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Neural networks for fault diagnosis and identification of industrial processes

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Abstract. In this work a model–based procedure exploiting analytical redundancy via state estimation techniques for the diagnosis of faults regarding sensors of a dynamic system is presented. Fault detection is based on Kalman filters designed in stochastic environment. Fault identification is therefore performed by means of different neural network architectures. In particular, neural networks are used as function approximators for estimating sensor fault sizes. The proposed fault diagnosis and identification tool is tested on a industrial gas turbine.

1 Introduction

Fault diagnosis and identification (FDI) have been widely developed during recent years. Model–based methods, fault tree approaches and pattern recognition techniques are among the most common methodologies used in such tasks. Neural networks (NNs) have been used in fault identification problems for model approximation and pattern recognition as well. However, because of difficulties to perform NN training on dynamic patterns, the second approach seems more adequate.

The fault diagnosis methodology here presented consist of two stages [4]. In the first stage, the fault can be detected on the basis of residuals generated from a bank of output estimators, while, in the second stage, fault identification is obtained from pattern recognition techniques implemented by NNs. Fault identification represents the problem of the estimation of the size of faults occurring in a dynamic system.

A NN is exploited in order to find the connection from a particular fault regarding system input and output measurements to a particular residual. In such a way the output predictor generates a residual which does not depend on the dynamic characteristics of the plant, but only on faults. Therefore, NNs

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classify static patterns of residuals, which are uniquely related to particular fault conditions independently from the plant dynamics. In recent years, NNs were studied when applied to fault diagnosis problem. NNs have been used both as predictor of dynamic models for fault diagnosis and pattern classifiers [1] and for fault identification [5, 3].

On the basis of such discussion, this work addresses a methodology in which model–based approach and NN are combined to detect and identify the fault occurring in industrial processes [4]. Fault signals create changes in several residuals obtained by using output predictors of the process under examination. A neural network is exploited in order to find the connection from a particular fault regarding input and output measurements to a particular residual. In such a way the predictors generate residuals independent of the dynamic characteristics of the plant and dependent only on sensors faults. The problem here addressed regards the detection and identification of the faults on the basis of the knowledge of the measured input–output sequences acquired from the monitored process. Moreover, it is commonly assumed that single faults may occur in the plant under investigation.

2 Problem description

In the following it is assumed that the dynamic process under observation is described by a discrete–time, time–invariant linear dynamic model of the type

$$\begin{cases} x(t+1) &= Ax(t) + B\hat{u}(t) \\ \hat{y}(t) &= Cx(t), \quad t = 1, 2, \dots \end{cases} \tag{1}$$

where $x(t) \in \Re^n$ is the state vector, $\hat{y}(t) \in \Re^m$ the output vector of the system and $\hat{u}(t) \in \Re^r$ the control input vector. A, B and C are constant matrices of appropriate dimensions obtained by means of modelling techniques or identification procedures.

In real applications, variables $\hat{u}(t)$ and $\hat{y}(t)$ are measured by means of sensors whose outputs, due to technological reasons, are affected by noise. The actual measurement process, which generates the signals $u(t)$ and $y(t)$, is modelled as follows

$$\begin{cases} u(t) &= \hat{u}(t) + \tilde{u}(t) + f_u(t) \\ y(t) &= \hat{y}(t) + \tilde{y}(t) + f_y(t) \end{cases} \tag{2}$$

in which the sequences $\tilde{u}(t)$ and $\tilde{y}(t)$ are the noises affecting sensors usually modelled as white Gaussian processes. $f_u(t) = [f_{u_1}(t) \dots f_{u_r}(t)]^T$ and $f_y(t) = [f_{y_1}(t) \dots f_{y_m}(t)]^T$ are additive signals which assume values different from zero only in the presence of faults. They are described by step functions representing abrupt faults (e.g. bias). Figure (1(a)) shows the structure of the measurement process. Descriptions of types (1) and (2) are known as errors–in–variables (EIV) models [4].

The problem treated in this work regards the detection and diagnosis of the sensor faults on the basis of the knowledge of the measured sequences $u(t)$ and

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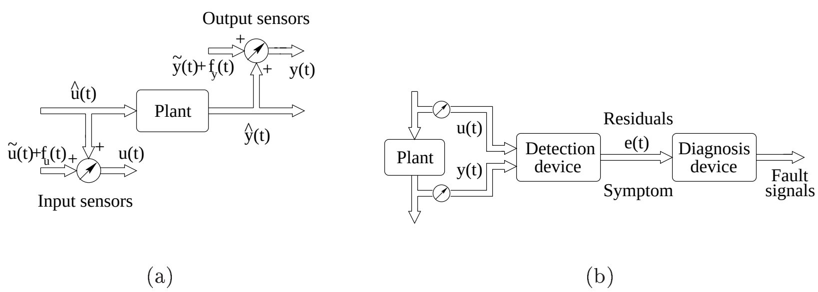

Figure 1: (a) The plant sensors and (b) the fault detection system.

$y(t)$. Moreover, it is assumed that only a single fault may occur in the input or output sensors. The structure of the fault detection and diagnosis device is depicted in Figure (1(b)).

3 The residual generation device

The fault detection and diagnosis system produces and elaborates a set of residuals from which it will be possible to estimate the amplitudes of the faults regarding input-output sensors. With reference to Fig. (1(b)) the symptom generator is designed to produce a set of signals which are somehow redundant. These signals are differences between estimated signals given by Kalman filters and the actual ones supplied by the sensors.

In order to experiment with learning capabilities of artificial neural networks, on which the diagnosis device in Fig. (1(b)) is based, a bank of classic Kalman filters is used [4]. The number of filters is equal to the number m of system outputs, and each filter is driven by a single output measurement and all the input measurements of the plant [1]. The basic principle of fault detection by using Kalman filtering is illustrated in Figure (2(a)).

With reference to the time–invariant, discrete–time, linear dynamic system described by Eq. (1) the i-th Kalman filter has the structure

$$\left\{ \begin{array}{lcl} x_F^i(t+1|t) & = & A(I-K_i(t)C_i)x_F^i(t|t-1) + Bu(t) + AK_i(t)y(t) \\ y_F^i(t|t) & = & C_i(I-K_i(t)C_i)x_F^i(t|t-1) + C_iK_i(t)y(t) \end{array} \right. \quad (3)$$

Filter residuals are given by $e_i(t+1) = y_i(t+1) - y_F^i(t+1|t) = y_i(t+1) - C_i x_F^i(t+1|t)$. These signal are used for the fault detection task [4].

4 Model of the process

The technique for input-output sensor fault detection and identification presented in this paper was tested on a non–linear process designed in the SIMULINK®

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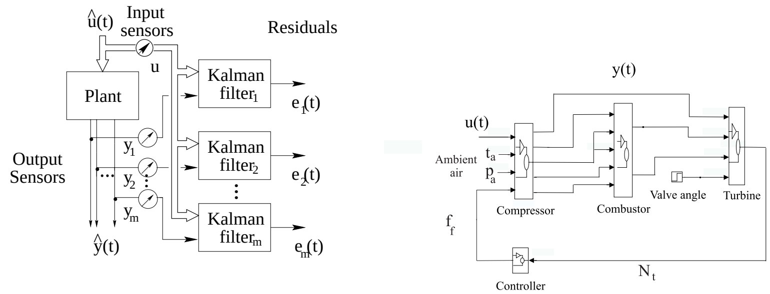
environment. It is an industrial gas turbine with variable Inlet Guide Vane (IGV) angle working in parallel with electrical mains. Figure (2(b)) shows the gas turbine layout as well as the inputs and outputs: the input control sensors are used for the measurement of the angular position α of the IGV ($u_1(t)$) and of the fuel mass flow rate M_f ($u_2(t)$).



(a) (b)

Figure 2: (a) KF for residual generation and (b) the monitored system.

The output sensors are those employed for the measurement of the pressure p_{ic} at the compressor inlet ($y_1(t)$), the pressure p_{oc} at the compressor outlet ($y_2(t)$), the pressure p_{ot} at the turbine outlet ($y_3(t)$), the temperature T_{oc} at the compressor outlet ($y_4(t)$), the temperature T_{ot} at the turbine outlet ($y_5(t)$) and the electrical power P_e at the generator terminal ($y_6(t)$).

The time series of data used to perform simulations ($u(t)$ and $y(t)$) were generated with the non–linear dynamic model and they were taken with a sampling rate of 0.1 s. The data are affected by noise due to measurement uncertainty which is always present in the real measurement systems. Measurement noises $\tilde{u}(t)$ and $\tilde{y}(t)$ typical of an actual measurement process. The Frisch scheme can be applied to perform the dynamic system identification of the EIV model [4]. Such a scheme allows to determine the linear discrete dynamic system which has generated the noisy sequences as well as the variances of the noises $\tilde{u}(t)$ and $\tilde{y}(t)$ affecting the data. The next step is the transformation of linear input-output discrete-time model into a state-space representation (A,B,C). The state–space model of the plant obtained from the Frisch scheme was used to build Kalman filters.

5 Neural networks for fault diagnosis

Neural networks in fault diagnosis has been usually exploited to classify measurement patterns according to the operation of the process. In this work the

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problem is tackled by using a detection device which generates residuals independent of the dynamic characteristics of the plant and dependent on sensor faults. Static patterns can be therefore used to train the neural network. The classification method is typically an off–line procedure where the fault mode is first defined and the data collected. In this situation, certain measurement patterns correspond to normal operation and other patterns correspond to faulty operations: the training of neural networks using this kind of information is called supervised. Multi Layer Perceptron (MLP) and Radial Basis Function (RBF) networks are typical examples of supervised trained network architectures [2].

Neural networks presented were designed in the MATLAB® environment by exploiting the *Neural Network Toolbox*. In order to determine the network architecture which gives the best fault diagnosis results in a noisy environment, MLP and RBF were tested. They are both able to approximate any continuous function with an arbitrary degree of accuracy, provided with a sufficient number of neurons.

Firstly, a three-layered RBF network. The hidden layer was composed of radial basis neurons performing a non–linear mapping of input space. In the output layer linear neurons were used in order to perform the function approximation. The parameters of a radial basis network were obtained with the training procedure. The simulations concern basically two aspects, namely the generation of patterns for the neural network training and the fault diagnosis validation. The first step regarded the generation of pattern residuals and fault signals. The training set includes simulated faults on the sensors of variables M_f and IGV. A six inputs-one output RBF network has been trained by using steady-state residual sequences composed of 1100 samples. Each input and output pattern respectively, comprise 11 fault conditions, namely no fault and faults varying from a 5%, 10% to 90% of the maximum value of input measurements. Each fault condition is composed of 100 samples. The network training is performed with a trial and error procedure in order to arrange the number of hidden neurons with respect to the network output error. Even if the convergence of the network was reached with more than 100 hidden neurons, generalisation properties were unsatisfactory.

A different supervised neural network architecture was then considered, namely a so called back-propagation or multilayered feed–forward network [5, 3]. Such a neural network consists of an input layer, one or more hidden layers and an output layer. A six inputs-one output MLP network was designed with one hidden layer. The training patterns were the ones used for the RBF network.

The results of training sessions regarding the inputs M_f and IGV allow to estimate the input sensor fault amplitude with an accuracy of 1% at least. Minimal fault values concerning both input and output sensors are collected in the Table (1). They are indicated by (NN). Those values were obtained by using statistical tests on Kalman filter innovations (KF) [4, 1].

Fault sizes are expressed as per cent of the mean signal values. The minimal

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Method	Input sensors	Output sensors
(NN)	3%	1.5%
(KF)	2.5%	1%

Table 1: Minimal detectable faults.

detectable values obtained by using statistical tests on Kalman filter residuals (KF) appear comparable to the fault sizes estimated by neural networks (NN). The minimal detectable faults on the various sensors seem to be adequate to the industrial diagnostic applications.

6 Conclusions

A complete design procedure for fault diagnosis and identification in the input–output sensors of industrial processes is described in this paper. The fault detection was performed by using a bank of Kalman filters. The fault identification was achieved by experimenting with two supervised neural network architectures. The procedure was applied to a model of a industrial gas turbine obtained by means of the Frisch scheme identification method. Input and output sensor faults modelled by step functions were considered. Simulations show how multilayer perceptron networks can reliably classify the training patterns and allow to obtain satisfactory performance.

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