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An incipient fault detection system based on the probabilistic radial basis function network: Application to the diagnosis of the condenser of a coal power plant

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Abstract

This paper introduces the probabilistic radial basis function network (PRBFN) and a new incipient fault detection system based on it. The PRBFN is a neural network model able to estimate I/O mappings and probability density functions. These capabilities play a crucial role in the design of the proposed fault detection system, where faults are detected by comparing the actual behaviour of the plant with the predicted using a model of normal operation conditions. Once the reliable domain of the model has been defined, a comparison is made through a local estimation of the upper bound of the resulting residual under normal operation conditions. This procedure automatically adjusts the sensitivity of the fault detection system to the intrinsic characteristics of the underlying process and prevents false alarms by detecting unknown operating conditions. © 1998 Elsevier Science B.V. All rights reserved.

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1. Introduction

The diagnosis of industrial processes is very important for increasing the security, reliability and availability of the different components involved in the production

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scheme. It includes the tasks of fault detection, isolation, identification and accommodation. This paper is devoted to the first task, introducing a new incipient fault detection method based on a connectionist characterisation of the normal behaviour of the components under study in an industrial process.

This characterisation is based on analytical redundancy and takes the form of a dynamic black-box model using the PRBFN as function approximator. The model is trained to predict the evolution of a particular set of output variables as a function of another set of input variables. Both types of variables are obtained from files of their real measurements. Fault detection is then performed by comparing the predicted outputs with the measured ones. This model-based approach to fault detection is significantly improved by the definition of the reliable domain of the model and by the local estimation of the residuals upper bounds.

The first part of this article will introduce the structure and learning strategies of the probabilistic radial basis function network (PRBFN). The second part will be devoted to the description of the proposed incipient fault detection method. Finally, the proposed fault detection system will be tested on a real-world problem: the diagnosis of the condenser of a coal power plant.

2. The probabilistic radial basis function network (PRBFN)

2.1. Structure

The probabilistic radial basis function network (PRBFN, see Ref. [18]) is an extension of the general regression neural network (GRNN) proposed by Specht [28]. Given an input vector $x \in \Re^n$, and a scalar "desired" output variable $d \in \Re$, the expression

$$p(\boldsymbol{x}, d) = \frac{1}{h} \sum_{i=1}^{h} \left[\left(\prod_{k=0}^{n} \frac{1}{\sqrt{2\pi|\sigma_{ik}|}} \right) \exp\left(-\sum_{k=1}^{n} \frac{1}{2\sigma_{ik}^2} (x_k - r_{ik})^2 \right) \times \exp\left(-\frac{1}{2\sigma_{i0}^2} (d - v_i)^2 \right) \right] \quad (1)$$

has the form of a joint probability density function (pdf), obtained as a sum of h Gaussian distributions centred on the points $[\boldsymbol{r}_i, v_i]^{\mathrm{T}}$ and with diagonal covariance matrices $diag(\sigma_{i1}, \ldots, \sigma_{in}, \sigma_{i0})$ (with $\sigma_{ik} > 0$ for all i and k). Let us assume that $p(\boldsymbol{x}, d)$ is an estimation of the underlying joint pdf. This *kernel* estimator [26] of the joint pdf can be used as a function approximator of the I/O mapping $x \to d$ by applying the general regression principle:

$$y(\boldsymbol{x}) = E\left(\frac{d}{\boldsymbol{x}}\right) = \frac{\int_{-\infty}^{+\infty} d \cdot p(\boldsymbol{x}, d)\, \mathrm{d}d}{\int_{-\infty}^{+\infty} p(\boldsymbol{x}, d)\, \mathrm{d}d} = \frac{\sum_{i=1}^{h} a_i(\boldsymbol{x}) v_i}{\sum_{i=1}^{h} a_i(\boldsymbol{x})} \quad (2)$$

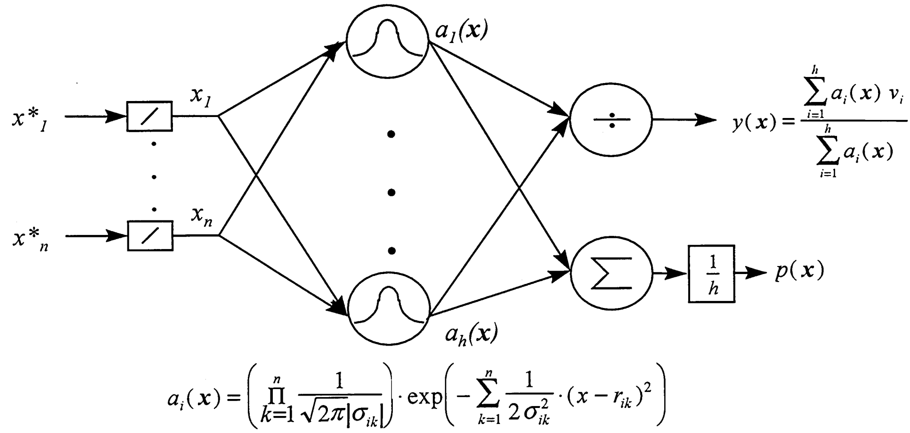

Fig. 1. Structure of the PRBFN.

where the activations a_i are given by

$$a_i(\boldsymbol{x}) = \left(\prod_{k=1}^{n} \frac{1}{\sqrt{2\pi}|\sigma_{ik}|}\right)\exp\left(-\sum_{k=1}^{n} \frac{1}{2\sigma_{ik}^2}(x - r_{ik})^2\right). \tag{3}$$

An estimation of the input vector pdf can also be obtained by integrating Eq. (1):

$$p(\boldsymbol{x}) = \frac{1}{h}\sum_{i=1}^{h} a_i. \tag{4}$$

Eqs. (2)–(4) can be structured as a two-layered neural network, giving rise to the PRBFN structure as shown in Fig. 1.

2.2. Learning strategies

Depending on the learning strategy (cost function) used to train the network, the PRBFN can be used in three different ways:

(a) as a function approximator of the I/O mapping $\boldsymbol{x} \to y$,
(b) as an estimator of the input vector pdf $p(\boldsymbol{x})$,
(c) as both, a function approximator and a pdf estimator.

In all three cases, a low-memory quasi-Newton method will be used to minimise a cost function defined over the training set. Cross-validation with a different validation set will be used as stopping criterion during the optimisation procedure.

(a) *Training a PRBFN as a function approximator.* Given a training set $\{(\boldsymbol{x}[i], d[i]), i = 1, \ldots, N\}$, the free parameters of the network (weights) are initialised in the same way as a standard RBFN [17]: a clustering algorithm (k-means) is applied in order to distribute the centres $\boldsymbol{r}_i$ on the input space, the p-nearest-neighbour heuristic (with $p = 2$) is used to initialise the widths $\boldsymbol{\sigma}_i$, and the LMS algorithm estimates the initial values of v_i. The cost function minimised during the learning phase is the mean squared error (MSE)

$$R = \frac{1}{N} \sum_{i=1}^{N} (d[i] - y[i])^2, \tag{5}$$

where $y[i]$ is the response of the PRBFN to the input pattern $\boldsymbol{x}[i]$ (the pdf output of the network is not used in this case).

(b) *Training a PRBFN as a pdf estimator.* In this case the only parameters that need to be adjusted in each hidden unit are r_{ik} and σ_{ik}. These weights are initialised as in the previous case, and adjusted by the maximisation of the log-likelihood [9,29]:

$$V = \frac{1}{N} \sum_{i=1}^{N} \log(p(\boldsymbol{x}[i])). \tag{6}$$

(c) *Training a PRBFN as function approximator and pdf estimator simultaneously.* The weights of the network are initialised as in the first case. The simplest way to use a PRBFN as both, a function approximator and an input vector pdf estimator, is to perform the training in two phases: in the first phase the weights r_{ik} and σ_{ik} are adjusted to maximise the log-likelihood V, and in the second phase the weights v_i are obtained by LMS. However, if the estimation of the I/O mapping, $x \rightarrow y$ is considered to be more relevant than the estimation of $p(\boldsymbol{x})$, a better model can be obtained by the minimisation of the cost function

$$RV = \frac{1}{N} \left(\sum_{i=1}^{N} (d[i] - y(x[i]))^2 \right) - \lambda \frac{1}{N} \sum_{i=1}^{N} \log(p(x[i])), \tag{7}$$

where λ is a control parameter of the trade-off between the two objectives (R and V).

3. Incipient fault detection system

3.1. Principle of operation: Analytical redundancy

Many fault detection methods have been previously described in the literature. The simplest and most frequently applied one is the *limit checking* of individual plant variables. This method has two important drawbacks [8]: (1) the check thresholds have to be set rather conservatively in order to cover all the normal operating conditions and (2) the fault isolation task becomes very difficult because a single-component fault may cause many plant variables to exceed their limits.

Another important kind of fault detection methods are the statistical ones. An example of these methods is the application of *quality control* techniques [3,16] to the statistical characterisation of the normal behaviour of the plant components (see for example Ref. [25]). The main limitation of this approach is the lack of flexibility of the proposed statistical models. The *pattern recognition* approach can be considered as

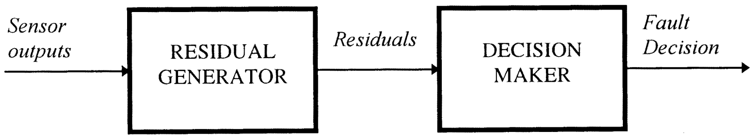

Fig. 2. Structure of an analytical redundancy based fault detection system.

another statistical method. This method solves the fault detection problem as a classification task, where the feature vectors describing the dynamic state of the process are mapped onto the space of possible faults ("normal condition, fault # 1, fault # 2, ... "). The practical implementation of this mapping requires the availability of a fault dictionary including the description of the behaviour of the process (in terms of feature vectors) under the considered faults. Many classification algorithms may be applied for this purpose (as the Bayes classifier [6] or the K-nearest-neighbour algorithm [2]), but the most "popular" ones during the past 10 years have been based on artificial neural networks (ANN) [4,10–12,30]. The performance of a fault detection system based on pattern recognition techniques is directly related to the quality of the fault dictionary. This database can sometimes be obtained by accessing a historical recording or by simulation, but in practice it usually represents a serious bottleneck.

For this reason an increasing predominance of *analytical redundancy* methods in fault detection systems has been observed (see [1,5,7,19–21,23,24]). These systems perform the fault detection task in two steps (see Fig. 2): residual generation and decision making.

Residuals are quantities that represent the inconsistency between the actual plant variables and the predicted ones by a mathematical model of the normal condition operation of the plant. They are computed from the plant variables (sensor outputs) and are ideally zero in the absence of anomalies. When particular faults occur, the residuals deviate from zero in characteristic ways. The decision maker is in charge of analysing the degree of significance of the residuals in order to determine if a fault has occurred.

A very common choice for the residual generator is a dynamic model of normal condition operation which predicts the evolution of one of the observed plant variables[2] (the *output* of the model) as a function of the evolution of a subset of the other observed plant variables (the *inputs* of the model). The corresponding estimation error may be used as a residual (see Fig. 3).

Most of the published applications of analytical redundancy methods make use of linear normal condition operation models, in the form of state equations or transfer functions, with an additive model for the treatment of faults. Under these circumstances, it is possible to define three different strategies for the generation of the

[2] We have restricted ourselves to multiple inputs single output (MISO) models for simplicity. However, the detection of different faults may require the generation of multiple residuals, leading to multiple inputs multiple outputs (MIMO) models, or multiple MISO models.

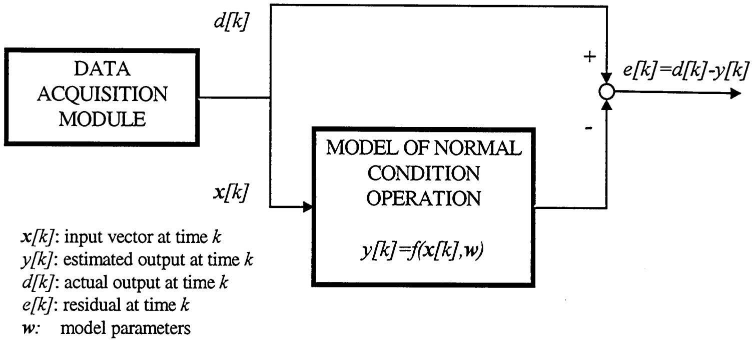

Fig. 3. Model of normal condition operation based residual generator.

residuals: parity equations, the diagnostic observer and the Kalman filter (see Ref. [8] for a survey on these methods).

In the general case of non-linear plants, two possible choices for the model of normal condition operation may be considered: physical or white-box models and black-box models. In the first case, physical laws are applied in order to link the plant variables. All the parameters of the model equations have a physical meaning so their values may be obtained from technical specifications, direct measurement or parameter estimation. However, it is not always practical to use physical models due to two main reasons: the complexity of the underlying processes and the unavailability of "reliable" design data. Black-box models are statistical tools able to characterise input/output relationships by means of a function approximator. As opposed to all the external variables of the model (inputs and outputs) which are physical variables, its internal variables and its free parameters may not have a direct physical interpretation. The black-box model of normal condition operation is adjusted with a set of input/output observations representative of the normal behaviour of the plant. A great amount of research devoted to ANN in the recent years has led to the extension of classical system identification techniques [14] to the non-linear case [15,27], with the use of supervised ANN [22] as function approximators.

The proposed incipient fault detection system is an analytical redundancy based system,. using supervised ANN's as function approximators in the model of normal condition operation and connectionist models also in the decision maker.

The first step in the development of a diagnosis system is the representation of the industrial process to be supervised as a hierarchical set of functional units or components. The depth of this representation will depend on the complexity of the process and the desired degree of detail in the diagnosis. A particular fault detection system is dedicated to each component, simplifying the fault isolation task.

The only indispensable requirement for the application of the proposed fault detection system is the availability of a continuous data acquisition system in charge of the periodic sampling of the variables representative of the state of the component. The existence of implicit redundancies among these variables is the basis of the methodology. A set of variables $\{X_1, X_2, \dots, X_{n'+1}\}$ is said to be representative of the state of the component, if under normal operation it is possible to define a set of *parity equations* or *parity relations* of the form

$$G_i(X_1, X_2, \dots, X_{n'+1}) = 0, \quad i = 1, \dots, m, \tag{8}$$

expressing the links between different lags of the state variables X_j, and such that in the presence of one of the faults to be detected at least one of the parity relations is not satisfied.

In the case of static processes, the relations G_i will constraint values of the state variables corresponding to the instant of time. In the case of dynamic processes, different lags of the state variables will be linked by the parity equations.

Each relation G_i will be modelled as a dynamic system by selecting one of the state variables as the output variable of the model. In that way, we will assume that the parity relations G_i $(i = 1, \dots, m)$ can be expressed as

$$d_i[k] = g_i\,(d_i^{\{k-1\}}, \boldsymbol{u}_i^{\{k\}}, \varepsilon_i^{\{k-1\}}) + \varepsilon_i[k], \tag{9}$$

where $d_i[k] \in \Re$ is the value of the selected output variable for the ith parity relation at time k (considered as the present time), $d_i^{\{k-1\}}$ is a vector containing lagged or past values of $d_i[k]$, $\boldsymbol{u}_i^{\{k\}}$ is a vector containing present and past values of the remaining n' input state variables (exogenous variables of the model), and $\{\varepsilon_i[k]\}$ is a white noise process.

Under this assumption, if the output variables $d_i[k]$ can be estimated by an unbiased non-linear model of the form

$$y_i[k] = f_i\,(d_i^{\{k-1\}}, \boldsymbol{u}_i^{\{k\}}, e_i^{\{k-1\}}), \tag{10}$$

then the estimation errors

$$e_i[k] = d_i[k] - y_i[k], \quad i = 1, \dots, m, \tag{11}$$

can be used as residuals for diagnostic purposes. The set of equations given by Eq. (3), for $i = 1, \dots, m$, define the *model of normal condition operation* of the component. The most general dynamic model represented by Eq. (3) is the non-linear autoregressive moving-average model with exogenous variables (NARMAX).

3.2. Structure of the fault detection system

3.2.1. Model of operation under normal conditions

Let us assume that the model of normal condition operation of the component under study has a single output (only one parity relation). In that case, the model of normal condition operation can be expressed as

$$y[k] = f\,(d^{\{k-1\}}, \boldsymbol{u}^{\{k\}}, e^{\{k-1\}}) = f\,(\boldsymbol{x}[k]), \tag{12}$$

where $x[k] \in \Re^n$ is the input or regressor vector at time k, containing the appropriate lagged values of the different variables identified as relevant by the non-linear system identification procedure. The residual is then obtained from the comparison of the actual measured output $d[k]$ with the above estimation:

$$e[k] = d[k] - y[k]. \tag{13}$$

Once the residual has been generated, the proposed decision-making procedure is equivalent to the application of the rule:

> "*If the absolute value of the residual is significantly high and the prediction* $y[k]$ *is reliable, then conclude that there is a fault in the component*".

The application of this rule requires the quantitative definition of the two concepts: *the reliability of a prediction* and *the degree of significance of* a *residual* (the same concepts are considered in Ref. [13], but quantified in a different way).

3.2.2. Reliable domain of the model

In order to quantify the reliability of a prediction, we have to consider the nature of the proposed model of normal condition operation. This model is a black-box model which is the result of the fitting of a function approximator to a set of samples of the input/output relationship (the *training set*). The estimation will hence be reliable inside the region of the input space $\boldsymbol{X} \subset \Re^n$ represented by the input samples of the training set. This region of the input space will be called the *reliable domain* of the model. The proposed method for delimiting the reliable domain of the model is based on the PRBFN estimation of the probability density function (pdf) of the input vector in the training set. Let $p_x[k]$ be the estimated pdf of $\boldsymbol{x}[k]$. High values of $p_x[k]$ indicate a good representation of the environment of $\boldsymbol{x}[k]$ in the training set, and hence a good characterisation of the residual $e[k]$ under normal condition operation in the same environment. Low values of $p_x[k]$ would indicate a poor representation of the actual input vector $\boldsymbol{x}[k]$ in the training set and therefore a low level of reliability on the estimation $y[k]$. By defining an extrapolation lower bound $p_{\min}$, we will consider as *unknown* all input vectors $\boldsymbol{x}$ such that $p(\boldsymbol{x}) < p_{\min}$. The region of the input space satisfying $p(\boldsymbol{x}) > p_{\min}$ will be taken as the reliable domain of the model.

3.2.3. Degree of significance of the residuals

In order to quantify the degree of significance of the residual $e[k]$, we propose to estimate the standard deviation ($s_e[k]$) of the residual as a function of the input vector $\boldsymbol{x}[k]$. The output layer of the PRBFN used to estimate $p(\boldsymbol{x})$ can be used for this purpose, by assigning its output weights v_i to the expected residual local variances in each cluster:

$$v_i = s_{e,i}^2 = \sum_{k=1}^{N} a_i[k]e^2[k] \Big/ \sum_{k=1}^{N} a_i[k] \tag{14}$$

and interpolating them by general regression to obtain the estimated residual variance:

$$s_e^2[k] = \frac{\sum_{i=1}^{h} a_i[k] \cdot s_{e,i}^2}{\sum_{i=1}^{h} a_i[k]}. \tag{15}$$

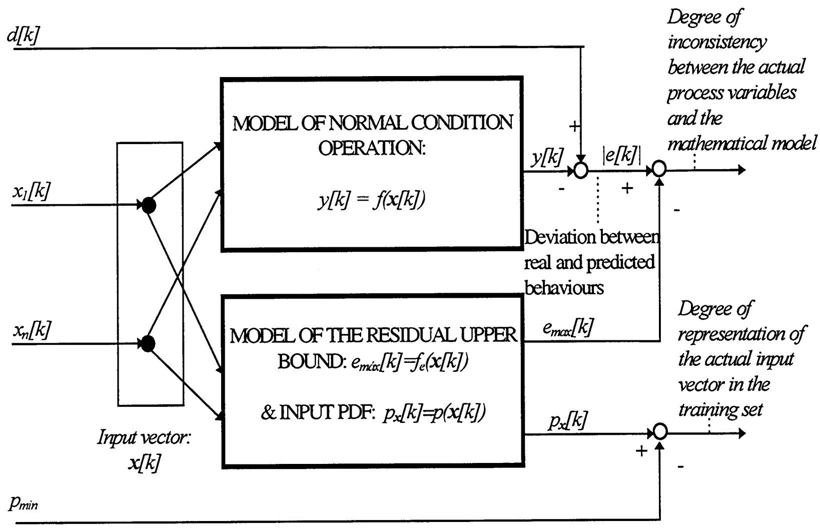

Fig. 4. Structure of the fault detection system.

Assuming a Gaussian local distribution of the residual in the input space under normal condition operation, we will state that the residual is significantly high with a confidence degree of 95% if its absolute value exceeds the residual upper bound $e_{\max}[k]$ given by

$$e_{\max}[k] = 2 \cdot s_e[k]. \tag{16}$$

This criterion comes from the quality control theory [3,16] where it is usual to assume a Gaussian distribution with constant mean and variance for the variable under study. We are assuming a constant zero mean for the residual, but we are estimating its variance as a function of the input vector $\boldsymbol{x}$. This procedure leads to a different residual threshold for each operating condition, adjusting the sensitivity of the fault detection system to the underlying characteristics of the process. The estimation of the residual standard deviation will also be reliable inside the reliable domain, due to the use of the same training set for the fitting of its model (outside this region of the input space the residual distribution is unknown).

The structure of the proposed fault detection system is shown in Fig. 4.

4. Application of the fault detection system to the diagnosis of the condenser of a coal power plant

The condensing system of a coal power plant is simply a heat-exchange process in which the steam exhausted from the low-pressure turbines is condensed back into water (condensate) before being returned to the boiler (see Fig. 5). Unfortunately,

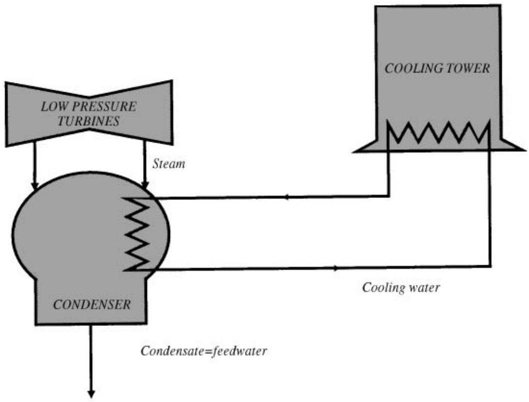

Fig. 5. Condensing system of a coal power plant.

because of the very large amounts of low-grade heat involved, it has the potential to seriously impair the unit efficiency if poorly designed or operated and it is the one item in the turbine house which requiries constant monitoring. Most of the condensers are of the surface type, i.e., tubed, with circulating water (which is drawn from the sea, river or from the cooling tower ponds) pumped through the tube banks whilst the exhaust steam surrounds the banks. Water has a much smaller comparative volume than steam and a vacuum is created as the steam condenses, allowing the steam to expand down to a very low absolute value and enabling more energy to be extracted, thereby improving the cycle efficiency [31].

4.1. Model of normal condition operation: Estimation of the back pressure

The low back pressure (vacuum) created inside the condenser by the cooling water is a key issue for the cycle efficiency. This variable will be taken as the output variable of the model of normal condition operation of the condenser. In order to maximise the unit efficiency, operating nomograms are used to determine target back pressure values as a function of the plant load and the cooling water temperature. These two variables will be taken as input or explanatory variables of the model of normal condition operation, which takes the form

$$\hat{P} = f(L, T), \tag{17}$$

where $\hat{P}$ is the estimated back pressure (in mbar), L is the plant load (in MW) and T is the input cooling water temperature (in °C). It is important to note that this model is not a physical or thermodynamic model of the condenser, but rather a model of its normal operation where implicitly incorporates the control strategies established in the power plant. The training set (used to adjust the model parameters), testing set (used to prevent overfitting) and validation set (used to finally validate the model) were collected from real operation data coming from a Spanish power plant owned by

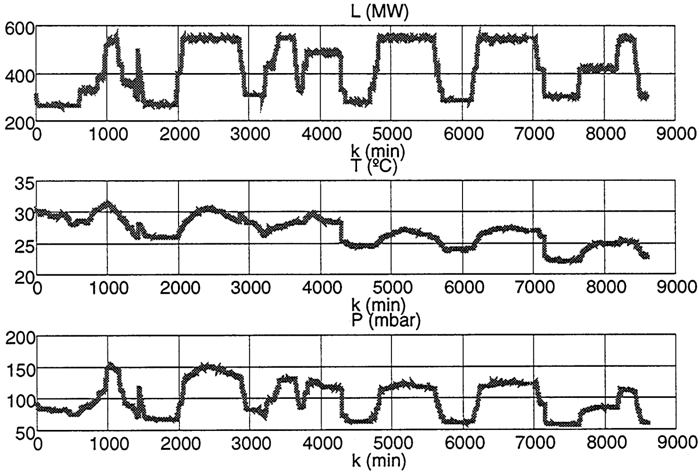

Fig. 6. Data corresponding to normal condition operation (training set).

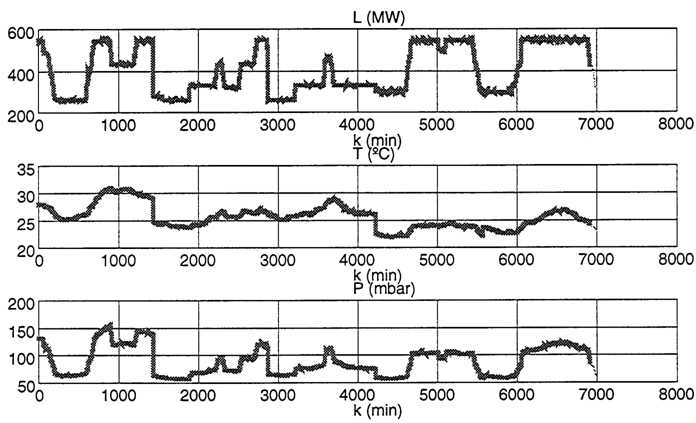

Fig. 7. Data corresponding to normal condition operation (test and validation sets).

the electrical utility Unión Fenosa S.A. Figs. 6 and 7 are examples of the evolution of the three variables involved in the model under normal condition operation (these data sets were part of the training, testing and validation sets). The sampling interval is 1 min in all cases.

A PRBFN was used as function approximator in the normal condition operation model. The model was trained with a low-memory quasi-Newton method and cross-validation was applied in order to select the number of hidden units (10 hidden units were selected) and prevent overfitting. The evaluation of the resulting model under different operating conditions leads to the contour plot shown in Fig. 8. This

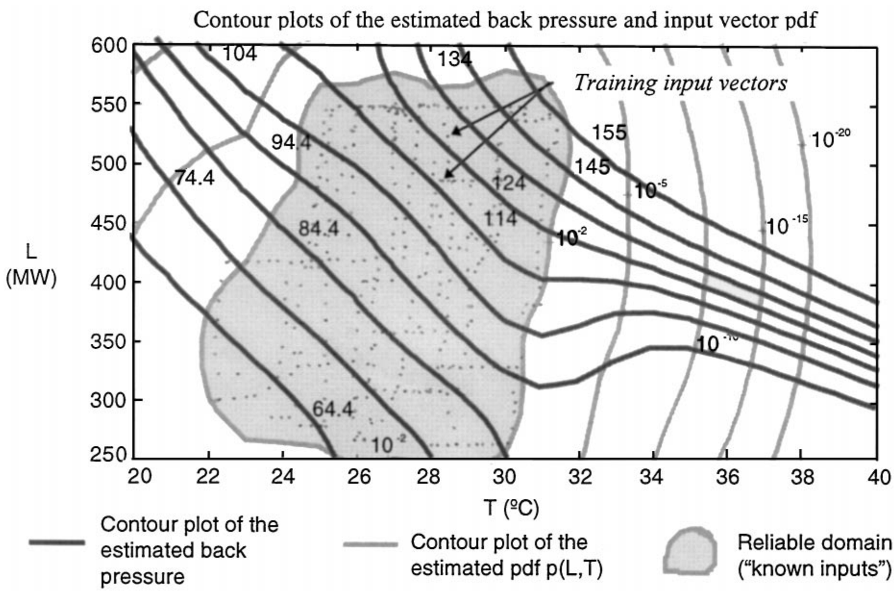

Fig. 8. Contour plots of the estimated back pressure and input vector pdf.

figure also shows the reliable domain of the model obtained by the estimation of the input vector pdf $p(L, T)$.

4.2. Model of the input vector pdf: Estimation of the reliable domain

The input vector in this case is a two-dimensional vector composed of the load of the power plant and the input cooling water temperature. A new PRBFN with 10 hidden units was trained to predict the input vector pdf $p(L, T)$ of the same training set used to adjust the model of normal condition operation. The weights of the PRBFN hidden layer were adjusted by maximising the log-likelihood of the input vector training samples (6). Fig. 8 shows the contour plot of the estimated input vector pdf along with the input training samples.

The analysis of the distribution of $p(L, T)$ over the training set shows that 98% of the training input vectors produce a value of $p(L, T)$ greater than 10^{-2}. This value will be used as extrapolation lower bound: $p_{\min} = 10^{-2}$. The reliable domain of the model can then be defined as the region of the input space corresponding to $p(L, T) > p_{\min}$.

4.3. Model of the residual variance: Estimation of the degree of significance of the residuals

A residual will be considered as significant if its value exceeds twice the estimated standard deviation of the model residuals. Following Eqs. (14) and (15), the output

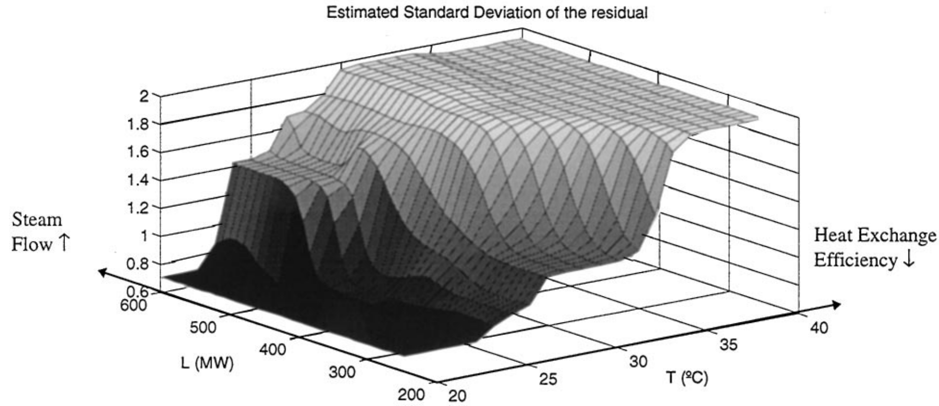

Fig. 9. Estimated standard deviation of the residual as a function of the input vector (L, T).

layer of the PRBFN used to estimate $p(L, T)$ will be used to predict the residual variance s_e^2 as a function of the input variables L and T. Fig. 9 shows the resulting residual variance estimation.

The observed relationship between the residual variance and the two input variables reveals two important phenomena: as the temperature of the cooling water increases, the residual variance increases due to a decrease in the heat exchange process which makes it more difficult to maintain the low back pressure. In the same way, the residual variance also increases as the load increases, due to the corresponding rise in the steam flow which tends to elevate the back pressure in the condenser. These considerations stress the importance of a local estimation of the residual variance, which enables the system to adjust its sensibility to the stability of the underlying process.

4.4. Evaluation of the fault detection system under normal condition operation

The application of the fault detection system under normal condition operation is illustrated in Fig. 10. The measured back pressure does not exceed in any case the limits of normal condition operation, remaining very close to its estimated values. However the system has detected an unknown operating condition which has generated a low value of $p(L, T)$. This situation corresponds to a period of high load with low temperatures not included in the training set (see Fig. 7). These data should be included in the training set for retraining.

4.5. Evaluation of the fault detection system under anomalous condition operation

Fig. 11 illustrates the response of the fault detection system under a fault in the condenser vacuum system. In this case an internal fault in the condenser is detected

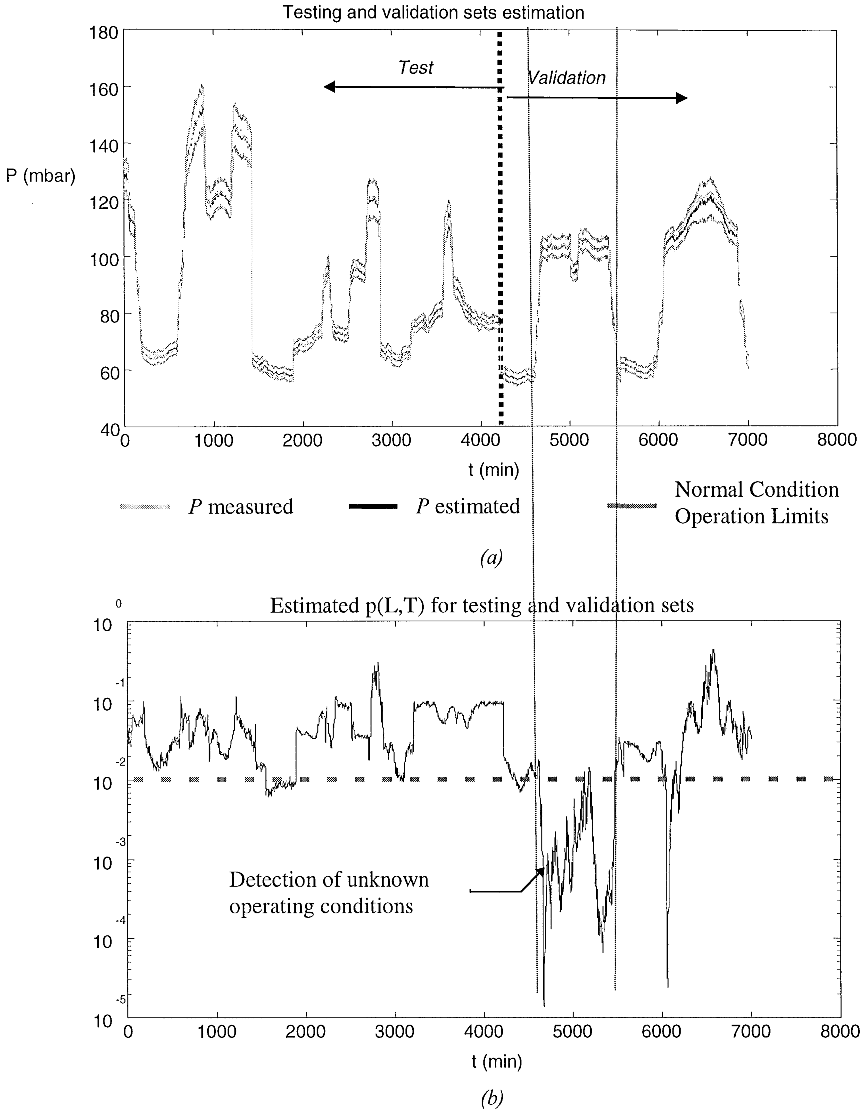

Fig. 10. Application of the fault detection system under normal condition operation (testing and validation sets): (a) normal condition operation limits; (b) estimated input vector pdf p(PG,TAC).

when the measured back pressure exceeds the normal operation limits, whereas the input vector remains inside the reliable domain of the model (the estimated input vector pdf is greater than its extrapolation lower bound $p_{\min}$).

Fig. 12 is an example of the response of the condenser fault detection system when confronted to an external fault, located in the HP turbine. In this case the

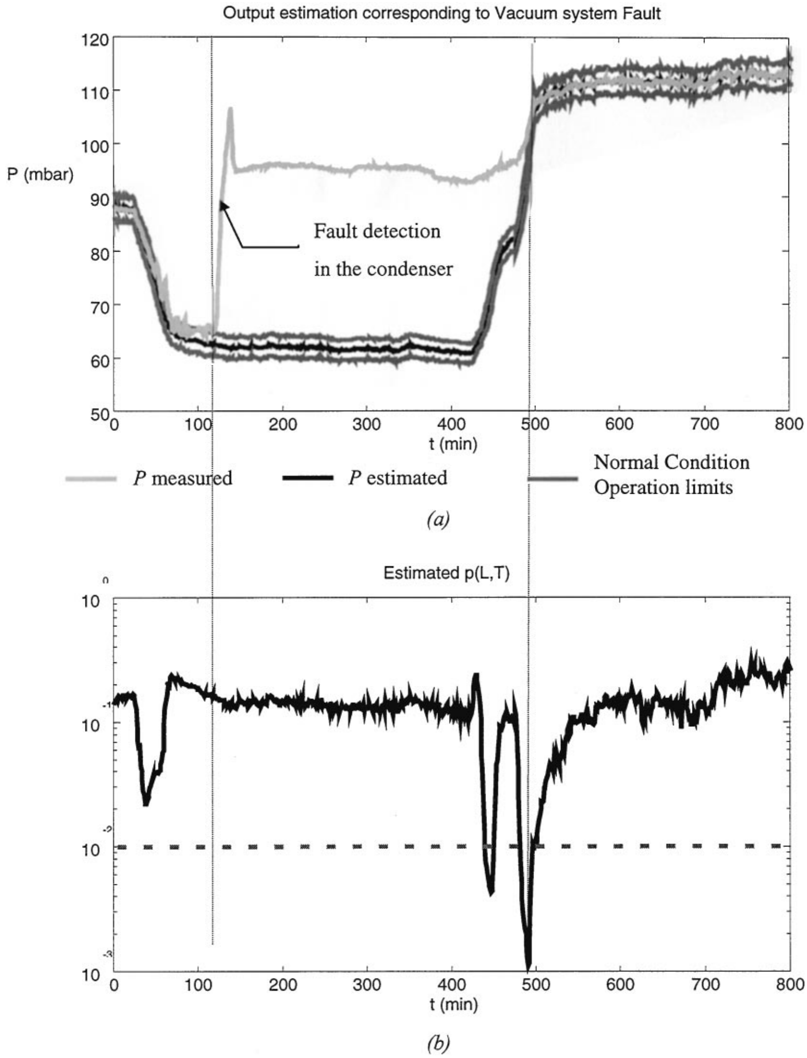

Fig. 11. Application of the fault detection system under anomalous condition operation (fault in the condenser vacuum system). (a) normal condition operation limits; (b) estimated input vector pdf p(PG,TAC).

measured back pressure also exceeds the normal operation limits, but at the same time the estimated input vector pdf $p(L, T)$ reveals an unknown operating condition. The consideration of the reliable domain of the model allows the fault detection system to distinguish an internal fault from an external one, preventing false alarms.

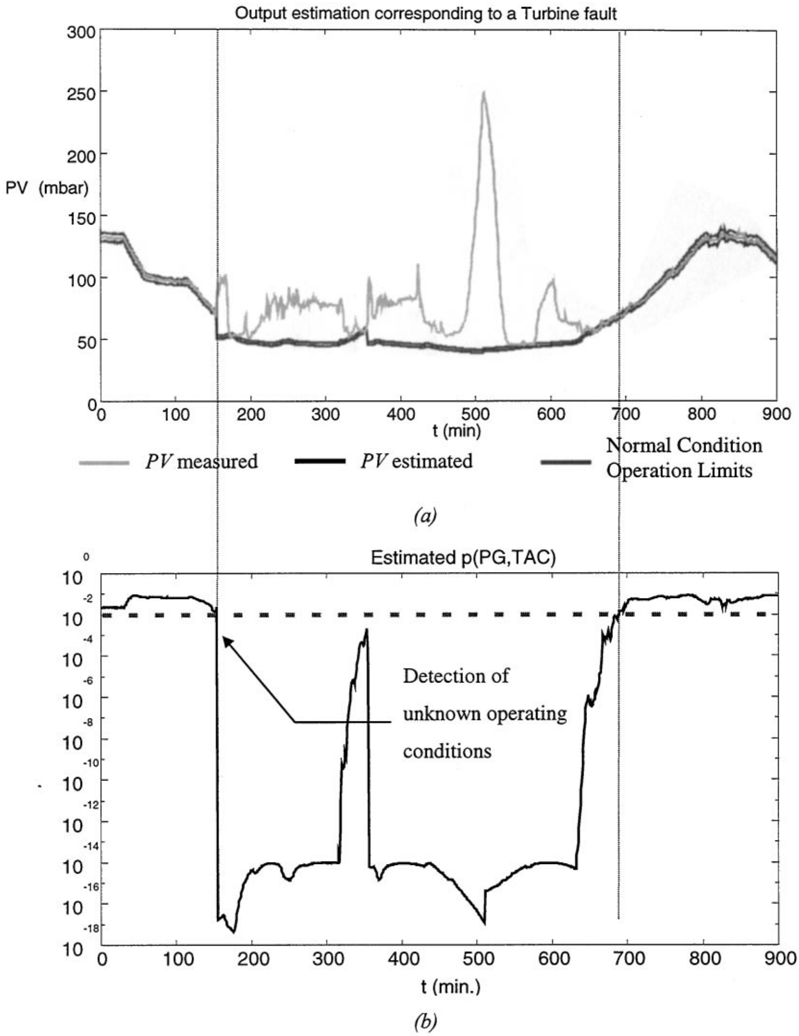

Fig. 12. Application of the fault detection system under anomalous condition operation (fault in HP turbine): (a) normal condition operation limits; (b) estimated input vector pdf p(PG,TAC).

5. Conclusions

A new incipient fault detection method based on the PRBFN has been introduced in this article. The proposed model performs the fault detection task by comparing the actual behaviour of the plant with the predicted by a connectionist model of normal condition operation. This comparison is made through a local estimation of the upper bound of the resulting error, once the reliable domain of the model has been delimited.

This procedure automatically adjusts the sensitivity of the fault detection system to the intrinsic characteristics of the underlying process and prevents false alarms by detecting unknown operating conditions.

The performance of the proposed fault detection system has been tested on a real world problem: the diagnosis of the condenser of a coal power plant. The simplicity of the model of normal condition operation used in this case has permitted to graphically illustrate the concepts of reliable domain of the model and the local estimation of the residual variance. This system has been tested under real anomalous conditions registered by the power plant acquisition system.

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