Parametric Fault Detection in Nonlinear Systems
A Recursive Subspace-based Approach

Paulo Gil[1,2], Fábio Santos[3], Alberto Cardoso[2] and Luís Palma[1]

[1]*Departmento de Engenharia Electrotécnica, Faculdade de Ciências e Tecnologia Universidade Nova de Lisboa, 2829-516 Caparica, Portugal*

[2]*CISUC, Informatics Engineering Department, University of Coimbra, Pólo II, 3030-290 Coimbra, Portugal*

[3]*Visteon Corporation Ltd, Electronics Product Group, 2951-503 Palmela, Portugal*

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Abstract: This paper deals with the problem of detecting nolinear systems' parametric faults modeled as changes in the eigenvalues of a local linear state-space model. The linear state-space model approximations are obtained by recursive subspace system identification techniques, from which the eigenvalues are extracted at each sampling time. Residuals are generated by comparing the eigenvalues against those associated with a local nominal model derived from a neural network predictor describing the nonlinear plant dynamics in free fault conditions. Parametric fault symptoms are generated from the eigenvalues residuals, whenever a given predefined threshold is exceeded. The feasibility and effectiveness of the proposed framework is demonstrated in a practical case study.

1 INTRODUCTION

Fault Detection and Isolation (FDI) consists of making a binary decision concerning a malfunctioning hypothesis, and in case of a given fault event to determine its nature and location (Isermann and Ballé, 1997), (Isermann, 2011). In general, FDI frameworks incorporate the concept of redundancy, either in terms of hardware or analytical. While the former approaches rely essentially on duplicative signals provided by additional hardware, the analytical or software redundancy uses a mathematical model of the plant along with dedicated estimation methods (Hwang et al., 2010). Since this methodology normally does not require additional hardware it is usually more cost effective. However, this approach is more challenging owing to the need of coping with model uncertainties, noise and unknown/unmeasurable disturbances that ultimately distorts the computed residuals and may lead to a misclassification of symptoms.

Model-based fault detection and diagnosis methods use residuals between the plant and a mathematical model prediction in conjunction with a classifier or voter that, according to the residuals' magnitude and additional features, generates an alarm and provides information regarding the detected symptom. Concerning residual generation methods, they can be implemented based on state and output observers (Chen and Patton, 1999), parity relations (Gertler, 1998) or on parameters estimation using system identification techniques (Isermann, 1997), (Brito Palma et al., 2005).

For a number of applications the FDI problem of interest is to detect changes in the eigenstructure of linear dynamic systems, being the structural vibration monitoring a typical example. A straightforward approach relies on subspace-based linear system identification (see e.g. (Moor et al., 1999)). In (Basseville et al., 2000) subspace-based methods along with the statistical local approach have been analysed in the context of designing fault detection algorithms and suggested to be useful for in-operation modal analysis and monitoring of mechanical structures subject to vibration, while in (Basseville et al., 2007) it is presented an overview of theory and practice of covariance-driven input/output and output only subspace-based algorithms for structural identification, damage detection and diagnosis, and sensor data fusion.

In the preceding FDI works it is assumed that the underlying system under monitoring is linear and time-invariant. In the case of nonlinear systems these methods are doomed to fail as a result of unreliable

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residuals due to the cumulative effect of model-plant mismatch.

The main contribution of this work is to develop a new framework to detect parametric faults in nonlinear dynamic systems, modelled as changes in the internal system dynamics, by taking advantages of recursive subspace-based system identification techniques, and the approximation capabilities of nonlinear autoregressive with exogenous inputs Nonlinear Autoregressive with Exogenous Inputs (NARX) neural networks. By assuming the input-output certainty equivalence principle, the approach first computes the residuals of the underlying local eigenstructures. Subsequently, by analysing these residuals, the change detection module evaluates whether a parametric fault has occurred.

2 SYSTEM IDENTIFICATION

In the context of fault detection and isolation a model of the plant under normal or nominal operating conditions is obtained by regression, upon selecting a particular model structure and a parametrization. When a given fault affects the system it is most likely that the system's behaviour, in terms of outputs, inputs or internal dynamics, would differ from the behaviour predicted by the nominal operating model. This means that fault events will be reflected in a change of the models' parameters. It is exactly this basic assumption that most model-based identification methods for FDI consider in order to detecting and isolating faults based on residual signals.

Among possible model structures to approximate the input-output behaviour of the plant, the present work considers linear state-space system models and NARX neural networks, with the choice of these model structures dictated by the nature of the proposed FDI framework. In the case of linear state-space model-based identification the underlying matrices are estimated by considering recursive subspace techniques, while for NARX neural network predictors their training is carried out offline using an iterative optimization procedure.

2.1 Recursive Subspace Identification

2.1.1 Preliminaries

In the case of offline SID methods it is implicitly assumed that a sequence of input-output data collected from the plant is available, that is,

$$\begin{aligned} U^N &= \{u(0), u(1), \ldots, u(N-1)\} \\ Y^N &= \{y(1), y(2), \ldots, y(N)\} \end{aligned} \tag{1}$$

In order to come up with estimates for the state-space matrices (A, B, C, D) (up to within a similarity transformation (Mercère, 2005)) and error covariance matrices (Q, R, S) the estimation data are organized under the form of past and future block Hankel matrices. In what the input sequence is concerned, these block Hankel matrices take the following form:

$$U_p = \begin{pmatrix} u(0) & u(1) & \cdots & u(j-1) \\ u(1) & u(2) & \cdots & u(j) \\ \vdots & \vdots & \ddots & \vdots \\ u(i-1) & u(i) & \cdots & u(i+j-2) \end{pmatrix} \tag{2}$$

$$U_f = \begin{pmatrix} u(i) & u(i+1) & \cdots & u(i+j-1) \\ u(i+1) & u(i+2) & \cdots & u(i+j) \\ \vdots & \vdots & \ddots & \vdots \\ u(2i-1) & u(2i) & \cdots & u(2i+j-2) \end{pmatrix} \tag{3}$$

and the past and future output block Hankel matrices, $Y_p \equiv Y_{0|i-1}$ and $Y_f \equiv Y_{i|2i-1}$ given according to,

$$Y_p = \begin{pmatrix} y(0) & y(1) & \cdots & y(j-1) \\ y(1) & y(2) & \cdots & y(j) \\ \vdots & \vdots & \ddots & \vdots \\ y(i-1) & y(i) & \cdots & y(i+j-2) \end{pmatrix} \tag{4}$$

$$Y_f = \begin{pmatrix} y(i) & y(i+1) & \cdots & y(i+j-1) \\ y(i+1) & y(i+2) & \cdots & y(i+j) \\ \vdots & \vdots & \ddots & \vdots \\ y(2i-1) & y(2i) & \cdots & y(2i+j-2) \end{pmatrix} \tag{5}$$

The block Hankel matrices of the stochastic subsystem, built in with the outputs $y^s(k)$, the process noise $\omega(k)$ and the measurement noise $\upsilon(k)$ are defined as above, namely, (Y_p^s, Y_f^s), (M_p^s, M_f^s) and (N_p^s, N_f^s), respectively.

The past and future state vector sequence, respectively, X_p and X_f take the following form:

$$\begin{aligned} X_p &= \begin{pmatrix} x(0), & x(1), & \cdots & x(j-1) \end{pmatrix} \\ X_f &= \begin{pmatrix} x(i), & x(i+1), & \cdots & x(i+j-1) \end{pmatrix} \end{aligned} \tag{6}$$

while the Toeplitz matrices associated with the deterministic and the stochastic subsystems are given by:

$$H_i^d = \begin{pmatrix} D & 0 & 0 & \cdots & 0 \\ CB & D & 0 & \cdots & 0 \\ CAB & CB & D & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{i-2}B & CA^{i-3}B & CA^{i-4}B & \cdots & D \end{pmatrix} \tag{7}$$

$$H_i^s = \begin{pmatrix} 0 & 0 & 0 & \cdots & 0 \\ C & 0 & 0 & \cdots & 0 \\ CA & CB & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{i-2} & CA^{i-3} & CA^{i-4} & \cdots & 0 \end{pmatrix} \tag{8}$$

The extended observability matrix associated with the deterministic system is given by:

$$\Gamma_i = \begin{pmatrix} C \\ CA \\ CA^2 \\ \vdots \\ CA^{i-1} \end{pmatrix} \tag{9}$$

The following input-output matrix equations play a fundamental role in subspace identification (Bart De Moor, 1999):

$$\begin{aligned} Y_p &= \Gamma_i X_p^d + H_i^d U_p + Y_p^s \\ Y_f &= \Gamma_i X_f^d + H_i^d U_f + Y_f^s \\ Y_p^s &= \Gamma_i X_p^s + H_i^s M_p + N_p \\ Y_f^s &= \Gamma_i X_f^s + H_i^s M_f + N_f \end{aligned} \tag{10}$$

2.1.2 Recursive Algorithm

The algorithm implemented in this work comprises two main stages: *i*) Online updating of the observation vector, using the QR factorization, along with Givens rotations (see e.g. (Oku and Kimura, 2002), (Mercère et al., 2004)) , and *ii*) Recursive estimation of the extended observability matrix, considering the online updating of the propagator.

i) *QR Factorization Updating*

Consider the following decomposition:

$$\begin{pmatrix} U_p \\ \Psi \\ Y_p \end{pmatrix} = \begin{pmatrix} R_{11} & 0 & 0 \\ R_{21} & R_{22} & 0 \\ R_{31} & R_{32} & R_{33} \end{pmatrix} \begin{pmatrix} Q_1 \\ Q_2 \\ Q_3 \end{pmatrix} \tag{11}$$

with Ψ the instrumental variable comprising past inputs and outputs, such that $\lim_{j\to\infty} \frac{1}{J}\Theta_i \Psi^T = 0$, $\Theta_i = H_i^s M_f + N_f$ and $\operatorname{rank}(X\Psi^T) = n$. In such conditions the following expression holds:

$$\lim_{j\to\infty} \frac{1}{\sqrt{j}} R_{32} Q_2 = \lim_{j\to\infty} \frac{1}{\sqrt{j}} \Gamma_i X \tag{12}$$

The procedure for updating the QR factorization with the next data pair $\{u(\tau), y(\tau)\}$ is as follows:

$$\left(\sqrt{\lambda} \begin{pmatrix} R_{11} & 0 & 0 \\ R_{21} & R_{22} & 0 \\ R_{31} & R_{32} & R_{33} \end{pmatrix} \begin{matrix} u_i(\tau+1) \\ \psi(\tau+1) \\ y_i(\tau+1) \end{matrix} \right) \begin{pmatrix} Q_1(\tau) & 0 \\ Q_2(\tau) & 0 \\ 0 & 1 \end{pmatrix} \tag{13}$$

with $\lambda \in \mathbb{R}^+$ a forgetting factor considered to weight past information.

Now, by applying two sequences of Givens rotations in (13) the factor R in the QR decomposition is converted into the following block lower triangular matrix:

$$\begin{aligned} &\left(\sqrt{\lambda} \begin{pmatrix} R_{11} & 0 & 0 \\ R_{21} & R_{22} & 0 \\ R_{31} & R_{32} & R_{33} \end{pmatrix} \begin{matrix} u_i(\tau+1) \\ \psi(\tau+1) \\ y_i(\tau+1) \end{matrix} \right) \\ &\operatorname{rot}_{G_1}(\tau+1) \cdot \operatorname{rot}_{G_2}(\tau+1) = \\ &= \begin{pmatrix} R_{11}(\tau+1) & 0 & 0 & 0 \\ R_{21}(\tau+1) & \sqrt{\lambda} R_{22}(\tau) & 0 & \breve{\psi}(\tau+1) \\ R_{31}(\tau+1) & \sqrt{\lambda} R_{32}(\tau) & \sqrt{\lambda} R_{33}(\tau) & \check{z}(\tau+1) \end{pmatrix} \\ &\operatorname{rot}_{G_2}(\tau+1) = \\ &= \begin{pmatrix} R_{11}(\tau+1) & 0 & 0 & 0 \\ R_{21}(\tau+1) & R_{22}(\tau+1) & 0 & 0 \\ R_{31}(\tau+1) & R_{32}(\tau+1) & \sqrt{\lambda} R_{33}(\tau) & \check{\check{z}}_i(\tau+1) \end{pmatrix} \end{aligned} \tag{14}$$

with $\breve{\psi}$ and $\check{z}$ vectors obtained after applying the first Givens rotation, and accounting for the information included in u_i, while $\check{\check{z}}$ is the vector obtained after the second Givens rotation in order to include the information embedded in $\breve{\psi}$.

Taking into account (12) it follows that,

$$\mathcal{E}\left[\check{z}_i \check{z}_i^T - \check{\check{z}}_i \check{\check{z}}_i^T\right] = \Gamma_i R_x \Gamma_i^T \tag{15}$$

Equation (15) shows that (14) leads asymptotically to a given covariance matrix R_{z_i}, from which the subspace spanned by the columns of the extended observability can consistently be extracted. The procedure of recursively updating this covariance matrix is presented in the following equation:

$$\tilde{R}_{z_i}(k) = \lambda \hat{R}_{f_i}(k-1) + \check{z}_i(k)\check{z}_i^T(k) - \check{\check{z}}_i(k)\check{\check{z}}_i^T(k) \tag{16}$$

ii) *Extended observability subspace basis updating*

The process followed in this work for updating a given basis for the extended observability matrix relies on the propagator method (Munier and Delisle, 1991). This method has the advantage of enabling its use in the context of coloured unknown disturbances.

Assume that the pair (A, C) is observable and the system's order n is known in advanced. Then, it is possible to derive a given permutation matrix $S \in \mathbb{R}^{li \times li}$ such that the extended observability Γ_i can be decomposed in two blocks:

$$S\Gamma_i = \begin{pmatrix} \Gamma_{i_1} \in \mathbb{R}^{n\times n} \\ \Gamma_{i_2} \in \mathbb{R}^{(li-n)\times n} \end{pmatrix} \tag{17}$$

Taking into account the propagator operator, (17) can rewritten as,

$$S\Gamma_i = \begin{pmatrix} I_n \\ P_i^T \end{pmatrix} \Gamma_{f_1} \tag{18}$$

Now, by replacing (18) into (15) it follows that

$$R_{z_i} = \begin{pmatrix} I_n \\ P_i^{\mathrm{T}} \end{pmatrix} R_{\bar{x}} \begin{pmatrix} I_n & P_i \end{pmatrix} \tag{19}$$

which can be rewitten as,

$$\begin{aligned} R_{z_i} &= \begin{pmatrix} R_{\check{z}_{i_1}} - R_{\check{\check{z}}_{i_1}} & R_{\check{z}_{i_1}\check{z}_{i_2}} - R_{\check{\check{z}}_{i_1}\check{\check{z}}_{i_2}} \\ R_{\check{z}_{i_2}\check{z}_{i_1}} - R_{\check{\check{z}}_{i_2}\check{\check{z}}_{i_1}} & R_{\check{z}_{i_2}} - R_{\check{\check{z}}_{i_2}} \end{pmatrix} \\ &= \begin{pmatrix} R_{\bar{x}} & R_{\bar{x}} P_i \\ P_i^T R_{\bar{x}} & P_i^T R_{\bar{x}} P_i \end{pmatrix} \end{aligned} \tag{20}$$

Equation (20) shows that the propagator can be found by minimizing the following Frobenius norm:

$$J(P_i) = \left\| \hat{R}_{\check{z}_{i_2}\check{z}_{i_1}} - \hat{R}_{\check{\check{z}}_{i_2}\check{\check{z}}_{i_1}} - P_i^{\mathrm{T}} \left(\hat{R}_{\check{z}_{i_1}} - \hat{R}_{\check{\check{z}}_{i_1}} \right) \right\|_{\mathrm{F}}^2 \tag{21}$$

In the case of all the involved matrices are nonsingular (see (Mercère and Lovera, 2007)) the argument of minimizing Eq. (21) is given by (Mercère et al., 2008):

$$\hat{P}_i^T = \left(\hat{R}_{\check{z}_{i_2}\check{z}_{i_1}} - \hat{R}_{\check{\check{z}}_{i_2}\check{\check{z}}_{i_1}} \right) \left(\hat{R}_{\check{z}_{i_1}} - \hat{R}_{\check{\check{z}}_{i_1}} \right)^{-1} \tag{22}$$

This optimal solution can be recursively updated by means of a Recursive Least Squares (RLS) algorithm.

iii) Estimation of State-space Matrices

Since recursive subspace identification methods assume that the vectorial basis dimension is known in advanced the computation of estimates for the state-space matrices is readily obtained from the extended observability matrix and input-output data. For matrices A and C the corresponding estimates are obtained as follows:

$$\begin{aligned} \hat{C} &= \hat{\Gamma}_i(1:l,:) \\ \hat{A} &= \left[\hat{\Gamma}_i(1:l(i-1),:) \right]^{\dagger} \hat{\Gamma}_i(l+1:li,:) \end{aligned} \tag{23}$$

with $\hat{\Gamma}_i = \begin{pmatrix} I_n & \hat{P}_i \end{pmatrix}^{\mathrm{T}}$.

Concerning B and D estimates, they are found by means of a least squares estimator applied to the elements of $\zeta(B,D)$ defined as (dos Santos and de Carvalho, 2003):

$$\zeta(B,D) = \begin{pmatrix} B & \hat{\Gamma}_{i-1}^{\dagger} H_{i-1}^{d} \\ D & 0 \end{pmatrix} - \begin{pmatrix} \hat{A} \\ \hat{C} \end{pmatrix} \hat{\Gamma}_i^{\dagger} H_i^{d} \tag{24}$$

2.2 Neural Network Predictor

Multilayer perceptrons comprising one hidden layer are universal approximators, that is, they are able to approximate any nonlinear function with any desired accuracy provided that some particular conditions are held (see e.g. (Leshno et al., 1993), (Chen et al., 1995)).

An important subclass of multilayer perceptrons, quite appealing in the context of nonlinear control and identification, is the NARX neural networks, whose input vector consists of past inputs and past outputs (the regressor). This architecture can be analytically represented as follows:

$$y_{net}(k) = g(\varphi(k), \theta) \tag{25}$$

with θ the neural network parameters vector consisting of weights and biases, and the regressor $\varphi(k)$ given by:

$$\begin{aligned} \varphi^{\mathrm{T}}(k) = (&y(k-1), \ldots, y(k-n_y), \\ &u(k-1), \ldots, u(k-n_u)) \end{aligned} \tag{26}$$

where $u(k)$ and $y(k)$ denoting the system's input and output, n_u and n_y the lag windows for past inputs and outputs, and $g(\cdot)$ a nonlinear mapping performed by the NARX neural network. This input-output relationship can be rewritten as follows:

Regarding the activation functions of neurons included in the output layer, they are all linear, while the nonlinear activation functions $\sigma(\cdot)$ associated with hidden layer neurons are chosen as continuous and differentiable sigmoidal functions, upper and lower bounded, satisfying the following conditions (Dong et al., 2002):

- $\lim_{t \to \pm\infty} \sigma(t) = \pm 1$;
- $\sigma(t) = 0 \Leftarrow t = 0$;
- $\sigma'(t) > 0$;
- $\lim_{t \to \pm\infty} \sigma'(t) = 0$;
- $\max(\sigma'(t)) \leq 1 \Leftarrow t = 0$.

For the number of neurons to be incorporated within each layer, only those associated with the output layer are directly related to the number of outputs of the system. Concerning the hidden and input layers, the number of neurons should be carefully selected in order to enable the neural predictor to generalize well to unseen data, while presenting the minimal structural complexity. As such, there is a trade-off between structural complexity and generalization capability.

In the case of a three-layer NARX(N_u, N_h, N_o) neural network, where N_u, N_h and N_o, are respectively, the number of input layer, hidden layer and output layer neurons, with sigmoid activation functions in the hidden layer and linear activation functions in the remaining two layers, the corresponding output is given by,

$$y_{net}(k) = W_2 \sigma (W_1 \cdot \varphi(k) + b_1) + b_2 \qquad (27)$$

with $W_1 \in \mathbb{R}^{N_h \times N_u}$, $W_2 \in \mathbb{R}^{N_o \times N_h}$, $b_1 \in \mathbb{R}^{N_h}$, $b_2 \in \mathbb{R}^{N_o}$ and the regressor vector given by (26).

3 ARCHITECTURE

The framework for detecting parametric faults in nonlinear dynamic systems is based on comparing the eigenstructure of two linear state-space realizations, one for the nonlinear system under monitoring and the other for the NARX neural network predictor. The neural predictor was previously trained offline with an informative enough dataset collected from the nonlinear system in a fault-free context.

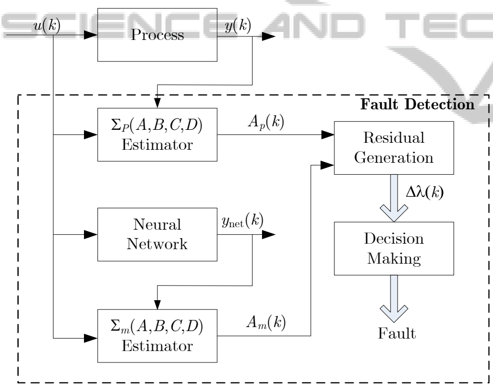

Figure 1: Parametric fault detection architecture.

Basically, the architecture (see Fig. 1) consists of a linear state-space identification module that estimates, through recursive subspace system identification techniques, local linear system matrices associated with both the plant and the NARX neural network predictor. Additionally, the platform includes a residual generator module that computes, at each discrete time k, and based on the eigenvalues of the system matrices $A_p(k)$ and $A_m(k)$ a residual vector $\Delta\lambda(k)$ given by:

$$\Delta\lambda(k) = |\lambda_p(k) - \lambda_m(k)| \qquad (28)$$

with $|\cdot|$ the element-wise absolute value operator.

The residuals $\Delta\lambda(k)$ are subsequently analysed in the decision making module, which uses statistical tools in order to test whether they have "significantly" deviated from zero. In particular, the decision criterion is based on a threshold computed offline based on the three-sigma limits approach (Montgomery, 2001). If a residual exceeds the computed threshold the system is considered in faulty operation and some effective measures should be taken to accommodate its effects. Finally, it should be mentioned that fault accommodation techniques are not the focus of this work.

4 CASE STUDY

In this section the proposed approach for detecting parametric faults in nonlinear dynamic systems is experimentally tested and validated using a laboratory test-bed.

4.1 Test-bed

The test-bed consists of a heating system from Feedback®, namely, the Process Trainer PCT 37-100 (Fig. 2). It comprises a variable-speed axial fan adjusted manually via a potentiometer, which circulates an air-stream along a polypropylene tube. The airflow rate is heated by means of a heating element under the form of a grid with a maximum power of 80 W for an input voltage of +10 V controlled by a thyristor circuit. A thermistor detector is included in the set-up for sensing the temperature at one of the three available measurement points along the tube length.

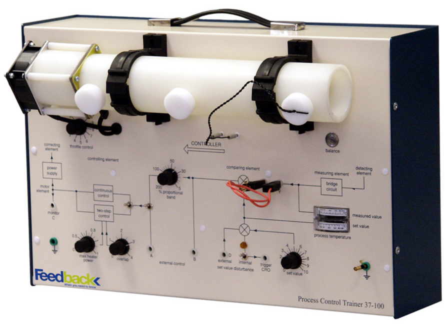

Figure 2: Feedback® Process Trainer PCT 37-100.

This setup represents a nonlinear time-varying system, where the main source of nonlinearities are associated with the input dependent static gain, while the time variant behavior is essentially due to thermal energy storage in the course of experiments. As can be observed in Fig. 3, which shows the normalized static gain as a function of the normalized input fed to the system, the systems static gain varies with the operation regime.

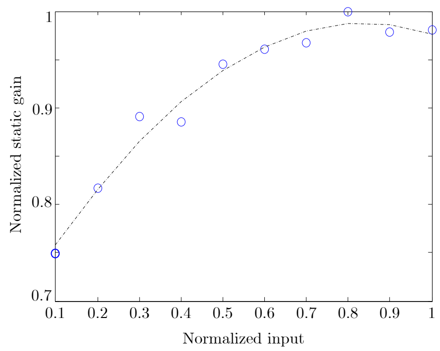

Figure 3: Feedback® Process Trainer PCT 37-100 static gain.

The communication infrastructure between the digital computer, where the fault detection platform is installed, and the process trainer PCT 37-100 consists of a peer-to-peer interconnection based on a data acquisition board PMD-1208LS series, from the Measurement Computing®. This device includes two 10-bit analog outputs, 8 single-ended or 4 differential analog inputs, and 16 digital I/O [1].

4.2 Experiment

The experiment shown here was carried out considering the following nominal configuration: fan speed referred to the potentiometer's position 5, temperature sensor located at position II (140 mm from the heater grid), and a sampling interval of 10 ms. Regarding the linear state-space models' complexity, for $\Sigma_p = (A_p, B_p, C_p, D_p)$ and $\Sigma_m = (A_m, B_m, C_m, D_m)$, they were both chosen to be of 3^{rd} order, as suggested by the offline subspace algorithm. Regarding the three-layered NARX neural network consisted of four neurons in the input layer, seven neurons in the hidden layer and one neuron in the output layer, while the input to the network u_{net} was represented by an array of four elements, namely:

$$u_{net}(k) = [u(k-1)\ u(k-2)\ y(k-1)\ y(k-2)]^{\mathrm{T}} \quad (29)$$

In the experiment run the system's fan potentiometer was initially at position 5 and, subsequently, at sample 420, the fan speed was manually changed to 1. This change resulted in a major air flow rate reduction, which impacted the static gain and pure delay of the system. Fig. 4 shows the three residuals over time, computed from the eigenvalues of Σ_p and Σ_m, and the experimental threshold associated with each residual, while in Fig. 5 it is presented the number of symptoms (out of three) corresponding to residuals outside the thresholds.

[1] see http://www.mccdaq.com.

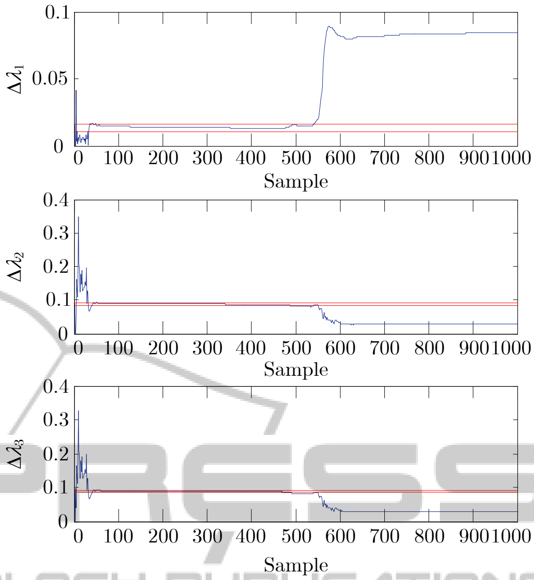

Figure 4: Parametric fault - residuals and thresholds.

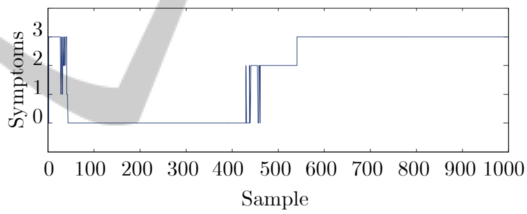

Figure 5: Parametric fault - symptoms.

As can be observed in Fig. 5 at the beginning of the experiment run, even still with no fault injected on the system, the fault detection platform generates unexpected symptoms. This behaviour is due to the initialization of the subspace recursive estimation algorithm, which in the initial phase is responsible for residuals outside experimental thresholds. After this initial time frame, the number of symptoms stabilizes at zero, which is in line with the presence of no parametric fault acting on the system. With the fault injected at sample 420 the system dynamics underwent a noticeable change, which should be reflected in the linear adaptive model of the process, and ultimately be expressed by residuals lying outside the thresholds.

5 CONCLUSIONS

This paper addressed the problem of nonlinear parametric fault detection in nonlinear dynamic systems.

The proposed framework is based on recursive subspace system identification techniques to generate fault dependent symptoms from eigenvalues residuals. The parametric fault detection architecture was tested on a nonlinear plant whose results demonstrate the feasibility of the proposed approach in detecting parametric faults.

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