Sensor fault diagnosis of a power plant: an approach based on state estimation techniques

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Abstract: - The design of fault diagnosis and detection devices for the input and output sensors of dynamic systems requires the knowledge of an accurate mathematical model of the process since modeling uncertainty affects the sensitivity to the faults and increases the false–alarm probability. For this reason, the technique used in this paper gives weight to the identification procedure which exploits equation error and errors–in–variables models in connection with the values of the signal to noise ratios concerning the input and output measurements. The fault detection is performed by analyzing residuals, which are generated by a bank of dynamic observers and unknown input observers or, when the measurement noises are not negligible, by a bank of classical Kalman filters and Kalman filters with unknown inputs. The effectiveness of the procedure has been tested on real data acquired from the 120MW power plant of Pont sur Sambre.

Key-Words: - Fault diagnosis and detection; analytical redundancy; residuals generation; dynamic observers; Frisch scheme; Kalman filters.

1 Introduction

In order to ensure reliable operations of an industrial process and safety of the plant, it is necessary to use correct measurements from actual system inputs and outputs. This requires the use of fault diagnosis and detection (FDD) techniques to recognize the failures regarding the sensors of the system under investigation.

The design of FDD devices for the input and output sensors of dynamic systems has received great attention during the last two decades and a wide variety of model-based approaches have been proposed [1].

These different methods are principally based on the parity space approach [2, 3], the state estimation approach [4, 5, 6, 7], the fault detection filter approach [7, 8, 9] and the parameter identification approach [4, 6, 10]. In every case, 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 [11, 12].

In recent years, there is also a clear trend towards 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 [7, 10, 13].

Owing to the generality of the problem formulation and the mathematical rigor of the treatment, the state estimation approach shows considerable advantages for residual generation which may be used in sensor FDD of industrial systems, both for the deterministic case (the state observer) and the stochastic case (the Kalman filter).

This paper concerns the design of FDD devices for the input and output sensors of an industrial power plant.

An accurate mathematical model of the process is obtained by using an identification procedure which exploits equation error and errors–in–variables models in connection with the values of the signal to noise ratios concerning the input and output measurements.

The input sensor FDD uses unknown input observers (UIO) or, when the measurement noises are not negligible, Kalman filters with unknown inputs (UIKF). The i–th device is designed to be insensitive to the i–th input of the system. On the other hand, output sensor faults affecting a single residual are detected by means of Luenberger observers [14] or classical Kalman filters [15] driven by a single output and all the inputs of the system.

These diagnostic tools have been already applied to a simulated model of an single-shaft industrial gas turbine [16, 17, 13]. In this work the effectiveness of these procedures have been simulated on real data acquired from the 120MW power plant of Pont sur Sambre proposed in [18].

The remainder of this paper is organized as follows. In Section (2) the problem statement is given and the structure of the measurement process is described from a mathematical point of view. The design of dynamic observers and Kalman filters is illustrated in Section (3). In Section (4) the characteristics of the power plant of Pont sur Sambre are shown and some examples illustrate the FDD of the input–output sensors by processing measured data. Finally, some concluding remarks are included in Section (5).

2 Problem Formulation

In the following the process under observation depicted in Figure (1) is represented as a discrete–time, time–invariant linear dynamic system of the type

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

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

In real situations, the input–output sensors may be affected by noise and faults which degrade their reliability. The variables $\hat{u}(t)$ and $\hat{y}(t)$ acquired

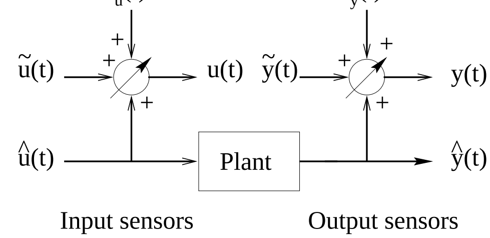

Figure 1: The structure of the plant sensors.

from sensors can be expressed as

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

in which the sequences $\tilde{u}(t)$ and $\tilde{y}(t)$ are usually described as white, zero–mean, uncorrelated Gaussian noises. $f_u(t) = [f_{u_1}(t) \ldots f_{u_r}(t)]^T$ and $f_y(t) = [f_{y_1}(t) \ldots f_{y_m}(t)]^T$ 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. Figure (1) also shows the configuration of the input–output measurement sensors.

Descriptions of types (1) and (2) when $f_u(t) = f_y(t) = 0$ are known as errors–in–variables (EIV) models.

The problem treated in this work regards the FDD of the input–output sensors 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.

The structure of the FDD device is depicted in Figure (2). The symptom generation is implemented by means of dynamic observers or Kalman filters. The symptom evaluation refers to the logic device which processes the redundant signals generated by the first block in order to estimate when a fault occurs and to univocally detect the faulty sensor.

The design of a FDD device requires the knowledge of a state–space model (1) of the system under investigation and of the statistics of the noises affecting the data. In this work an identification approach has been considered.

If the measurement noises are negligible, equation error identification can be exploited and, in particular, different equation error models can be

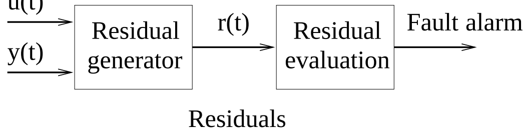

Figure 2: Logic diagram of the fault detection system.

extracted from the data, e.g. ARX or ARMAX discrete–time models.

In case the measurement noises are significant, the Frisch scheme [19] can be applied to perform the dynamic system identification [20]. Such a scheme allows to determine the linear discrete system which has generated the noisy sequences as well as the variances of the noises $\tilde{u}(t)$ and $\tilde{y}(t)$ affecting the data.

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, whilst the ones coming from the Frisch scheme can be used in order to build Kalman filters.

3 Residual generation

In this work, the observer–based method is used to estimate the outputs of the system from the input and output measurements.

In particular, to univocally isolate a fault concerning one of the *input sensors*, under the assumption that output sensors are fault–free, a bank of UIO is used. 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.

The structure of the UIO bank concerning the FDD for the input sensors is shown in Figure (3). Note that the output sensors are not depicted since attention is focused on the input sensor FDD. In such a case, output measurements are assumed fault–free.

The i–th UIO residual (symptom) generator is

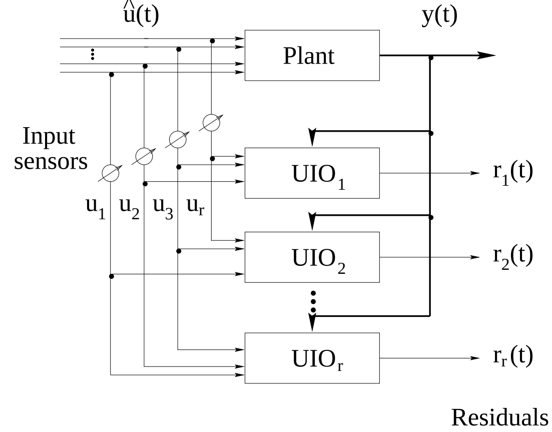

Figure 3: Scheme for input sensor FDI.

thus described as [21]

$$\begin{aligned} z^i(t+1) &= N^i z^i(t) + L^i y(t) + G^i u(t) \\ y_e^i(t) &= C\big(z^i(t) - D^i y(t)\big) \\ r_i(t) &= y(t) - y_e^i(t) \end{aligned} \tag{3}$$

where $z^i(t) \in \Re^n$ denotes the i–th observer state vector, $y_e^i(t)$ is the estimate of the output $y(t)$ of the system (1), whilst $r_i(t) \in \Re^m$ is the residual vector. A design procedure is used for finding suitable matrices N^i, L^i, G^i and D^i with appropriate dimension.

Under the hypotheses of observability of the system (1) and in the absence of sensor faults and noise, $f_u(t) = f_y(t) = 0$ and $\tilde{u}(t) = \tilde{y}(t) = 0$, with the choices

$$\begin{aligned} D^i &= -B_i(CB_i)^\dagger, \\ P^i &= I + D^i C, \\ N^i P^i &= P^i A - L^i C \\ G^i &= P^i B \\ L^i &= P^i A D_i, \end{aligned} \tag{4}$$

where † denotes the pseudoinverse operator and B_i the i–th column of the matrix B, $y_e^i(t)$ will asymptotically approach $y(t)$ and $r_i(t) \to 0$.

On the other hand, 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. 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.

The basic principle of output sensor FDD by using state estimation is illustrated in Figure (4).

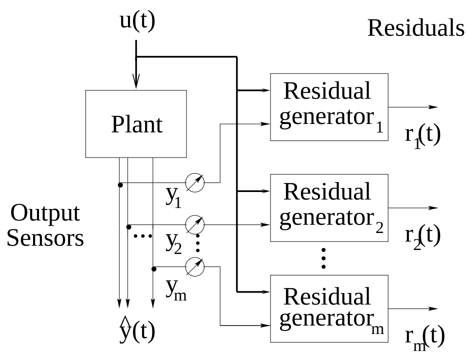

Figure 4: Bank of estimators for output residual generation.

The input sensors are not sketched because the output sensor FDD is emphasized. In this case input measurements are supposed fault–free.

With reference to Figure (4), when the measurement noises are negligible, ($\tilde{u}(t) \cong 0$, $\tilde{y}(t) \cong 0$) and $f_u(t) = 0$, the structure of the i-th observer to diagnose a fault on the i-th output sensor ($i = 1, 2, \ldots, m$) has the form

$$\begin{aligned} x^i(t+1) &= A^i x^i(t) + B^i u(t) + \\ &\quad + K^i\big(y_i(t) - C^i x^i(t)\big). \end{aligned} \tag{5}$$

$x^i(t)$ is the observer state vector, $y_i(t)$ the i–th component of the output vector $y(t)$, $f_{y_i}(t)$ represents a fault on the i-th output sensor 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 $\hat{y}_i(t)$. 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. The output equation of the observer is described by the expression

$$y^i(t) = C^i x^i(t) \tag{6}$$

where $y^i(t)$ is the estimate of the i-th component $y_i(t)$ of the output vector $y(t)$.

In the absence of faults, i.e. $f_y(t) = 0$, it can be verified that the steady–state solution

$$\lim_{t\to\infty} r_i(t) = \lim_{t\to\infty} \big(y_i(t) - y^i(t)\big) \tag{7}$$

is equal to zero 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) of 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.

In case of significant measurement noises, residuals are generated by exploiting classical Kalman filter and Kalman filters with unknown inputs (UIKF). Such a solution improves the performance of the FDD system with respect to the one using dynamic observers and UIO. In particular, in this situation, the mathematical formulation of the UIKF follows from Eqs. (3) with conditions similar to the ones described by Eqs. (4) [22, 23]. Moreover, the filter design must now satisfy a Riccati equation [24]. 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.

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 $r_i(t)$ of the output observer or Kalman filters driven by the i–th output. On the other hand, multiple faults on the input sensors can not be isolated by means of this technique since all the UIO or UIKF residual functions $r_i(t)$ are sensitive to faults regarding the different inputs.

4 Fault diagnosis of the plant sensors

The techniques for input–output sensor FDD was applied to a 120MW power plant of Pont sur Sambre. It consists in a double–shaft industrial gas turbine working in parallel with electrical mains.

The block-diagram of the plant is shown in Figure (5) where the numbers refer to: 1 - super heater (radiation), 2 - super heater (convection), 3 - super heater, 4 - reheater, 5 - dampers, 6 - condenser, 7 - drum, 8 - water pump and 9 - burner. The available input data were 2200 samples from normal operating records of C_b (gas flow), O_s (turbine valves opening), Q_d (super heater spray flow), R_y (gas dampers) and Q_a (air flow). The output data were the corresponding values of P_v (steam

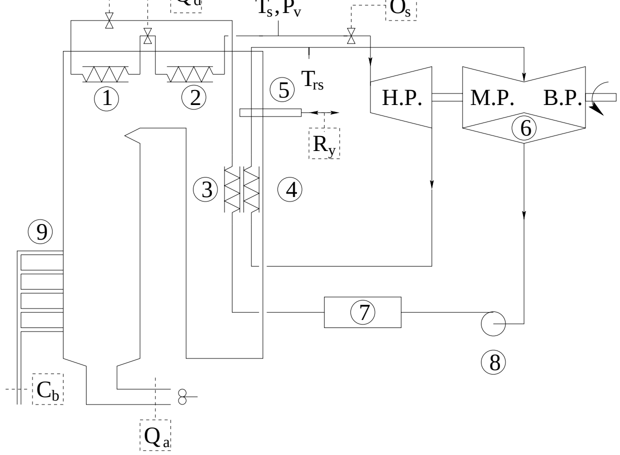

Figure 5: The structure of the power plant.

pressure), T_s (main steam temperature) and T_{rs} (reheat steam temperature). The sampling time was of 10 seconds and since this value is very little with respect to the time constants of the plant, it has been increased to 60 seconds. The number of samples has thus been reduced to 367.

The computational steps which have been performed on the data are the identification of the triple (A,B,C) from the ARX model as well as the identification of the triple (A,B,C) from the EIV model and the estimation of the input-output noise variances.

The design of the UIO (3) requires, in fact, the knowledge of a minimal form model (A, B, C) for the system (1). The matrices A, B and C were obtained by grouping the A_i, B_i and C_i ($i = 1, \ldots, m$) corresponding to the MISO subsystem which links each output with the five ($r = 5$) inputs. Three subsystems ($m = 3$) with order two have thus been considered.

The determination of the order of every subsystem has been performed by considering the FPE, AIC and MDL identification criteria [25].

Faults in single input–output sensors were generated by adding variations (step and ramp functions of different amplitudes) in the input–output signals. A fault occurring respectively at the instant of the minimum and maximum values of the observer and filter 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 model approximation is maximum and therefore it represents the most critical case [26, 16].

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 fault occurrence according to whether their values are lower or higher than the thresholds fixed in fault–free conditions.

In order to determine the thresholds above which the faults are detectable, the simulation of different amplitude faults in the sensor signals was performed. The threshold value depends on the residual error amount due to the model approximation and on the measurement noises $\tilde{u}(t)$ and $\tilde{y}(t)$. These thresholds were settled on the basis of fault-free residuals. A margin of 10% between the thresholds and the residual values was imposed.

In Figures (6) and (7) an example of the residuals given by UIO (3) for the diagnosis of O_s input sensor is shown.

In particular, Figure (6) shows the fault-free residual generated by the input observer driven by the signal of O_s input sensor $u_2(t)$ and insensitive to the signal of C_b input sensor $u_1(t)$. In this condition, it is possible to determine the thresholds above which the fault on the O_s sensor can be detected.

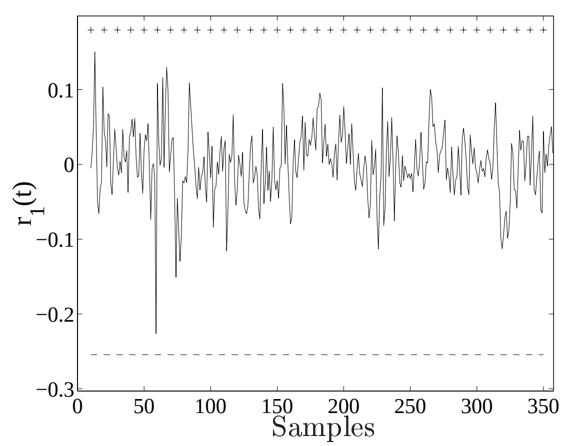

Figure 6: Fault-free residual function of the UIO driven by the O_s signal with minimum positive ('+') and negative ('-') thresholds.

The eigenvalues of the state distribution matrix (matrix N^i in Equations (3) with $i = 1$) of the input observer are placed with a trial and error procedure near to 0.2 in order to maximize the fault detection sensibility and promptness and to

Figure (7) shows how a fault of 25% on the mean value of O_s signal at the sample $T = 150$ causes an abrupt change of the residual.

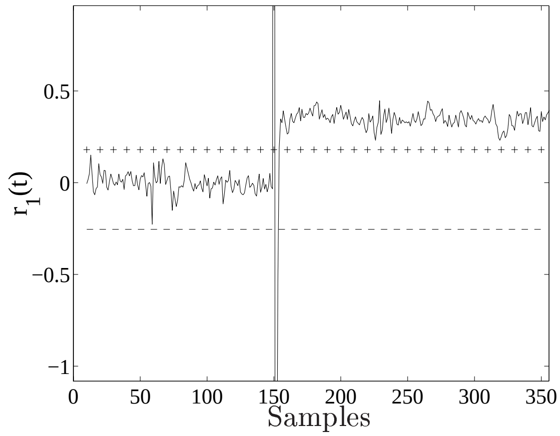

Figure 7: Residual function of the UIO driven by the O_s signal in the presence of a failure.

Figures (8) and (9) illustrate an example of the diagnostic technique for output sensor fault regarding the T_{rs} signal.

Figure (8) shows the fault-free residual (Eq. 7) obtained from the difference between the values computed by the observer of the output $y_3(t)$ (T_{rs} signal) and the one given by the sensor $y^3(t)$. Obviously, the non zero value of the residual is due to the ARX model approximation and actual measurement noise.

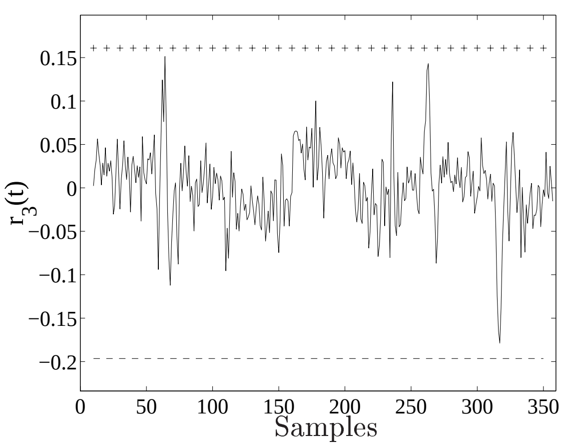

Figure 8: Fault-free residual function of output observer driven by T_{rs} signal with minimum positive ('+') and negative ('-') thresholds.

The eigenvalues of the state distribution matrix (matrix $(A^i - K^i C^i)$ in Eq. (5) with $i = 3$) of output state observer are placed with a trial and error the fault detection sensibility and promptness and to minimize the occurrence of false alarms.

In Figure (9) the abrupt change of T_{rs} residual caused by a fault of 10% on the mean value of T_{rs} signal occurring at the instant of $T = 150$ is shown.

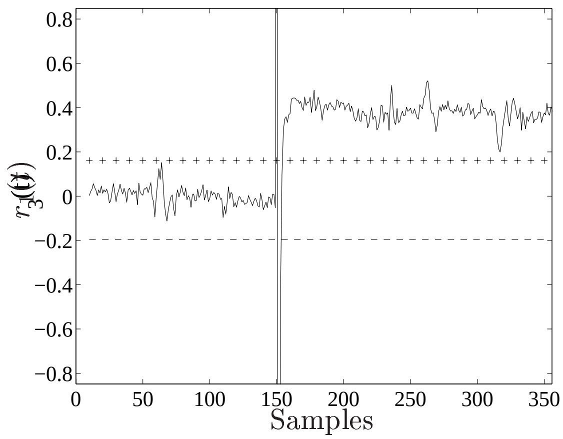

Figure 9: Residual function of output observer driven by T_{rs} signal with a failure.

The instantaneous peaks which appear in Figures (7) 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.

To summarize the performance of the FDD technique using classical observers and UIO, the minimal detectable failures on the various sensors referred to the mean signal values are collected in Table (1), in case of step and ramp faults.

Sensor	C_b	O_s	Q_d	R_y
Step	30%	25%	20%	40%
Ramp	40%	30%	35%	55%
Sensor	Q_a	P_v	T_s	T_{rs}
Step	45%	15%	5%	10%
Ramp	50%	40%	20%	30%

Table 1: Minimal detectable step and ramp faults with classical observers and UIO.

Finally, Table (2) reports the mean square values of the output estimation errors corresponding to the state–space systems obtained by the equation errors models in deterministic case.

An improvement on the performance of the FDD device was obtained by using classical Kalman filters and UIKF. The noises affecting the ing the Frisch scheme method.

Output	P_v	T_s	T_{rs}
Equation error	0.0146	0.0273	0.0051

Table 2: The three output estimation errors with equation error models.

Also in this case, the comparison of the residuals with the thresholds fixed under no fault conditions remains the detection rule.

Table (3) shows the minimal detectable faults in stochastic case.

Sensor	C_b	O_s	Q_d	R_y
Step	25%	15%	12%	35%
Ramp	35%	20%	20%	45%
Sensor	Q_a	P_v	T_s	T_{rs}
Step	35%	10%	3%	5%
Ramp	40%	30%	5%	8%

Table 3: Minimal detectable step and ramp faults with classical Kalman filters and UIKF.

Table (4) reports the mean square values of the output estimation errors when EIV models identified by the dynamic Frisch scheme are used.

Output	P_v	T_s	T_{rs}
EIV	0.0026	0.0018	0.0012

Table 4: The three output estimation errors with EIV models.

Compared with the ones concerning the deterministic case, the output estimation errors with EIV models are smaller because the noise rejection is achieved by means of the dynamic Frisch scheme. Consequently, the residuals obtained by Kalman filters are more sensitive to a fault occurring on the sensors. Moreover, smaller thresholds can be placed on the residual signals to declare the occurrence of faults.

5 Conclusion

This work addressed the problem of the design of FDD devices for the input and output sensors of an industrial power plant.

The technique presented gives weight to the identification procedure which exploits equation error and errors–in–variables models in connection with the values of the signal to noise ratios concerning the input and output measurements.

The fault detection was performed by analyzing residuals, which are generated by a bank of dynamic observers and UIO or, when the measurement noises are not negligible, by a bank of Kalman filters and UIKF.

The effectiveness of these procedures were tested on real data acquired from the 120MW power plant of Pont sur Sambre.

The results obtained indicate that the minimal detectable faults on the various sensors are of interest for industrial diagnostic applications.

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