

# Diagnosis Techniques for Sensor Faults of Industrial Processes

S. Simani, C. Fantuzzi, and S. Beghelli

**Abstract**—In this paper a model-based procedure exploiting analytical redundancy for the detection and isolation of faults in input–output control sensors of a dynamic system is presented. The diagnosis system is based on state estimators, namely dynamic observers or Kalman filters designed in deterministic and stochastic environment, respectively, and uses residual analysis and statistical tests for fault detection and isolation. The state estimators are obtained from input–output data process and standard identification techniques based on ARX or errors-in-variables models, depending on signal to noise ratio. In the latter case the Kalman filter parameters, i.e., the model parameters and input–output noise variances, are obtained by processing the noisy data according to the Frisch scheme rules. The proposed fault detection and isolation tool has been tested on a single-shaft industrial gas turbine model. Results from simulation show that minimum detectable faults are perfectly compatible with the industrial target of this application.

**Index Terms**—Fault detection and isolation, industrial gas turbine, Kalman filter, model-based approach, unknown input observers.

## I. INTRODUCTION

The control devices which are currently exploited to improve the overall performance of the industrial processes involve both sophisticated digital system design techniques and complex hardware (sensors, actuators, processing units). In such a way, the probability of failure occurrence on such equipment may result significant and an automatic supervision control should be used to detect and isolate anomalous working conditions as early as possible.

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]–[14].

These different methods, however, can be brought down to a few basic concepts such as the parity space approach [1]–[3], the state estimation approach [4]–[9], the fault detection filter approach [7], [10], [11], and the parameter identification approach [4], [6], [12]. 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.

Frequency domain representations are typically applied when the effects of faults have frequency characteristics which differ from each other and thus the frequency spectra serve as criterion to distinguish faults [13], [14].

In recent years, there is also a clear trend toward an enlarged involvement of knowledge-based and artificial intelligence methods, including qualitative models concerning the residual generation, fuzzy logic and neural networks for the evaluation of the residuals [12], [7], [15].

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

This paper aims to define a comprehensive methodology for sensor fault detection by using a state estimation approach, 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. The final result consists in a fault FDI strategy based on fault diagnosis methods well known in literature to generate redundant residuals.

The diagnosis procedure may be further specialized for input or output sensors. In particular the fault diagnosis of input sensors uses an unknown input observer (UIO) in high signal to noise ratio conditions or a Kalman filter with unknown inputs (UIKF), otherwise. The  $i$ th UIO or UIKF is designed to be insensitive to the  $i$ th input of the system. On the other side, output sensor faults affecting a single residual are detected by means of a Luenberger observer or a classical Kalman filter, driven by a single output and all the inputs of the system.

The suggested method does not require the physical knowledge of the process under observation since the input–output links are 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 is based on the rules of the Frisch scheme, traditionally exploited to analyze economic systems. This approach gives a reliable model of the plant under investigation, as well as the variances of the input–output noises, which are required in the design of the Kalman filters.

The FDI technique presented in this paper is applied to the input–output sensor fault detection of a single-shaft industrial gas turbine whose linear mathematical description is obtained by using identification procedures.

## II. MODEL DESCRIPTION

In the following we assume that the dynamic process under observation is described by a discrete-time time-invariant linear dynamic model of the type

$$\begin{aligned} x(t+1) &= Ax(t) + Bu^*(t) \\ y^*(t) &= Cx(t), \quad t = 1, 2, \dots \end{aligned} \quad (1)$$

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where

$$\begin{aligned} x(t) &\in \mathbb{R}^n && \text{state vector;} \\ y^*(t) &\in \mathbb{R}^m && \text{output vector of the system;} \\ u^*(t) &\in \mathbb{R}^r && \text{control input vector.} \end{aligned}$$

$A$ ,  $B$ , and  $C$  are constant matrices of appropriate dimensions obtained by means of modeling techniques or identification procedures. In real applications variables  $u^*(t)$  and  $y^*(t)$  are measured by means of sensors whose outputs, due to technological reasons, are affected by noise.

The measured signals  $u(t)$  and  $y(t)$ , by neglecting sensor dynamics, are modeled as

$$\begin{aligned} u(t) &= u^*(t) + \tilde{u}(t) \\ y(t) &= y^*(t) + \tilde{y}(t) \end{aligned} \quad (2)$$

in which the sequences  $\tilde{u}(t)$  and  $\tilde{y}(t)$  are usually described as white, zero-mean, uncorrelated Gaussian noises. Descriptions of types (1) and (2) are known as errors-in-variables (EIV) models.

The input–output sensors may be affected by faults which degrade their reliability. In this case (2) must be replaced by

$$\begin{aligned} u(t) &= u^*(t) + \tilde{u}(t) + f_u(t) \\ y(t) &= y^*(t) + \tilde{y}(t) + f_y(t) \end{aligned} \quad (3)$$

where the vectors  $f_u(t) = [f_{u_1}(t) \cdots f_{u_r}(t)]^T$  and  $f_y(t) = [f_{y_1}(t) \cdots f_{y_m}(t)]^T$  are additive signals which assume values different from zero only in the presence of faults. Usually these signals are described by step and ramp functions representing abrupt and incipient faults (bias or drift), respectively. The problem treated in this work regards the detection and isolation of the sensor faults on the basis of the knowledge of the measured sequences  $u(t)$  and  $y(t)$ . Moreover, it is assumed that only a single fault may occur in the input or output sensors. Fig. 1 shows the structure of the measurement process.

The FDI device is implemented by means of dynamic observers in high signal to noise ratio conditions or Kalman filters otherwise, in order to produce a set of signals from which it will be possible to isolate faults associated to input–output sensors. The design of these state estimators requires the knowledge of a state-space model (1) of the system under investigation and of the statistics of the noises affecting the data. When classical modeling techniques cannot be used since the complete physical knowledge of the system is not available or the model parameters are unknown, an identification approach can be considered.

In case of high signal to noise ratios, equation error identification can be exploited and, in particular, different equation error models can be extracted from the data. A specific linear discrete-time model, e.g., ARX or ARMAX, can be selected only inside an assumed family of models. On the other side, if the signal to noise ratios on the input and output of the process are low, the Frisch scheme can be applied to perform the dynamic system identification [16]. Such a scheme allows to determine the linear discrete-time 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. In the Frisch scheme these signals are assumed zero-mean white noises, mutually uncorrelated and uncorrelated with every component of  $u^*(t)$  and  $y^*(t)$ .

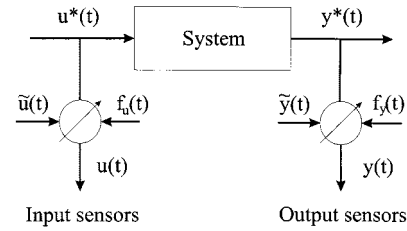


Fig. 1. Structure of the plant sensors.

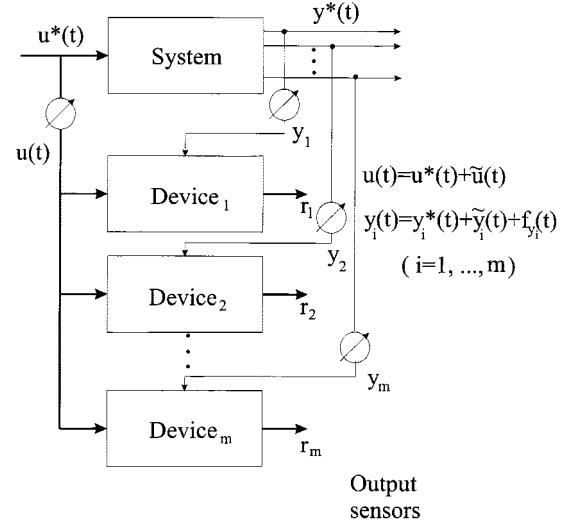


Fig. 2. Bank of estimators for output residual generation.

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

### III. RESIDUAL GENERATION FOR FAULT DETECTION AND ISOLATION OF INPUT–OUTPUT SENSORS

To univocally isolate a fault concerning one of the *output sensors*, under the hypothesis that input sensors are fault-free, a bank of classical dynamic observers or Kalman filters is used (Fig. 2). The number of these estimators is equal to the number  $m$  of system outputs, and each device is driven by a single output and all the inputs of the system. In this case a fault on the  $i$ th output sensor affects only the residual function of the output observer or filter driven by the  $i$ th output.

To univocally isolate a fault concerning one of the *input sensors*, under the assumption that output sensors are fault-free, a bank of UIO or UIKF is used (Fig. 3). The number of these devices is equal to the number  $r$  of control inputs. The  $i$ th device is driven by all but the  $i$ th input sensor and all outputs of the system and generates a residual function which is sensitive to all but the  $i$ th input sensor fault. In this way the detection of single input measurement sensor faults is possible, since a fault on the  $i$ th input sensor affects all the residual functions except that of the device which is insensitive to the  $i$ th input.

In order to summarize the FDI capabilities of the presented schemes, Table I shows the “fault signatures” in case of a single

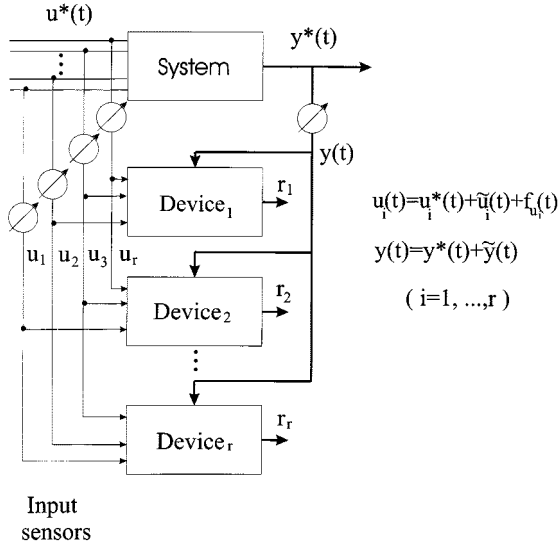


Fig. 3. Scheme for input sensor FDI.

fault in each input–output sensor. The residuals which are affected by input and output faults are marked with the presence of “1” in the correspondent table entry, while an entry “0” means that the input or output fault does not affect the correspondent residual. Note how multiple faults in the output sensors can be isolated since a fault on the  $i$ th output sensor affects only the residual function  $r_{O_i}$  of the output observer driven by the  $i$ th output, but all the UIO or UIKF residual functions  $r_{UIO_i}$ . On the other hand, multiple faults on the input sensors cannot be isolated by means of this technique since all the residual functions are sensitive to faults regarding different inputs.

With reference to Fig. 2, in order to diagnose a fault on the  $i$ th output sensor when the measurement noises are negligible ( $\tilde{u}(t) \cong 0$ ,  $\tilde{y}(t) \cong 0$ ) and  $f_u(t) = 0$  the model of the  $i$ th observer ( $i = 1, 2, \dots, m$ ) has the form

$$\dot{x}^i(t) = A^i x^i(t) + B^i u(t) + K^i (y_i(t) - C^i x^i(t)) \quad (4)$$

where  $x^i(t)$  is the observer state vector and the triple  $(A^i, B^i, C^i)$  is a minimal state-space representation (completely observable) of the link among the inputs of the process and its  $i$ th output  $y_i(t)$ . Such a triple can be obtained by means of a realization procedure, starting from a multi-input single-output (MISO) identified model.

The entries of  $K^i$  must be designed in order to assign to the  $(A^i - K^i C^i)$  matrix stable eigenvalues chosen suitably within the unit circle. In this situation and in the absence of faults, i.e.,  $f_y(t) = 0$ , it can be verified that for the  $i$ th output residual  $\lim_{t \rightarrow \infty} r_i(t) = \lim_{t \rightarrow \infty} (y_i(t) - C^i x^i(t)) = 0$  and the rate of convergence depends on the position of the eigenvalues of the  $(A^i - K^i C^i)$  matrix inside the unit circle. In the presence of a fault (step or ramp signal) on the  $i$ th output sensor only the  $i$ th output residual reaches a value different from zero and this situation leads to a complete failure diagnosis.

With reference to the devices for the FDI of input sensors, depicted in Fig. 3, the structure of the  $i$ th UIO ( $i = 1, 2, \dots, r$ ),

TABLE I  
FAULT SIGNATURES

	$u_1$	$u_2$	...	$u_r$	$y_1$	$y_2$	...	$y_m$
$r_{UIO_1}$	0	1	...	1	1	1	...	1
$r_{UIO_2}$	1	0	...	1	1	1	...	1
...	...	...	...	...	...	...	...	...
$r_{UIO_r}$	1	1	...	0	1	1	...	1
$r_{O_1}$	1	1	...	1	1	0	...	0
$r_{O_2}$	1	1	...	1	0	1	...	0
...	...	...	...	...	...	...	...	...
$r_{O_m}$	1	1	...	1	0	0	...	1

under the assumptions  $\tilde{u}(t) \cong 0$ ,  $\tilde{y}(t) \cong 0$  and  $f_y(t) = 0$ , is the following:

$$\begin{aligned} z^i(t+1) &= (T^i A - K^i C) z^i(t) + J^i u(t) + S^i y(t) \\ r^i(t) &= L_1^i z^i(t) + L_2^i y(t) \end{aligned} \quad (5)$$

where

- $z^i(t) \in \mathbb{R}^n$  observer state vector;
- $r^i(t) \in \mathbb{R}^m$  residual vector;
- $T^i, K^i, J^i, S^i, L_1^i, L_2^i$  matrices to be designed with appropriate dimensions [10], [12], [17].

Under the hypothesis of observability of the system (1) and in the absence of input sensor fault ( $f_u(t) = 0$ ), it can be seen that the  $i$ th residual vector reaches zero as  $t$  approaches infinity and the rate of convergence depends on the position of the eigenvalues of  $T^i A - K^i C$  matrix inside the unit circle. In the presence of a fault on the  $i$ th input sensor the  $i$ th residual reaches asymptotically zero while the residuals of the  $r - 1$  remaining observers are sensitive to the fault signal and this situation leads to a complete fault diagnosis for the input sensors.

The design of these UIO requires the knowledge of a minimal form model  $(A, B, C)$  for the system (1). Such a triple can be computed by using a realization procedure from a multi-input multi-output (MIMO) identified model. On the other hand, if the process is mathematically described by  $m$  MISO models, the triple  $(A, B, C)$  can be directly obtained by grouping the  $(A^i, B^i, C^i)$  representations ( $i = 1, 2, \dots, m$ ).

When the signal to noise ratios  $\|u^*(t)\|_2^2 / \|\tilde{u}(t)\|_2^2$  and  $\|y^*(t)\|_2^2 / \|\tilde{y}(t)\|_2^2$  are low, a bank of Kalman filters must be employed to improve the performance of the FDI system. Even in this situation, the mathematical formulation of the classical Kalman filter and of the UIKF is similar to the one described by (4)–(5). The essential difference regards the feedback matrix  $K^i$  which becomes time-dependent and is computed by solving a Riccati equation. The solution of this equation requires the knowledge of the covariance matrices of the input and the output noises which can be identified by means of the dynamic Frisch scheme.

#### IV. FDI TECHNIQUE FOR INDUSTRIAL GAS TURBINE

The technique for input–output sensor FDI presented in this paper was applied to a model of a real single-shaft industrial gas turbine with variable inlet guide vane (IGV) angle working in parallel with electrical mains.

Fig. 4 shows the gas turbine layout and the main features under ISO design conditions. The input control sensors are used

for the measurement of the angular position  $\alpha$  of the IGV ( $u_1(t)$ ) and of the fuel mass flow rate  $M_f$  ( $u_2(t)$ ). The output sensors are those used 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 identify the models were generated with a nonlinear dynamic model in SIMULINK environment. The nonlinear model was previously validated by means of measurements taken during transients on a gas turbine in operation [18] and presents an accuracy of less than 1% for all the measured variables and for a range of ambient temperature  $0 \div 40^\circ\text{C}$  and load conditions  $70 \div 100\%$ .

Fig. 5 reports the plots of the control input variables  $u_1(t)$  and  $u_2(t)$ . The time series of data simulate measurements taken on the machine with a sampling rate of 0.1 s and without noise due to measurement uncertainty which, instead, is always present in the real measurement systems. Zero-mean white Gaussian measurement noises  $\tilde{u}(t)$  and  $\tilde{y}(t)$  were generated by **nrand** function in the MATLAB environment. Their typical standard deviations are reported in Table II.

The FDI problem was at first approached by using a bank of dynamic observers. The design of output observers requires the identification of a number of Auto Regressive eXogenous (ARX) MISO models equal to the number of the output variables. The ARX models are usually represented as follows:

$$y_i(t+n) = \sum_{k=0}^{n-1} \alpha_{ik} y_i(t+k) + \sum_{j=1}^2 \sum_{k=0}^{n-1} \beta_{ikj} u_j(t+k) + \varepsilon_i(t+n) \quad (6)$$

where  $n$ ,  $\alpha_{ik}$ , and  $\beta_{ikj}$  are the parameters to be determined and  $\varepsilon_i(t)$  is the model error. In the following this term will be neglected.

The  $i$ th model ( $i = 1, \dots, 6$ ) is driven by  $u_1(t)$  and  $u_2(t)$  and gives the prediction 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 0.1%.

The parameters of each ARX model have shown remarkable properties of robustness with respect to the amplitudes of the noises corrupting the data. As an example, Table III shows the parameter variations of the ARX model (6) relative to the  $p_{ic}$  ( $i = 1$ ) measurement versus the measurement noise. In this situation, the different measurement noises were assumed all of equal size.

Moreover, different time series of data generated by the gas turbine nonlinear 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%.

When the measurement noises exceed the 20%, ARX input-output models are not suitable to describe the dynamics of the process and an EIV identification procedure (e.g., Frisch scheme) must be used. The design of input observers require the knowledge of a state-space representation ( $A, B, C$ ) of

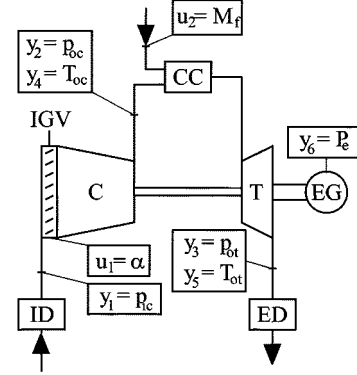


Fig. 4. Layout of the single-shaft industrial gas turbine.

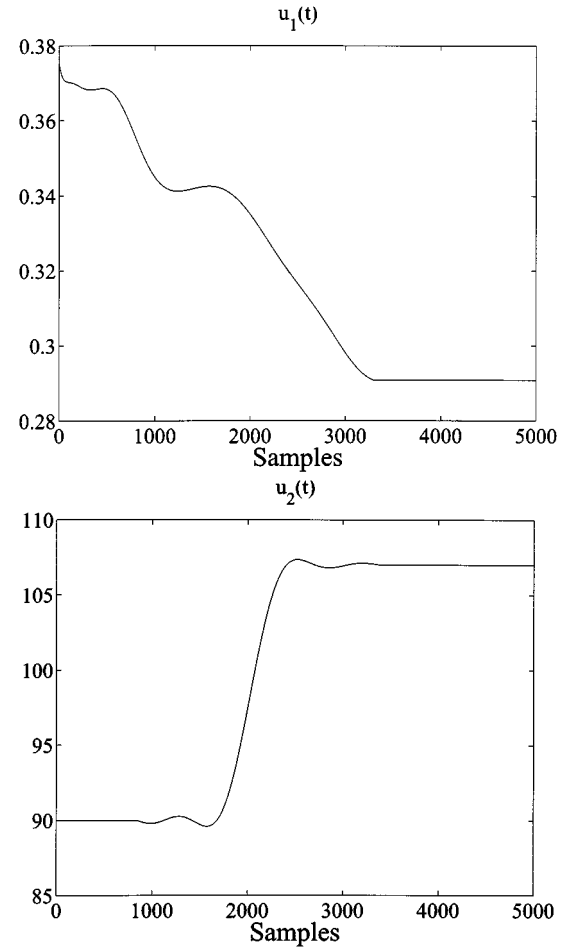


Fig. 5. (a)  $u_1(t)$  and (b)  $u_2(t)$  control inputs of the gas turbine.

TABLE II  
STANDARD DEVIATIONS OF MEASUREMENT NOISES

$\alpha$	$M_f$	$p_{ic}$	$p_{oc}$
1.08 deg	0.0076 kg/s	0.41 KPa	3.66 kPa
$p_{ot}$	$T_{oc}$	$T_{ot}$	$P_e$
0.41 kPa	3.59 K	5.59 K	23.90 kW

the gas turbine, which has been computed by grouping the ( $A^i, B^i, C^i$ ) representation associated to the ARX identified models (6).

TABLE III  
PARAMETER VARIATIONS OF THE  $P_{ic}$  ARX MODEL VERSUS MEASUREMENT  
NOISE STANDARD DEVIATIONS

Noise	0 %	2 %	10 %	20 %
$\alpha_{12}$	-0.9963	-0.9941	-0.9513	-0.9325
$\alpha_{11}$	1.9963	1.9949	1.9712	1.9486
$\beta_{111}$	0.9205	0.9368	0.9680	0.9458
$\beta_{112}$	-0.9176	-0.9455	-0.9682	-0.9864
$\beta_{121}$	0.0044	0.0178	0.0176	0.0220
$\beta_{122}$	-0.0044	-0.0092	-0.0108	-0.0197

TABLE IV  
FAULT DETECTABILITY THRESHOLDS

measurement	$T_{oc}$	$T_{ot}$	$P_{ot}$	$P_{oc}$
positive threshold	+0.85	+0.20	+0.022	+0.55
negative threshold	-0.85	-0.22	-0.024	-0.65

measurement	$p_{ic}$	$P_e$	$M_f$	$\alpha$
positive threshold	+0.022	+2.0	+1.1	+0.27
negative threshold	-0.0225	-2.2	-1.1	-0.41

Faults in single input-output sensors were generated by producing positive and negative variations (step and ramp functions of different amplitudes and slopes, respectively) in the input-output signals. A positive and negative fault occurring, respectively, at the instant of the minimum and maximum values of the observer residuals were chosen, since these conditions represent the worst case in failure detection. Moreover, it was decided to consider a fault during a transient since, in this case, the residual error due to ARX model approximation is maximum and therefore it represents the most critical case.

The fault occurring on the single sensor causes alteration of the sensor signal and of the residuals given by observers and filters using this signal as input. These residuals indicate a fault occurrence when their values are lower or higher than the thresholds fixed in fault-free conditions.

In order to determine these thresholds, the simulation of different amplitude faults in the sensor signals was performed. The threshold value depends on the residual error amount due to the ARX model approximation and on the measurement noises  $\hat{u}(t)$  and  $\hat{y}(t)$ . In Table IV, the values fixed for the observer residual thresholds are shown. The positive and negative thresholds were settled on the basis of fault-free residuals generated by different time series of simulated data. A margin of 10% between the positive and negative thresholds and the maximum and minimum values, respectively, were imposed.

In order to analyze the diagnostic effectiveness of the FDI system in the presence of abrupt changes in measurements, faults modeled by step functions were generated.

Fig. 6 shows the fault-free residual generated by the UIO driven by the  $M_f$  signal and insensitive to the IGV signal. The thresholds regarding the  $M_f$  sensor are also depicted. The eigenvalues of the state distribution matrix [matrix  $(T^i A - K^i C)$  in (5)] of the UIO are placed with a trial and error procedure near to 0.2 in order to maximize the fault detection sensibility and promptness and to minimize the occurrence of false alarms.

Fig. 7 shows how a fault of -4% on the mean value of  $M_f$  signal at the instant of maximal residual value causes an abrupt change of the residual. Figs. 8 and 9 illustrate an example of

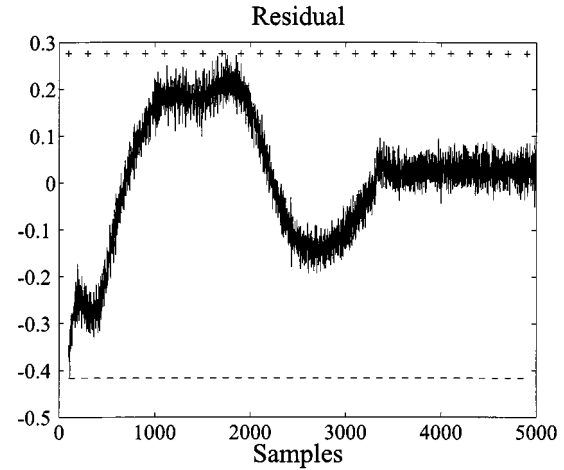


Fig. 6. Fault-free residual function of the UIO driven by the  $M_f$  signal.

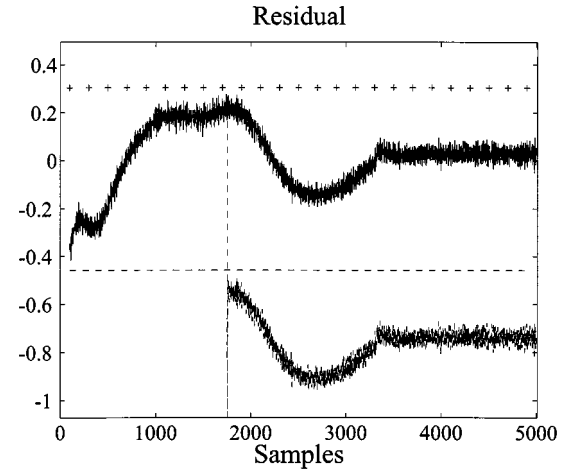


Fig. 7. Residual function of the UIO driven by the  $M_f$  signal with negative failure.

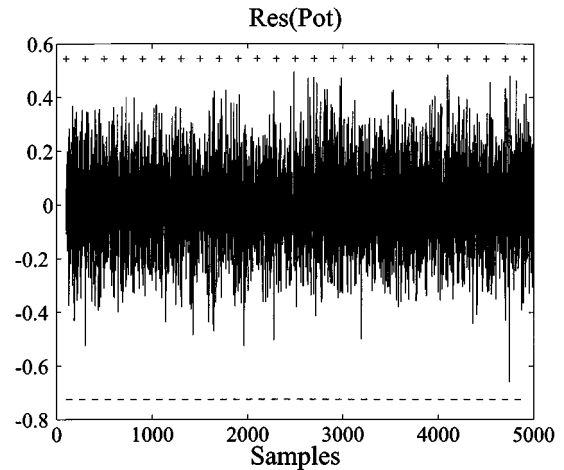


Fig. 8. Fault-free residual function of output observer driven by  $p_{ot}$  signal.

the diagnostic technique for output sensor fault regarding the  $p_{ot}$  signal. In particular, Fig. 8 shows the fault-free residual obtained from the difference between the values computed by the observer related to the output  $y_3(t)$  ( $p_{ot}$  signal) and the ones

given by the sensor. Obviously, the nonzero value of the residual is due to the ARX model approximation and measurement noise. Also in this case, the eigenvalues of the state distribution matrix of output observer (matrix  $A^i - K^i C^i$  in (4),  $i = 3$ ) are placed with a trial and error procedure between zero and 0.2 in order to maximize the fault detection sensibility and promptness and to minimize the occurrence of false alarms.

In Fig. 9, the abrupt change of  $p_{ot}$  residual caused by a fault of +5% on the mean value of  $p_{ot}$  signal occurring at the instant of the minimum residual value is shown. The instantaneous peaks which appear in Figs. 8 and 9 are generated by the abrupt change related to the fault occurrence and may be used as incipient detector of anomalous behavior of the sensors.

In order to analyze the diagnostic effectiveness of the FDI system in the presence of drifts in measurements, faults modeled by ramp functions were generated. In Figs. 10 and 11 the residual of the UIO driven by  $\alpha$  and the residual of the output observer regarding  $T_{oc}$  are shown as an example. The two ramp faults start at the sample 2500 and reach constant final values at the sample 4000. The final values are equal to 4% of the mean value of  $\alpha$  and to 5% of the mean value of  $T_{oc}$ .

To summarize the performance of the FDI technique, the minimal detectable faults on the various sensors, expressed as per cent of the mean values of the relative signals, are collected in Table V, in case of step faults, and in Table VI, in case of ramp faults.

The minimum values shown in Table V are relative to the case in which the fault must be detected as soon as it occurs. If a delay in detection is tolerable the amplitude of the minimal detectable fault is lower. Table VI shows how faults modeled by ramp functions may not be immediately detected, since the delay in the corresponding alarm normally depends on fault mode. An improvement of the FDI performance has been obtained by using a bank of Kalman filters designed on the basis of the model parameters and the noise variances identified under the assumptions of the Frisch scheme. In particular, since the Kalman filter produces zero-mean and independent white residuals when the system is operating normally, the failure detection and isolation is implemented by analyzing the whiteness of the sequence of innovations. The tests performed on the innovations are the classical ones for zero-mean and variance, as cumulative sum algorithms and independence, as  $\chi^2$ -type computed in a growing window. The comparison of the mean-value and whiteness of the residuals with the thresholds fixed under no fault conditions remains the detection rule. In particular, these thresholds can be settled as in the examples previously suggested or with the aid of chi-squared tables as a function of the false-alarms probability.

In Figs. 12 and 13 the examples of the statistical tests regarding the residual generated by the UIKF for the detection of abrupt faults regarding the  $\alpha$  input sensor are shown.

Fig. 12 shows the mean value computed on a growing window and generated by the UIKF driven by the signal of  $\alpha$  input sensor and insensitive to the signal of  $M_f$  input sensor. A fault of 3% on the mean value of  $\alpha$  signal causes an abrupt change of the mean value of the residual computed on a growing window. Finally, Fig. 13 shows how such a fault causes a change of the whiteness of the same residual computed on a growing window. The threshold whiteness value of 20.1 was calculated by assuming

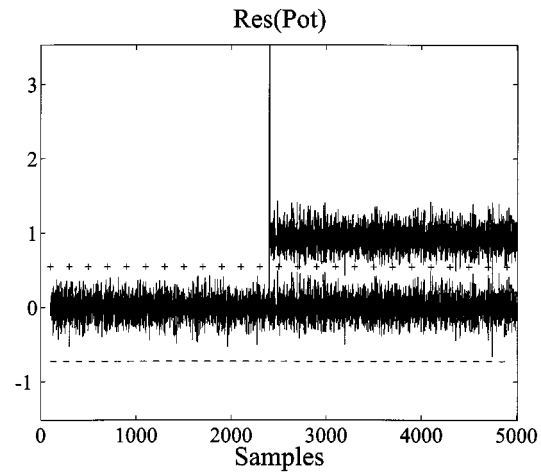


Fig. 9. Residual function of output observer driven by  $p_{ot}$  signal with positive failure.

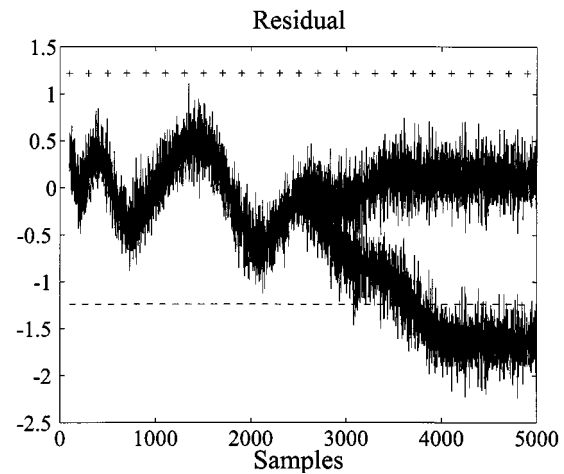


Fig. 10. Residual function in the presence of a drift in the  $\alpha$  measurement.

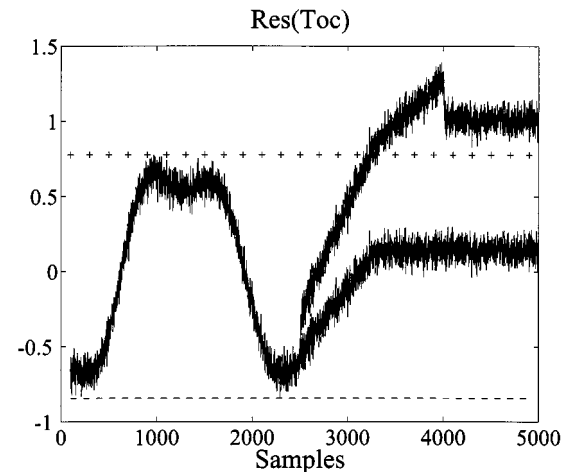


Fig. 11. Residual function in the presence of a drift in the  $T_{oc}$  measurement.

a false-alarms probability of 5%. The residual corresponding to the most sensible filter to a failure on the  $\alpha$  input was selected. Tables VII and VIII summarize the performance of the enhanced fault detection and isolation technique and collect the minimal

TABLE V  
MINIMAL DETECTABLE STEP FAULTS

$\alpha$	$M_f$	$p_{ic}$	$p_{oc}$	$p_{ot}$	$T_{oc}$	$T_{ot}$	$P_e$
4%	4%	5%	7%	5%	5%	2.5%	1.7%

TABLE VI  
MINIMAL DETECTABLE RAMP FAULTS

measurement fault	$T_{oc}$	$T_{ot}$	$p_{ot}$	$p_{oc}$
	5 %	3 %	5.5 %	7.5 %
detection delay [s]	50	100	75	0
measurement fault	$p_{ic}$	$P_e$	$M_f$	$\alpha$
	6 %	6 %	4 %	4 %
detection delay [s]	50	100	150	100

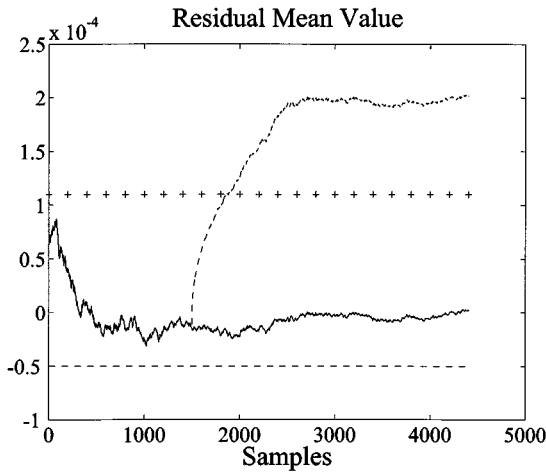


Fig. 12. Mean value of the residual computed by using Kalman filter with unknown input.

detectable fault on the various sensors. The fault sizes are expressed as per cent of the signal mean values.

The values shown in these tables VII and VIII are relative to the case in which the occurrence of a fault must be detected as soon as possible. Tables VII and VIII depicts the fault values obtained by monitoring the variations in the mean value and in the residual whiteness, respectively. It results that the values of the faults obtained by using statistical tests on Kalman filter residuals, collected in Tables VII and VIII, are lower than the ones reported in Table V. Moreover, 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. However, these improvements are not free of charge: they have been obtained with a procedure of greater complexity and, consequently, with a growing computational cost.

## V. CONCLUSIONS

A complete design procedure for fault detection and isolation in input-output control sensors of industrial processes is described in this paper. The fault diagnosis is performed by using a bank of dynamic observers or, when the measurement noises are not negligible, a bank of Kalman filters. Single fault on the input sensors and multiple faults on the output sensors have been considered. The suggested method does not require

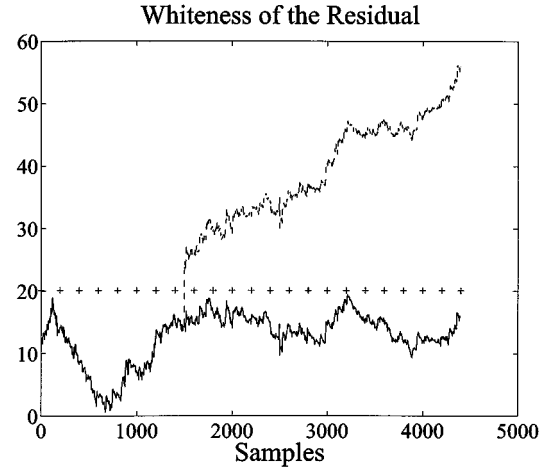


Fig. 13. Whiteness of the residual computed by using Kalman filter with unknown input.

TABLE VII  
MINIMUM DETECTABLE FAULTS BY MONITORING THE MEAN VALUE OF THE RESIDUALS

$\alpha$	$M_f$	$p_{ic}$	$p_{oc}$	$p_{ot}$	$T_{oc}$	$T_{ot}$	$P_e$
3 %	3 %	2.5 %	4 %	1.5 %	2 %	2.5 %	3 %

TABLE VIII  
MINIMUM DETECTABLE FAULTS BY MONITORING THE WHITENESS OF THE RESIDUALS

$\alpha$	$M_f$	$p_{ic}$	$p_{oc}$	$p_{ot}$	$T_{oc}$	$T_{ot}$	$P_e$
2 %	2.5 %	0.75 %	1 %	0.75 %	2 %	0.8 %	1.5 %

the physical knowledge of the process under observation since the input-output links are 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) gives the variances of the input-output noises, which are required in the design of the Kalman filters. The procedure has been applied to a model of a real single-shaft industrial gas turbine with variable inlet guided vane angle working in parallel with electrical mains. In order to analyze the diagnostic effectiveness of the FDI system in the presence of abrupt changes or drifts in measurements, faults modeled by step or ramp functions have been generated. The results obtained by this approach indicate that the minimal detectable faults on the various sensors are of interest for the industrial diagnostic applications.

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