Identification and fault diagnosis of an industrial gas turbine prototype model

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Abstract

This paper addresses a model-based procedure exploiting analytical redundancy for the detection and isolation of faults of a power plant. The residual generation is performed by means of output observers and Kalman filters in connection with the uncertainty affecting the measurements acquired from the monitored system. The model of the process under investigation required to design observers and filters is obtained by identification The proposed fault detection and isolation tool has been tested on a simulated model of an industrial gas turbine prototype.

Keywords: fault diagnosis, analytical redundancy, model-based approach, system identification, industrial gas turbine.

1 Introduction

The problem of fault detection and isolation (FDI) in linear time-invariant dynamic processes has received great attention during the last two decades and a wide variety of model-based approaches has been proposed [1, 2].

These different methods, however, can be brought down to a few basic concepts such as the parity space approach [3], the state estimation approach [4, 5], the fault detection filter approach [6, 7] and the parameter identification approach [4, 8]. In every case, for the detectability and distinguishability of faults, mathematical models of the process under investigation are required, either in state space or input-output form.

State space descriptions provide general and mathematically rigorous tools for system modelling and residual generation which may be used in fault detection of industrial systems, both for the deterministic (noise-free case) and the stochastic (noisy case) environment. Residuals should then be processed to detect an actual fault condition, rejecting any false alarms caused by noise or spurious signals.

This work aims to define a comprehensive methodology for the diagnosis of actuator, component and input-output sensor fault of an industrial process by using an output estimation approach [9], in conjunction with residual processing schemes which include a simple threshold detection, in deterministic case, as well as statistical analysis when data are affected by noise [2].

Two main aspects of the proposed methodology should be underlined. Firstly, the FDI model-based approach does not require any physical knowledge of the process under observation. A linear mathematical model (state-space or input-output descriptions) of the input-output links are, in fact, obtained by means of identification schemes which use Auto Regressive eXogenous (ARX) models in case of high signal to noise ratios, or Errors-In-Variables (EIV) models, otherwise [10]. In the last case the identification technique is based on the Frisch scheme methodology [11]. This approach gives a reliable model of the plant under investigation, as well as providing variances of the input-output noises [12]. Secondly, in this work linear prototypes for the design of linear output estimators [13, 14], [9] have been developed instead of complicated non-linear models obtained by modelling techniques in connection with non-linear observers. In fact, as the feature of system supervision is to monitor the operation and performance of the system with respect to an expected point of operation, linear system methods are still very valid.

The complete procedure of model identification, residual generation and fault identification and isolation have been tested on a single-shaft industrial gas turbine prototype. The results coming from a massive simulation tests are reported and widely commented.

2 Model description

In the following it is assumed that the monitored system, depicted in Figure (1), can be described in fault free condition, by a linear, discrete-time, time-invariant, dynamic model of the type

$$\begin{cases} \mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}^*(t) \\ \mathbf{y}^*(t) = \mathbf{C}\mathbf{x}(t) \end{cases} \quad t = 1, 2, \cdots \tag{1}$$

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

Under fault free conditions, the input and the output link of the sensors can be described by the following relation

$$\begin{cases} \mathbf{u}(t) = \mathbf{u}^*(t) + \tilde{\mathbf{u}}(t), \\ \mathbf{y}(t) = \mathbf{y}^*(t) + \tilde{\mathbf{y}}(t). \end{cases} \tag{2}$$

In real applications, variables $\tilde{\mathbf{u}}(t)$ and $\tilde{\mathbf{y}}(t)$ represent noises which, due to technological reasons, affect sensor behaviour. They are generally described as white, zero-mean, uncorrelated Gaussian noises. It is assumed that $\mathbf{u}(t)$ and $\mathbf{y}(t)$ are the only available measurements from the real process.

Vectors $\mathbf{f}_u(t) = \begin{bmatrix} f_{u_1} & \cdots & f_{u_r} \end{bmatrix}$ and $\mathbf{f}_y(t) = \begin{bmatrix} f_{y_1} & \cdots & f_{y_m} \end{bmatrix}$ model input and output sensor faults, respectively. The scheme shown in Figure (1) describes the relations among the actual sensor inputs $\mathbf{u}^*(t)$ and $\mathbf{y}^*(t)$, the sensor faults $\mathbf{f}_u(t)$ and $\mathbf{f}_y(t)$ and the sensor outputs $\mathbf{u}(t)$ and $\mathbf{y}(t)$.

According again to Figure (1), when a component fault $\mathbf{f}_s(t) \in \Re^n$ occurs in the plant described by Equations (1), the dynamic system will be modelled as

$$\mathbf{x}(t+1) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) + \mathbf{f}_s(t). \tag{3}$$

A fault $\mathbf{f}_c(t) = \mathbf{0}$ may also occur on the regulator in the control loop. In such a case, under the assumptions

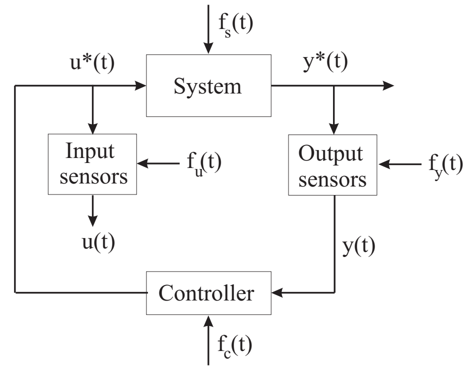

Figure 1: The monitored system

that $\mathbf{f}_u(t) = \mathbf{0}$ and $\mathbf{f}_y(t) = \mathbf{0}$, the link among the output $\mathbf{u}(t)$ of the regulator, its input $\mathbf{y}(t)$ and the controller fault $\mathbf{f}_c(t)$ will be modelled as

$$\mathbf{u}(t) = \tilde{\mathbf{u}}(t) + G\left(\mathbf{y}(\cdot)\right) + \mathbf{f}_c(t) \tag{4}$$

where $G(\cdot)$ represents the input-output behaviour of the controller.

Usually $\mathbf{f}_u(t)$, $\mathbf{f}_y(t)$, $\mathbf{f}_s(t)$ and $\mathbf{f}_c(t)$ signals are described by step and ramp functions representing abrupt and incipient faults (bias or drift), respectively.

Under fault-free assumptions, representations of types (1) and (2) are known as errors–in–variables (EIV) models.

The design of state observers and Kalman filters requires the knowledge of a state-space model of the system under investigation. When classical modelling techniques cannot be used since the complete physical knowledge of the system is not available or the model parameters are unknown, a black-box identification approach has to be considered [9].

3 Residual generation

The problem treated in this work regards the detection and isolation of the faults on the basis of the knowledge of the measured sequences $\mathbf{u}(t)$ and $\mathbf{y}(t)$. The structure of the fault detection device is depicted in Figure (2).

The symptom (residual, $\mathbf{r}(t)$) generation is implemented by means of dynamic observers or Kalman filters, driven by $\mathbf{u}(t)$ and $\mathbf{y}(t)$, in order to produce a set of signals, $\mathbf{f}(t)$, from which it will be possible to isolate faults associated to actuators, components and sensors. As depicted in Figure (2), the symptom evaluation refers to a logic device which processes the redundant signals generated by the first block in order to estimate and unequivocally identify a fault occurrence.

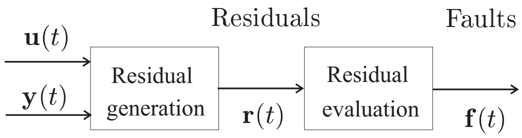

Figure 2: Logic diagram of the fault detection system.

4 Model identification

In case of high signal to noise ratios ($\tilde{\mathbf{u}}(t) \cong \mathbf{0}$ and $\tilde{\mathbf{y}}(t) \cong \mathbf{0}$), equation error identification can be exploited and, in particular, different equation error models can be extracted from the data. A specific discrete-time, time-invariant, linear dynamic model, e.g. ARX or ARMAX (Auto Regressive eXogenous or Auto Regressive Moving Average eXogenous), [15], can be selected only inside an assumed family of models.

If instead, the signal to noise ratios on the input and output of the process are low, the Frisch scheme [11] can be applied to perform the dynamic system identification. Such a scheme allows to determine the linear discrete system which has generated the noisy sequences as well as the variances of the noises $\tilde{\mathbf{u}}(t) \cong \mathbf{0}$ and $\tilde{\mathbf{y}}(t) \cong \mathbf{0}$ affecting the data [12]. In the Frisch scheme these signals are assumed zero-mean white noises, mutually uncorrelated and uncorrelated with every component of $\mathbf{u}^*(t)$ and $\mathbf{y}^*(t)$.

In particular, in this work, the input-output link will be mathematically described by performing the identification of a number of ARX Multi-Input Single-Output (MISO) models of the type

$$y_i^*(t) = \sum\nolimits_{j=1}^{n} \alpha_{i,j} y_i^*(t-j) + \sum\nolimits_{j=1}^{r} \sum\nolimits_{k=1}^{n} \beta_{i,j,k} u_j^*(t-k) \tag{5}$$

equal to the number m of the output variables has been performed. The order n and the parameters $\alpha_{i,j}$ and $\beta_{i,j,k}$, with $i = 1, \cdots, m$, of the model have to be determined by the identification approach.

The next step is the transformation of input-output discrete-time time-invariant linear models (5) into state-space representations. The state-space systems obtained by the equation errors models are useful to design dynamic observers, whilst the ones coming from the Frisch scheme can be used in order to build Kalman filters [9].

5 Fault diagnosis of a gas turbine

The aim of this paper consists in finding a procedure in order to detect and isolate faults on actuators, components and sensors of single-shaft industrial gas turbine. The model of such a turbine was developed in SIMULINK© environment [16].

Figure (3) shows the gas turbine layout as well as its inputs and outputs.

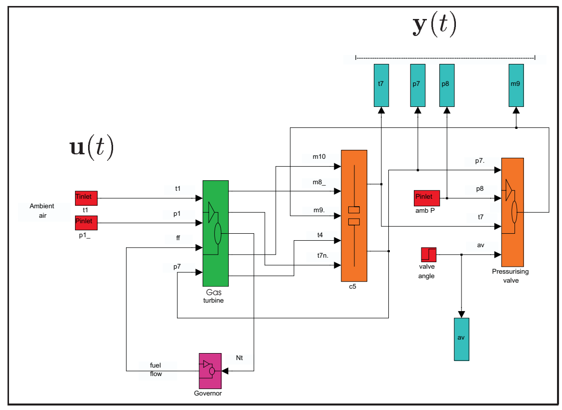

Figure 3: The monitored system.

The time series of data used to identify the models were generated with a non–linear dynamic model in SIMULINK© environment and they simulate measurements taken on the machine with a sampling rate of 0.08s and without noise ($\tilde{\mathbf{u}}(t) = \mathbf{0}$ and $\tilde{\mathbf{y}}(t) = \mathbf{0}$) due to measurement uncertainty which, instead, is always present in the real measurement systems. The model has $r = 2$ inputs and $m = 28$ output measurements.

For each output, an input-output MISO (multiple input–single output) model of the type (5) can be identified. In particular, the i–th model (with $i = 1, \cdots, m$ and $m = 28$) is driven by the input signals $a_v(t)$ and $f_f(t)$ ($r = 2$) giving the prediction $\hat{y}_i(t)$ of the i–th output, $y_i(t)$.

Each model was tested in different operating conditions and it has always provided an output reconstruction error lower than 0.5%. Moreover, other time series of data generated by the gas turbine non–linear model were exploited in order to validate the ARX models.

These models have always provided in full simulation an output reconstruction error lower than 1%.

5.1 Simulated Fault Conditions

Four gradually developing faults affecting the turbine model were considered as follows. *Case 1*: compressor contamination (core engine performance deterioration), $f_s(t)$. *Case 2*: thermocouple sensor fault (output sensor failure), $f_y(t)$. *Case 3*: high Pressure turbine seal damage (core engine performance deterioration), $f_s(t)$. *Case 4* fuel actuator friction wear (controller fault), $f_c(t)$.

In order to diagnose single fault on the monitored system, output observers or Kalman filters were exploited.

With reference to the block scheme of the monitored system depicted in Figure (1), the residual generation scheme with respect to the input and output measurements $\mathbf{u}(t)$ and $y_i(t)$ is represented by the structure shown in Figure (4).

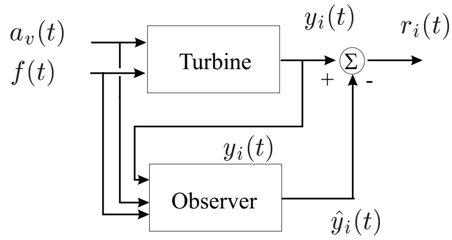

Figure 4: Residual generation logic scheme.

The residual $r_i(t)$ concerning the i-th output $y_i(t)$ is computed by the system depicted in Figure (4) and it is expressed as $r_i(t) = y_i(t) - \hat{y}_i(t)$, which is the difference between the estimated $\hat{y}_i(t)$ and the measured i-th output, $y_i(t)$.

Failure "case 1", represents fouling of the surfaces of the compressor blades, this reduces air flow, changes the blade aerodynamics and consequently changes the surface roughness. The failure is modelled as a gradual decrease in mass flow rate for a given pressure ratio. Failure "case 2" represents the malfunctioning of a thermocouple in the gas path leading to a slowly increasing or decreasing reading over time. Failure"case 3" represents failure $f_s(t)$ of an HP turbine seal. This results in a reduction in turbine efficiency. The fault is modelled as a gradual reduction in turbine efficiency over time. Failure "case 4", $f_c(t)$ represents the loss of performance due to wear of the fuel valve actuator. As there are no specific actuator dynamics in the current model, the wear effect of the valve actuator causing slower response to demanded flow rates is modelled as a simple first order lag on the resulting fuel flow.

An example of fault signal ("case 2") is depicted in Figure(5).

By performing residual sensitivity analysis, four measurements, i.e. the most sensitive output signals $y_i(t)$ to the four faults $f(t)$ were selected.

In order to detect and isolate faults on the i–th output measurements, when the measurement noises are negligible ($\tilde{\mathbf{u}}(t) = \mathbf{0}$ and, $\tilde{\mathbf{u}}(t) = \mathbf{0}$), with reference to system (1), the state-space model of the i–th output observer ($i = 1, \cdots, m$) has the form

$$\begin{cases} \mathbf{x}^i(t+1) = \mathbf{A}_i \mathbf{x}^i(t) + \mathbf{B}_i \mathbf{u}(t) + \mathbf{K}_i \left(y_i - \mathbf{C}_i \mathbf{x}^i(t) \right) \\ y^i(t) = \mathbf{C}_i \mathbf{x}^i(t) \end{cases} \quad (6)$$

where $\mathbf{x}^i(t)$ is the i–th observer state vector, $y^i(t)$ the estimate of the i–th output $y_i(t)$ and the triple ($\mathbf{A}_i$,$\mathbf{B}_i$,$\mathbf{C}_i$) is a minimal state-space representation (completely observable) of the link among the inputs of the process $\mathbf{u}(t)$ and its i–th output $y_i(t)$.

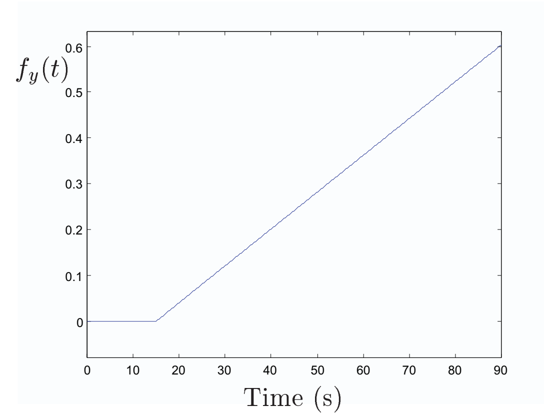

Figure 5: Example of fault fault "case 2".

In the absence of faults, it can be verified that, for the i–th output, the residual $r_i(t) = y_i(t) - y^i(t) = y_i(t) - \mathbf{C}_i \mathbf{x}^i(t)$ is equal to zero. In the presence of a fault on the i–th output sensor the i–th output residual reaches a value different from zero and this situation leads to a complete failure diagnosis.

In particular, the diagnosis and the isolation of the four faults requires the knowledge of four triples ($\mathbf{A}_i$,$\mathbf{B}_i$,$\mathbf{C}_i$) and therefore the identification of four ARX model with two inputs which gives the prediction of each i–th output $y_i(t)$. Four second order ($n = 2$) ARX MISO model ($r = 2$ and $m = 1$), driven by $a_v(t)$ and $f_f(t)$ input signals, were identified. These models presented always output reconstruction errors less than 1%.

The eigenvalues of the state distribution matrix of the output observers were placed with a trial and error procedure near to $0.2 \div 0.5$ in order to maximise the fault detection sensibility and promptness and to minimise the occurrence of false alarms.

As an example, Figure (5.1) shows the detection of a fault regarding the compressor ($f_s(t)$, fault "case 1") and occurring at the instant $t = 15$s. Fault-free (continuous line) and faulty residuals $r_i(t)$ (dotted line) are depicted. On the other hand, Figure (5.1) depicts the fault-free and the faulty residuals $r_i(t)$ in case of actuator fault, $f_c(t)$ (fault "case 4"), commencing at the instant $t = 15$s.

An improvement of the FDI performance has been obtained by using Kalman filters designed on the basis of the model parameters and the variances of the noises affecting the data and identified under the assumptions of the Frisch scheme [9]. In particular, since the Kalman

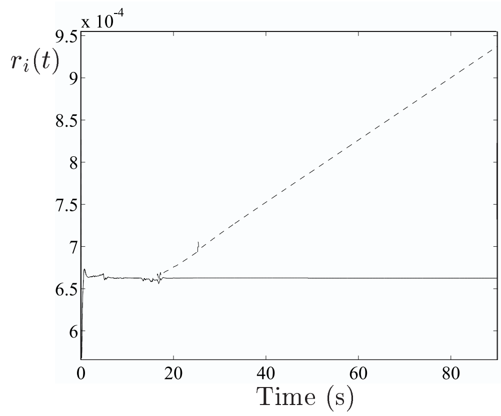

Figure 6: Fault free (continuous) and faulty (dotted) residuals for the diagnosis of "case 1" fault.

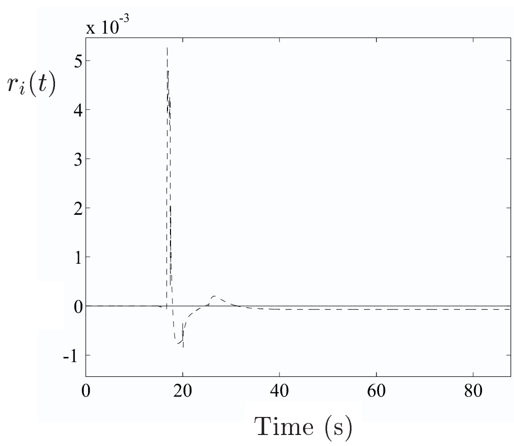

Figure 7: Fault free (continuous) and faulty (dotted) residuals for the diagnosis of fault "case 4".

filter produces zero-mean and white residuals when the system is operating normally, the FDI is implemented monitoring the sequence of innovations by means of residual geometrical analysis.

As an example, Figures (5.1), and (5.1) depict fault-free and faulty residuals $r_i(t)$ generated by the Kalman filter driven by the two inputs $\mathbf{u}(t)$ and by the output $y_i(t)$, taking into account measurement noises.

These figures depict the fault-free residual and their changes due to the fault occurrence, as in the previous cases without measurement noise.

Table (1) summarises the performance of the fault detection and isolation technique both in the deterministic and stochastic environment. It collects the minimal detectable fault on the four measurements, in case the residual or innovation value is monitored using a geometrical test and fixed thresholds.

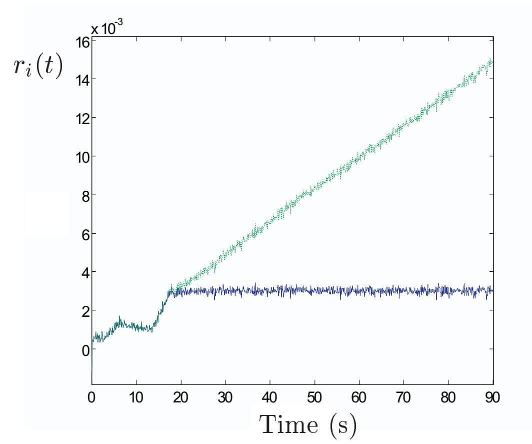

Figure 8: Diagnosis of "case 2" faults using Kalman filters.

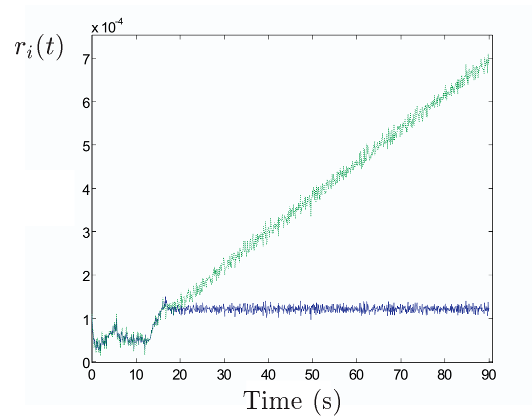

Figure 9: Diagnosis of fault "case 3" using Kalman filters.

The minimal detectable fault values in Table (1) are expressed as percentage of the signal reference values and they are relative to the case in which the occurrence of a fault must be detected as soon as possible.

Fault	Signal	Noise-free case	Noise case	Detection delay
Case 1	$q_c(t)$	0.5%	1%	30s
Case 2	$t_{3n}(t)$	10%	12%	30s
Case 3	$p_5(t)$	5%	7%	60s
Case 4	$p_3(t)$	1%	3%	10s

Table 1: Minimum detectable faults by monitoring residual and innovation values.

It results that the values of the faults obtained by using geometrical analysis of Kalman filter innovations are different than the ones computed in the deterministic environment exploiting classical observers. Faults modelled by ramp functions may not be immediately detected, since the *detection delay* in the corresponding alarm normally depends on fault mode.

The minimal detectable faults on the various sensors seem to be adequate to the industrial diagnostic applications, by considering also that the minimal detectable faults can be reduced if a delay in detection promptness is tolerable.

6 Conclusions

The complete design procedure for FDI in actuators, components and output sensors of an industrial process was described in this work. The fault diagnosis was performed by using a bank of dynamic observers or, when the measurement noises are not negligible, a bank of Kalman filters. Faults on the component of the system, actuator and output sensors were therefore considered The suggested method did not require any physical knowledge of the process under observation since the input-output links were obtained by means of an identification scheme, which uses ARX models in case of high signal to noise ratios or errors-in-variables models, otherwise. In last situation the identification technique (Frisch scheme) gave the variances of the input-output noises, which are required in the design of the Kalman filters.

Such a procedure was applied to a SIMULINK© model of a single-shaft industrial gas turbine. In order to analyse the diagnostic effectiveness of the FDI system in the presence of changes or drifts in measurements, faults modelled by ramp functions were generated. The results obtained by this approach indicated that the minimal detectable faults on the system actuator, component and output sensor are of interest for the industrial diagnostic applications.

The main aspect of this work was the use of linear system identification and modelling methods, although the system considered was non–linear. This is considered important to avoid the complexities that would otherwise be inevitable when non–linear models are used. There is certainly an increasing interest in the use of non–linear methods (non–linear observers, extended Kalman filters, fuzzy-logic methods, etc). However, as the feature of system supervision is to monitor the operation and performance of the system with respect to an expected point of operation, linear system methods are still very valid. Deviations from expected behaviour can be used to monitor system performance changes as well as system component malfunctions.

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