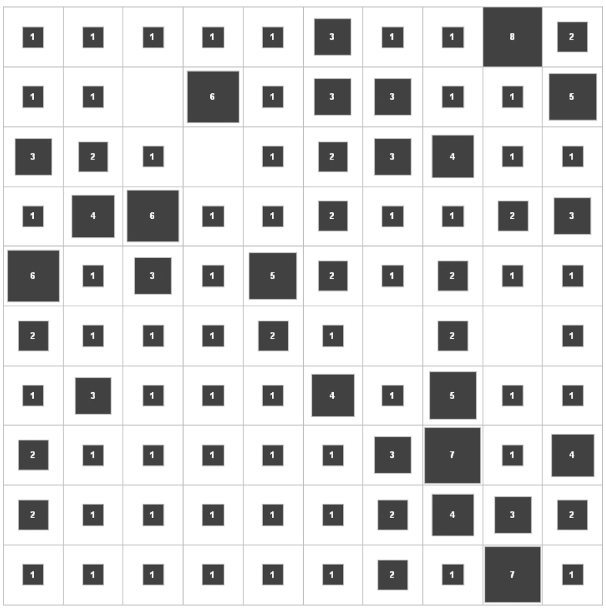

Fig. 11. Plot of SOM showing how many times each neuron has won during training.

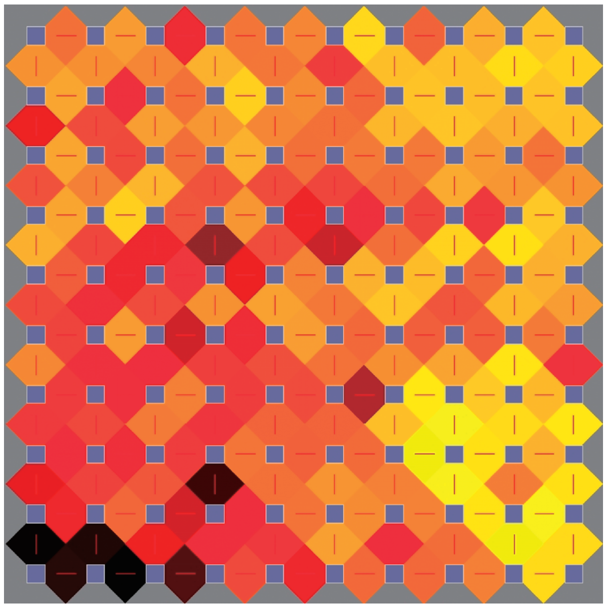

Fig. 12. Plot of the SOM showing how far each neuron is placed from its neighbours after boarder training (Legend: Black reflects far and Yellow shows near).

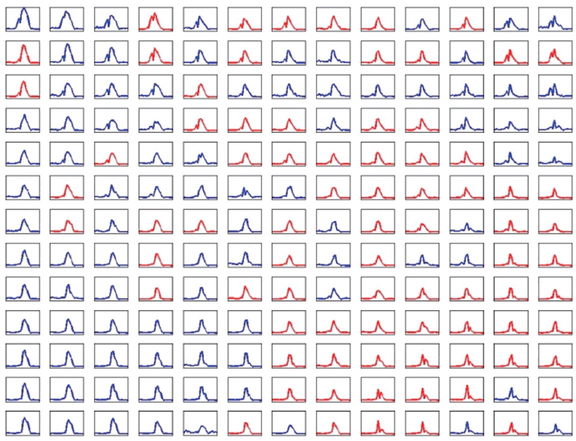

Fig. 13. Temperature patterns obtained by training the SOM subnet of 13×13 neurons (Legend: Red for “Optimum” and Blue for “Near-optimum” classes).

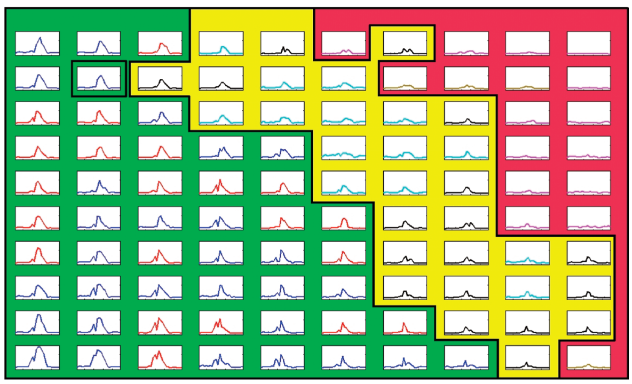

Fig. 14. Temperature patterns obtained by training the 10×10 neuron SOM network (Colours of the graphs: Red for “Optimum”, Blue for “Near-optimum”, Black for “Good”, Cyan for “Not good”, Brown for “Regular” and Magenta for “Poor” classes).

classes, green, yellow and red, yields a clear result and leads us to some observations:

- Green class: It collects the best classes of Table 1 ("Optimum" and "Near-optimum") so this colour indicates that the blast furnace is working smoothly.
- Yellow class: It collects the intermediate classes ("Good" and "Not good") showing a slight malfunction in the blast furnace.
- Red class: It collects the worst classes ("Regular" and "Poor"). This colour would act as a warning to plant operators that the blast furnace is not working properly.

The background of Fig. 14 depicts this new classification. The borders of each class are clearly defined showing a smooth transition between classes: from the left bottom to the right top the neurons vary gradually, unlike the borders established by the mathematical criteria.

4. Industrial Application

Once the SOM is trained and the patterns are classified into the classes reworking the typical blast furnace working process, it could be used to automatically classify any new temperature profiles provided by new thermocouple measurements.

4.1. Developed Software

A graphic user interface (GUI) program designed so the plant operators don't have worry about the variables, but only to look at the screen to see changes in the temperature profiles as soon as new data arrives from the thermocouples, was used. In order to help them to keep the blast furnace in the best working condition we propose a traffic light-based alert method: the graphs vary from green (Optimum) to red (Poor) colour according to their class. In this manner only a quick glance is needed to see how the blast furnace is doing, which allows quick action should the plant operator consider it necessary. It is remarkable that this software helps with decision making but is not an autonomous control tool, making the presence and the experience of the plant operator necessary in order to close the blast furnace control loop with this visual information. **Figure 15**, for instance, shows a green colour meaning that the blast furnace is working perfectly, at its optimum point without any problems. **Figures 16** and **17** show malfunction situations in the blast furnace. The plant operator can see the name of the class placed at the title of the figures at any moment.

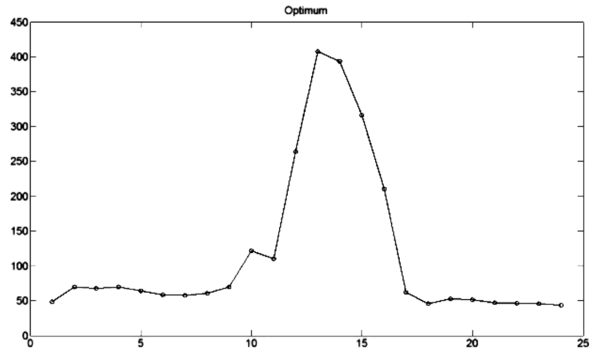

Fig. 15. Classification example of the blast furnace working point made by the developed aid software.

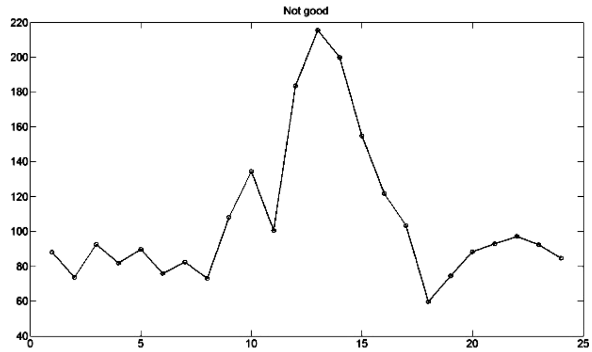

Fig. 16. Classification example of the blast furnace working point made by the developed aid software.

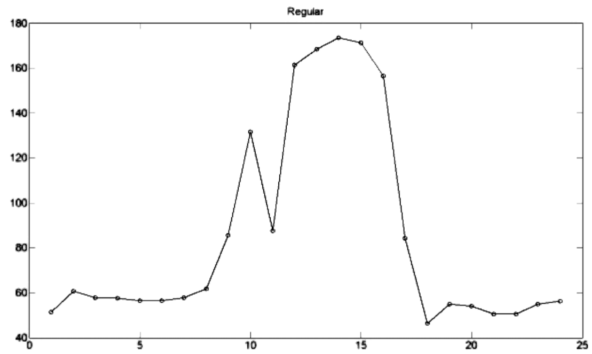

Fig. 17. Classification example of the blast furnace working point made by the developed aid software.

5. Correlation between Pig Iron Temperature and Temperature Profile Class

As seen in Sec. 2, there is a connection between the above burden top gas and the pig iron properties, such as temperature. Chen *et al.*[13] used a neural network to predict another property: the Si-content in the pig iron obtained in a blast furnace. Due to the slow working process of the blast furnace, we can consider that the pig iron temperature that we will obtain a few hours later depends at all times on the above burden temperature profile. The correlation hypothesis test was used in order to clarify this relationship. The correlation is given a numeric value that reflects the linear relationship or dependence between two variables. It can vary between -1 and 1; a correlation coefficient near to zero means that the variables are statistically and linearly uncorrelated or independent. In the hypothesis test, the *p*-value is a statistical value that indicates the probability of obtaining at least as significant as the obtained one if we accept the null-hypothesis: to consider that there isn't any linear relationship between the variables because a correlation of 0.1 could actually be zero. **Figure 18** shows the correlation coefficient and the associated *p*-values between the class predicted by Table 1 (blue) and the SOM (red), and the expected pig iron temperature depending on the delay. As can be seen, the dynamics of the blast furnace are extremely slow because current actions will affect the workings of the blast furnace for 15–18 h; assuming the null-hypothesis, the *p*-value during the first 15 h is smaller than 0.05 which indicates that the probability of obtaining such a

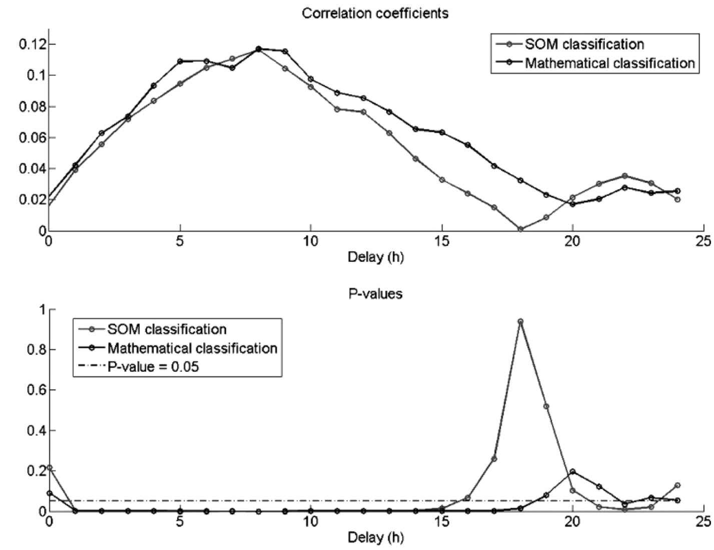

Fig. 18. Correlation coefficients and associated p-values of the non-correlation hypothesis (Blue: the mathematical classification; Red: the SOM classification).

result if the null-hypothesis is true is quite small (less than 5%) so we can say 95% confidence that the correlation is not accidental. Moreover, the highest correlation corresponds to an 8-h delay without depending on the classification, revealing that the quality of the top gas temperature profile will determine more or less 11% of the temperature (and, as a result, its quality) of the pig iron obtained 8 h later, which is useful information for the plant operator. This delay is accepted as the average time that the load needs to descend and to reach the zone where it begins to melt. We want to remark that this discussion only takes into account the linear relations between variables; there are certainly more complex non-linear relationships as well. The coincidence between the correlation calculated with the mathematical criteria and with the SOM demonstrate that it use is valid and its results are correct. The p-value peak located at 18 h, which is nearly 1, indicates that the probability of obtaining a result like that by chance, assuming the null-hypothesis is close to 100%, tells us at this moment the linear relationship is no longer significant. The range with a p-value smaller than 0.05 shows the length of the correlation: during this time (15–18 h) a variable (the top gas temperature profile) has a linear influence on the other variable (the pig iron temperature). As we can see in Fig. 18, the SOM classification yields a clearer result than the mathematical criteria.

6. Results Obtained

It is difficult to evaluate the results and the performances of the SOM. In supervised problems, with MLP networks it is easy to do so because both the true and the estimated class are known so we can compare them and measure the errors. Since SOM, an unsupervised network, was used, we have no idea what the true class is; we would have to ask the plant operators to know how well the SOM fits with regard to the real world. The 100 patterns recognized by the SOM show the bad performance of the mathematical classification because similar patterns can belong to two different classes. In fact, the rigid division based on the maximum temperature causes these problems. The SOM, however, shows a slow variation in the profile of the patterns. It preserves the nearness between samples and implements the following idea: similar samples must have similar classes, which can be demonstrated with the help of the plant operators.

Concerning the pig iron temperature, it can be said with 95% confidence that the above burden temperature profile classified at all times by the SOM has at least a linear relationship with the pig iron temperature obtained 8 h later, which is very interesting when considering quality control.

7. Conclusions

A neural network approach is put forward in this paper to help the plant blast furnace operators in controlling the furnaces. The reason for using a self-organized map to automatically classify the temperature profiles is that its application is a non-supervised problem so the SOM fits perfectly due to the impossibility of making an accurate set of rules describing blast furnace behaviour. The good results obtained have permitted the development of a graphical user interface which makes controlling the blast furnace easier by means of a colour-based automatic classification of temperature profiles, exempting the plant operator from constantly analyzing each datum. In addition, the SOM has revealed a significant linear relationship between the temperature profile class and the pig iron temperature obtained 5 h later. These results allow us to conclude that the use of neural networks in the iron making industry could improve iron quality and the control of blast furnaces with greatly reduced effort, that is, the training and tune time of the SOM. Even if the working conditions of the blast furnace change, the adjustment of the software to the new conditions is very easy: it is only necessary to train a new SOM with the new data.

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