Industrial Applications of Neural Networks

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NEURAL NETWORK APPROACH TO THE DIAGNOSIS OF THE BOILER COMBUSTION IN A COAL POWER PLANT

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This paper describes a prototype of an automatic diagnosis system whose primary aim is the detection of incipient anomalies in the flame of the boiler of a coal power plant. The system is based on the characterization of the normal behavior of the flame by means of the analysis of its digitalized images. This characterization is performed by a neural network structure able to evaluate the matching between the measured behavior of the flame and the stored normal behavior. Two neural network models have been tested: Kohonen Self Organing Maps and Radial Basis Function Networks. The prototype of this system is in operation at Meirama power plant since December 1993.

1. Introduction

Boiler optimization has been a very important concern within the area of the power plant improvement[2]. One of its objectives is the elimination of fuel air imbalances and the efficient production of the heat required in each moment. Any deviation in respect to the best optimization of the boiler can cause important consequences from a technical point of view (i.e. damage in water wall) and also from an economical point of view (i.e. excessive fuel consumption not required).

On the other hand, boiler control is difficult because the proper nature of the magnitudes involved can change unexpectedly. For example the coal in the boiler, one of the main components in the combustion, has different properties depending on multiple causes. For these reasons the monitoring of the variables that can supply information about the behaviour of the combustion and its effects in the plant is strongly recommended. To reach this objective, there are sensors installed in most power plants in order to obtain the most complete information about the evolution of those variables.

This paper describes in the following sections a prototype of an automatic diagnosis system to help the interpretation of the boiler combustion by the operators of the power plant. This system is based on a combination of artificial neural networks and mathematical techniques. It has been installed in the Meirama power plant (550 Mw) owned by the Spanish electrical utility Unión Eléctrica Fenosa, S.A.. It is located in the north-west of Spain. The project has been supported by the R&D program, PETRI, of the Spanish Government and Unión Eléctrica Fenosa, S.A. This paper is a reduced version of [14].

2. Visualization system

A visualization system was previouly installed in the plant to monitor the dynamic evolution of the flame. This system consisted of two conventional colour video cameras cooled by water. The pictures taken by these video cameras correspond respectively to the global fire ball, taken from the upper part of the boiler, and the image of one of the burners. The images supplied were very fuzzy and not useful for being interpreted by the operators.

An image digitalization system was then installed in order to process the original images to obtain a coloured map of the flame, showing the different regions of the flame that have similar light intensity. Using the information coming from the digitalized images, it became possible to obtain patterns of behaviour of the flame to be compared with its real evolution for detecting dangerous conditions. A video tape recorder was also included to record any anomalous situation for further analysis.

3. Supervision system

3.1 Overview

The primary aim of the supervision system is the detection of incipient anomalies in the flame of the boiler, by means of the characterization of its normal behaviour. For this purpose a complete set of sequences of images, corresponding to each operation condition considered as normal, was collected. Clustering techniques were then applied to the data corresponding to normal operation in order to select a representative set of sequences of histograms. This set will be called *the training set*.

Two methods have been used: the first one, based on a Kohonen Self Organizing Map, characterizes the normal behaviour of the flame in terms of its instantanous temperature distribution. Since this method doesn't take into account the dynamics of the process, a more powerfull one was finally applied. This method is based on the dynamical modelling of the flame intensity using an Autoregressive Radial Basis Function Network.

3.2 Kohonen Self Organising Map Supervision System

The Kohonen Self Organising Map (KSOM) [6] is a neural network structure that produces a topological ordered set of reference vectors ($\mathbf{m}_i \in \Re^n$) that tend to be located in the input space in such a way that they approximate the probability density function ($p(\mathbf{x})$) of the vectorial input variable ($\mathbf{x} \in \Re^n$). Their unsupervised learning strategy accomplish this by combining Vector Quantization techniques,[4],[10] which minimize the expected reconstruction squared error ($E = \int \|\mathbf{x} - \mathbf{m}_c\|^2 p(\mathbf{x}) d\mathbf{x}$) where $\mathbf{m}_c$ (the *winner*) is the nearest reference vector to $\mathbf{x}$ ($\|\mathbf{x} - \mathbf{m}_c\| = \min_i(\|\mathbf{x} - \mathbf{m}_i\|)$), with a spatially ordering algorithm of the reference vectors. The overall output of the network is the *winner index* (the index of the processing unit with the closest reference vector) and the output of the corresponding winner unit that will be called the *Kohonen distance* and is given by $\|\mathbf{x} - \mathbf{m}_c\|$.

In our case the input vectors are the eight-dimensional histograms of the processed images. A one dimensiontal KSOM trained with the histograms of the training set will has learnt the pdf of the flame temperature distribution under normal condition operation. If the evaluation of the KSOM produces a low value of the Kohonen distance, an unknown temperature distribution of the flame will be detected and the operators warned.

Next figures are an example of the results obtained during one week of normal condition operation. The x axis of the first three figures is measured in number of samples, stored every five minutes.

Figure 1 shows the evolution of the brightness of the digitalized images (total flame intensity). This graph outlines the sensibility of this variable to the dynamics of the underlying process and reveals three phenomena: a slow exponential decrease of the image intensity due to the continuous deposit of particles on the camera lens (the camera is cleaned once per week), the main dynamics of the power generation process (due to the load evolution) and an oscillating component during the high periods due to the periodic activation of the sprays.

Figure 2 corresponds to the evolution of the KSOM Winner Index. This figure shows how the KSOM has placed and grouped the reference vectors in the input space in such a way that different clusters, each one represented by a group of reference vectors, have been associated to different operating conditions.

Figure 3 shows the corresponding evolution of the Kohonen Distance. The learning algorithm applied to the KSOM has reduced the sum of squares of this series in order to obtain a representative set of reference vectors for normal condition operation. The Distribution Function of this variable has been plotted in

Figure 4. This plot can be used for the determination of a normal operation confidence interval. The 99% of the plotted normal operation data have a Kohonen Distance less than 0.15. Taking this value as an upper bound for the condition of normality, we can test the KSOM on two series corresponding to anomalous behaviours detected during the operation of the power plant.

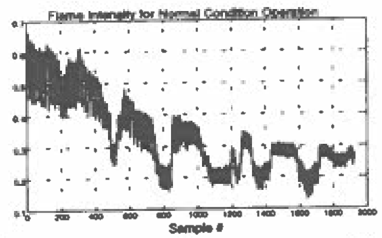

Figure 1: Flame Intensity for normal condition operation

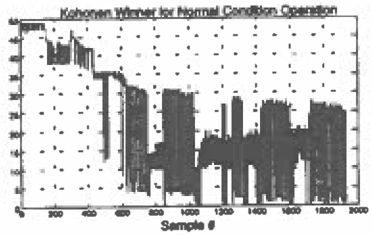

Figure 2: Winner Index for normal condition operation

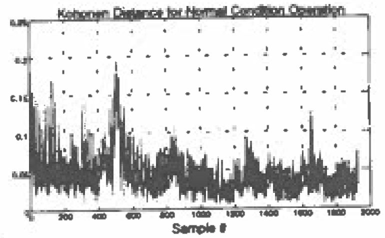

Figure 3: Kohonen Distance for normal condition operation

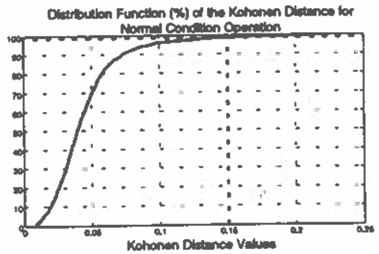

Figure 4: Distribution Function of the Kohonen Distance for normal condition operation

In order to test the KSOM, an anomaly example has been selected from the data taken at the power plant. Figure 5 shows the evolution of the flame intensity for this example while Figure 6 shows the corresponding Kohonen Distance. This index clearly exceeds the normality upper bound during the anomalous shot down of the flame.

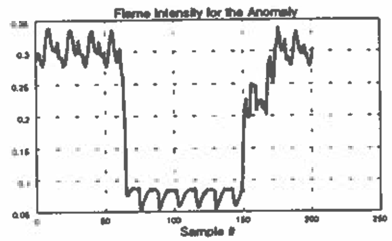

Figure 5: Flame Intensity for the Anomaly

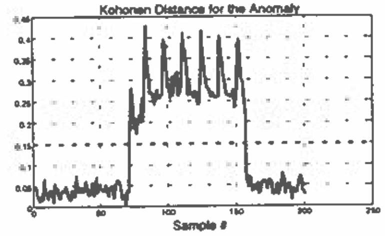

Figure 6: Kohonen Distance for the Anomaly

3.3 RBFN Supervision System

Radial Basis Function Networks (RBFN) have been widely used for function approximation[(7),(13)] and diagnosis.[(8),(9)] Their universal approximation capabilities have been reported in [(3),(15)]. We will introduce a probabilistic version of RBFN which is an extension of the General Regression Neural Network.[(17),(18)]

The RBFN is a neural network used for function approximation. Mathematical models can be fitted using a training data set containing data of normal operation. While other networks can also be used for this purpose, the RBFN can also give some very useful additional information: an estimation of the probability of the real output given the fitted model and the corresponding input, and an estimation of how well the new input data were represented in the training data set used to fit the model.

The regression of a dependent variable ($y \in \Re$, the same analysis can be done in a multidimensional output space), on an independent vector variable ($x \in \Re^n$), is the computation of the most probable value of y for each value of x based on a finite set of possibly noisy measurements of x and the associated values of y. This set will be called the training set ($\{(X_k, Y_k)\}$ with $k=1,\ldots,K$). If the joint probability density function f(x,y) (pdf) is known or can be estimated, given a particular measurement **X** of the variable **x**, the regression of y on **X** will correspond to the conditional mean of y given **X**:

$$E\left[{}^{y}\!/_{\mathbf{X}}\right] = \frac{\int_{-\infty}^{+\infty} y f(\mathbf{X}, y)\, dy}{\int_{-\infty}^{+\infty} f(\mathbf{X}, y)\, dy} \qquad [1]$$

In our case we will use an extension of the consistent estimators proposed by Parzen[16] and applied to the multidimensional case by Cacoullos.[1] We will make a first estimation of the joint pdf f(x,y) of the measured database by applying a clustering algorithm (the k-means algorithm[5]) to obtain a set of N_h reference vectors ($[\mathbf{r}_i, w_i]$, with $\mathbf{r}_i \in \Re^n$, $w_i \in \Re$ and $i=1,\ldots,N_h$) distributed according to f(x,y) in $\Re^{n+1}$, and assigning a gaussian sample probability of width σ_i (estimated as the mean distance between reference vector "i" and its two closest reference vectors) to each reference vector. The resulting estimation is given by:

$$f'(\mathbf{x},y)=\frac{1}{N_h}\sum_{i=1}^{N_h}\frac{1}{\left(\sqrt{2\Pi}\;\sigma_i\right)^{n+1}}\exp\left(-\frac{\|\mathbf{x}-\mathbf{r}_i\|^2}{2\,\sigma_i^2}\right)\exp\left(-\frac{(y-w_i)^2}{2\,\sigma_i^2}\right) \qquad [2]$$

If we define the local activation of cluster "i" as:

$$a_i(\mathbf{x})=\frac{1}{\left(\sqrt{2}\;\sigma_i\right)^n}\exp\left(-\frac{\|\mathbf{x}-\mathbf{r}_i\|^2}{2\,\sigma_i^2}\right) \qquad [3]$$

[2] can be rewritten as:

$$f'(\mathbf{x},y)=\frac{1}{N_h}\frac{1}{\sqrt{\Pi}^{N_h+1}}\sum_{i=1}^{N_h}a_i(\mathbf{x})\,\frac{1}{\sqrt{2}\;\sigma_i}\exp\left(-\frac{(y-w_i)^2}{2\,\sigma_i^2}\right) \qquad [4]$$

Using this estimator, [1] becomes:

$$y'=E\left[y/\mathbf{X}\right]=\frac{\int_{-\infty}^{+\infty} y\,f(\mathbf{X},y)\,dy}{\int_{-\infty}^{+\infty} f(\mathbf{X},y)\,dy}=\frac{\sum_{i=1}^{N_h}a_i(\mathbf{X})\,w_i}{\sum_{i=1}^{N_h}a_i(\mathbf{X})} \qquad [5]$$

where y' is the estimated output value given the input vector measurement **X**.

[4] can be used to estimate the pdf of the input vector **x** as follows:

$$f'(\mathbf{x})=\int_{-\infty}^{+\infty} f'(\mathbf{x},y)\,dy=\frac{1}{N_h}\frac{1}{\sqrt{\Pi}^{N_h}}\sum_{i=1}^{N_h}a_i(\mathbf{x}) \qquad [6]$$

and the conditional pdf of the output y, given a particular input vector **X**:

$$f'\left(y/\mathbf{X}\right)=\frac{f'(\mathbf{X},y)}{f'(\mathbf{X})} \qquad [7]$$

According to [5], this regression structure can be structured as a two layer neural network, where the first layer of gaussian processing units (of transfer function given by [3] and local parameters $\mathbf{r}_i$ and σ_i) is full connected to the input

vector **X** and computes the activation signals $a_i(\mathbf{X})$. The output layer computes the estimated output y' according to [5], the input vector estimated pdf $f'(\mathbf{X})$, and ,if an output value Y is supplied, the joint pdf $f'(\mathbf{X},Y)$ given by [2].

The definition of an error estimation criterion as the root mean square error (RMSE) given by:

$$RMSE=\frac{1}{K}\sum_{k=1}^{K}(y_k-y'_k)^2 \qquad [8]$$

allows the optimization of the RBFN parameters ($\mathbf{r}_i,\sigma_i,w_i$) using classical optimization methods. In this case we have applied a low-memory quasi-Newton method[12],[11] to minimize the RMSE for the training set and a second data set called the testing set has been used to stop this learning procedure at the minimum testing set RMSE (in order to avoid the overfitting of the training set).

This regression structure is a useful tool for the diagnosis of dynamic processes. When faults can not be modelled because of the lack of a complete data set corresponding to anomalous behaviours, the only way to supervise the normality of the process is to obtain a normal condition model and to evaluate the matching of the measured behaviour with the model.

In this case, a non-linear autoregressive model has been fitted to the training set using a Probabilistic RBFN. The training set contained the evolution of the flame intensity (let I(t) be the flame intensity time series) under normal conditions. The estimated model is given by:

$$I'(t) = RBFN(\,I(t-1)\,,\,I(t-2),\,\ldots\,,\,I(t-12)\,) \qquad [9]$$

so that the input space is the Cartesian product of the measured past values of the flame intensity. The value of the estimated input pdf $f(\mathbf{X})$ will be a measure of the matching of the measured flame intensity evolution to the model. Low values of $f(\mathbf{X})$ will indicate an anomalous past evolution of the flame intensity while the ratio:

$$\frac{f'(Y/\mathbf{X})}{f'(Y'/\mathbf{X})}=\frac{f'(\mathbf{X},Y)}{f'(\mathbf{X},Y')}=\frac{f'(I(t-1),\ldots,I(t-12),I(t))}{f'(I(t-1),\ldots,I(t-12),I'(t))} \qquad [10]$$

will be a robust measure of the normality of the last measure of the flame intensity, given its past evolution. We will call this ratio the normality index. This index is a measure of the probability of obtaining the measured output given the measured inputs using the fitted normality model. Values of this ratio corresponding to normal operation should be near 1, confirming the match of the estimated and measured flame intensity. Low values of this ratio correspond to anomalous values of the measured flame intensity at time t.

Figure 7 shows the estimation of the flame intensity during a week of normal condition operation for the same example used with the KSOM. Figure 9 corresponds to the distribution function of f(X) while Figure 11 plots the distribution function of the normality index, both for normal operation. These distributions are used to establish the lower bounds of the associated variables for the detection of anomalies in the flame.

To test the RBFN, the same anomaly example as before has been used. Figure 8 shows the estimated flame intensity, which significantly differs from the measured one during the anomalous period. Figure 10 shows the value given by the estimated pdf for the input values of the example. The low values obtained prove that the input past measured values of the flame intensity were not represented in the training set used to fit the model. A threshold can be established using a confidence level of 95% to test when the values were sufficiently represented in the training set. Finally Figure 12 shows the evolution of the normality index, confirming the anomalous condition.

4. Conclusions and future developments

This paper has described a prototype of a diagnosis system to detect anomalies in the boiler combustion process using images of the flame. The system combines techniques of digital image processing and artificial neural networks to reach its objective. Two approaches using different architectures of neural networks have been presented and results obtained from them have been analysed .

The prototype of this system is in operation at Meirama power plant since December 1993, being successful its performance and useful its suggestions.

A new project based on this good experience has been proposed. The objective of this new project is the detection of dangerous conditions for the life of the components of the steam circuit and boiler using information of different variables, one of them is relative to the monitoring of the flame by the system described in the paper.

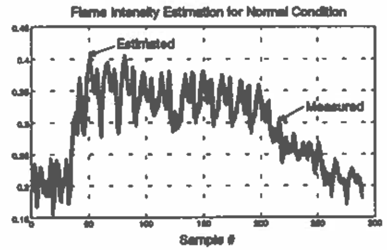

Figure 7 : Flame Intensity Estimation for one day of Normal Condition Operation (RBFN)

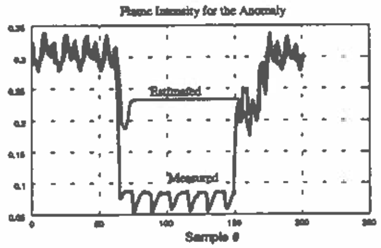

Figure 8: Flame Intensity Estimation for the Anomaly (RBFN)

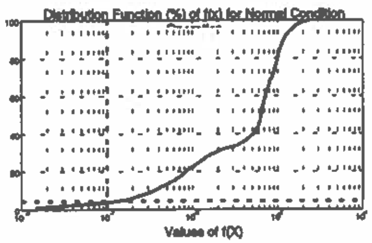

Figure 9: Distribution Function of f(X) for Normal Condition Operation (RBFN)

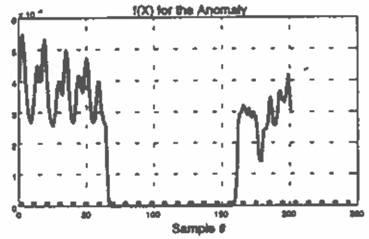

Figure 10: Input pdf f(X) for the Anomaly (RBFN)

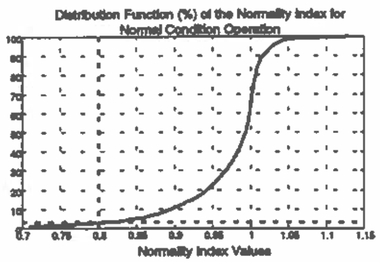

Figure 11: Distribution Function of the Normality Index for Normal Condition Operation (RBFN)

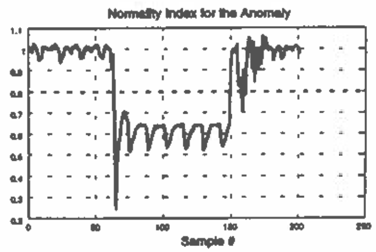

Figure 12: Normality Index for the Anomaly (RBFN)

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A REVIEW OF CONNECTIONIST MODELS FOR SHORT TERM ELECTRICAL LOAD FORECASTING

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Mastering the production, transmission and distribution of electrical energy is a challenge to which the electrical engineer is perpetually confronted with. A precise Short Term electrical Load Forecasting (STLF) results in economic cost savings and increased security operation's conditions, allowing electrical companies to commit their own production resources in order to optimize energy prices and exchanges with vendors and clients. In this review, we expose a classification in six sub-groups of Artificial Neural Networks based models used for short term electrical load forecasting, proposed in the last four years.

1. Introduction

Future introduction of different tariff periods will make the load forecasting much more important, not only for large utilities, but also for medium and small ones [1]. In fact the contribution of the marginal cost caused by the unforeseen deviation of the real load process from the forecasted load is essentially proportional to the variance of the estimated model. Particularly, overstepping the contracted maximal consumption could be extremely expensive. This is why there is a big interest in improved methods for short term electrical load forecasting.

The assumption that Artificial Neural Networks (ANN) are able to model non-linear correlations among dependent and regression variables, e.g. between electrical consumption and meteorological variables, and the use of innovative estimation procedures which 'learns' from past experiences, brought researchers to present a noticeable number of publications on the subject. When building a mathematical model to identify a system, one needs generally to select regressors variables, model structure, parameters estimation algorithms, and model evaluation and selection methods. The purpose of this review is to describe the