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Improved Observer for Sensor Fault Diagnosis of a Power Plant

Silvio Simani, Cesare Fantuzzi, Sergio Beghelli
Dipartimento di Ingegneria
Università di Ferrara
V. Saragat, 1, 44100 Ferrara - Italy.
E-mail: {sbeghelli, cfantuzzi, ssimani}@ing.unife.it

Abstract

The design of a fault detection and diagnosis device requires the knowledge of a mathematical model of the system under investigation. Modeling uncertainty is an unavoidable consequence of the complexity of industrial processes and an accurate dynamic model can never be fully obtained. Because the accuracy of the model affects the precision of the fault diagnosis technique, the paper focuses on the problem of the derivation of a suitable mathematical description of a power plant for diagnostic purpose.

The identification procedure suggested in this paper exploits equation error models. The effectiveness of the diagnostic tool obtained has been tested on real data acquired from the 120MW power plant of Pont sur Sambre and the results are compared with the ones obtained by using model-based classical observer.

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 detection and diagnosis (FDD) techniques for the recognition of the failures regarding the sensors of the system under investigation (Isermann and Ballé, 1997).

Recently, different methods based on analytical redundancy have been developed to detect and diagnose faults in linear, time-invariant, dynamic systems and a wide variety of model-based approaches has been proposed (Patton *et al.*, 1989). There are different model-based approaches to the FDD problem, namely parameter identification (Willsky, 1976), parity equations (Patton and Chen, 1991; Gertler, 1991), methods in frequency (Ding and Frank, 1990; Massoumnia *et al.*, 1989) or in state-space domain, such as diagnosis observers (Frank, 1990) and Kalman filters (Xie *et al.*, 1994; Xie and Soh, 1994).

Although the analytical redundancy method has been recognized as an effective technique for detecting and isolating faults, the critical problem of unavoidable modeling uncertainty has not been fully solved. The main problem regarding the reliability of FDD schemes is the modeling uncertainty which is due, for example, to process noise, parameter variations and nonlinearities. All model-based methods use a model of the monitored system to produce the so-called symptom generator. If the system is not complex and can be described accurately by the mathematical model, FDD is directly performed by using a simple geometrical analysis of residuals. In real industrial systems however, the modeling uncertainty is unavoidable. The design of an effective and reliable FDD scheme should take into account of the modeling uncertainty with respect to the sensitivity of the faults. Several papers addressed this problem. For example, optimal robust parity relations were proposed (Chow and Willsky, 1984; Lou *et al.*, 1986), and the threshold selector concept was introduced (Emami-Naeini *et al.*, 1988). Robust FDD using the disturbance decoupling technique was also used (Patton *et al.*, 1989; Patton, 1988).

The model-based FDD technique requires a high accuracy mathematical description of the monitored system. The better the model represents the dynamic behavior of the system, the better will be the FDD precision. If a FDD method can be developed which is insensitive to modeling uncertainty, a very accurate model is not necessarily needed.

All uncertainties can be are summarized as disturbances acting on the system. Although the disturbance vector is unknown, its distribution matrix can be obtained by an identification procedure. Under this assumption, the "disturbance decoupling" principle can be exploited to design a FDD scheme using the "unknown input observer" (UIO) (Patton *et al.*, 1989).

Under the hypothesis that the system can be described as an equation error model, this paper has studied the method of obtaining the disturbance distribution matrix from the fault-free system data, by taking into account the equation error term. The UIO performing the disturbance decoupling can be designed from the equation error model. Previous works also exploiting these models neglected the equation error term (Bettocchi and Spina, 1997; Simani and Spina, 1998; Simani *et al.*, 1998).

The remainder of this paper is organized as follows. In Section (2) the problem statement is given and it is described from a mathematical point of view. The identification scheme exploited to extract the disturbance distribution matrix from input-output data is also illustrated. In Section (3) the characteristics of the industrial process, such as the 120MW power plant of Pont sur Sambre, used to illustrate the method proposed in this paper, are shown. The results obtained by using observers with unknown input which perform the diagnosis of faults regarding input-output sensors are recalled in Section (4). These results are also compared with the ones obtained without disturbance decoupling. Finally, some concluding remarks are included in Section (5).

2 Model description

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

$$\hat{y}_i(t) = \sum_{k=1}^{n} \alpha_{ik}\hat{y}_i(t-k) + \sum_{j=1}^{r}\sum_{k=1}^{n} \beta_{ikj}u_j(t-k) + \varepsilon_i(t). \tag{1}$$

where $\hat{y}_i(t)$ $(i = 1, \ldots, m)$ is the i-component of the system output vector $\hat{y}(t)$ and $u(t) \in \Re^r$ the control input vector. n, α_{ik} and β_{ikj} are the parameters to be determined by an identification approach. The term $\varepsilon_i(t)$ takes into account the modeling error, which is due to process noises, parameter variations, etc.

In real applications variables $\hat{y}(t)$ are measured by means of sensors whose outputs are affected by faults.

Neglecting sensor dynamics, the measured signals $y(t)$ are modeled as

$$y(t) = \hat{y}(t) + f_y(t) \tag{2}$$

in which, the vector $f_y(t) = [f_{y_1}(t) \ldots f_{y_m}(t)]^T$ is composed of 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, respectively, abrupt and incipient faults (bias or drift).

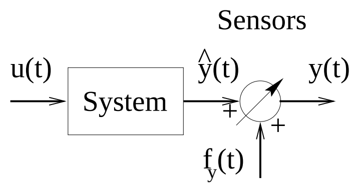


Figure 1: The monitored system.

By using the transfer function description, system (1) can be rewritten in the form

$$y_i(t) = F_i(z)u(t) + G_i(z)\varepsilon_i(t) \tag{3}$$

and its structure is depicted in Figure (2), in which z is the unitary advance operator.

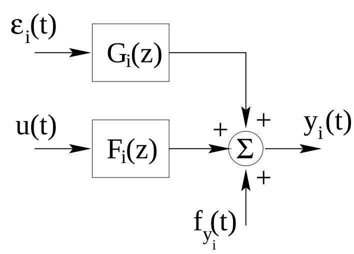


Figure 2: The structure of the equation error model.

There are different approaches to generate the residual. In this work, the observer-based method is used to estimate the outputs of the system from the measurements. In particular, the symptom generation is implemented by means of dynamic observers with unknown inputs, in order to produce a set of signals from which it will be possible to diagnose faults associated to output sensors. This choice should minimize the effects of disturbances, which act as a source of false alarms.

The design of the UIO requires the knowledge of a state-space model of the system under investigation. In particular, in this work, in order to design the UIO, the identification of a number of MISO models, of the type of (3) equal to the number of the output variables has been chosen.

It can be proved that a state-space formulation of the input-output equation error model for the i-th output becomes

$$\begin{aligned} x_i(t+1) &= A_i x_i(t) + B_i u(t) + E_i \varepsilon_i(t) \\ y_i(t) &= C_i x_i(t), \quad t = 1, 2, \ldots \end{aligned} \tag{4}$$

where the matrices $A_i(n \times n)$, $B_i(n \times r)$, $C_i(1 \times n)$ and $E_i(n \times 1)$ are functions of the α_{ik} and β_{ikj} parameters (Söderström and Stoica, 1987; Patton *et al.*, 1989). If the vector $\varepsilon_i(t)$ is considered as a disturbance and E_i its distribution matrix, the term $E_i\varepsilon_i(t)$ represents uncertainties acting upon the system.

The i-th residual (symptom) generator using an UIO is thus described as (Yang and Wilde, 1988)

$$\begin{aligned} z_i(t+1) &= N_i z_i(t) + L_i y_i(t) + G_i u(t) \\ r_i(t) &= y_i(t) - C_i\big(z_i(t) - D_i y_i(t)\big) \end{aligned} \tag{5}$$

where $z_i(t) \in \Re^n$ denotes the i-th observer state vector, $C_i\big(z_i(t) - D_i y_i(t)\big)$ represents the estimate of $y_i(t)$ whilst $r_i(t)$ 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. With the choices

$$\begin{aligned} D_i &= -E_i(C_i E_i)^{-1}, \\ P_i &= I + D_i C_i, \\ G_i &= P_i B_i \\ L_i &= P_i A_i E_i (C_i E_i)^{-1}, \end{aligned} \tag{6}$$

if N_i can be chosen suitably, so that

$$L_i C_i - P_i A_i = -N_i P_i \tag{7}$$

$r_i(t)$ will asymptotically approach zero in the absence of sensor faults, $f_y(t) = 0$.

3 Identification of the plant

The technique for output sensor FDD was applied to real data from the 120MW power plant of Pont sur Sambre. It consists of a double-shaft industrial gas turbine working in parallel with electrical mains.

The block-diagram of the plant is shown in Figure (3) 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 data from the control inputs 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 data from the output sensors were the corresponding values of P_v (steam 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 about 60 seconds. The number of samples has thus been reduced to 367. Their plots are reported in Figures (4) and (5).

The computational procedure which has been performed on the data is the identification of the triple (A_i,B_i,C_i) and of disturbance distribution matrix E_i from the equation error model ($i = 1, \ldots, m$) 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 (Söderström and Stoica, 1987).

4 Fault diagnosis of the input-output sensors of the power plant

Faults in a single output sensor were generated by producing positive and negative variations (step and ramp functions of different amplitudes) in the output signals. A positive and negative fault occurring respectively at the instant of the minimum and maximum values of the observer were chosen since these conditions represent the worst case in failure detection.

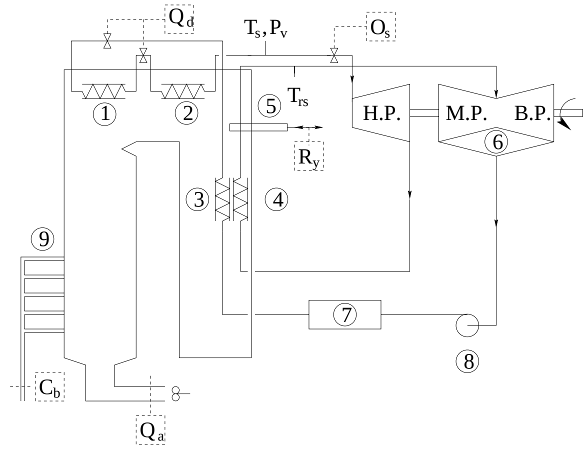
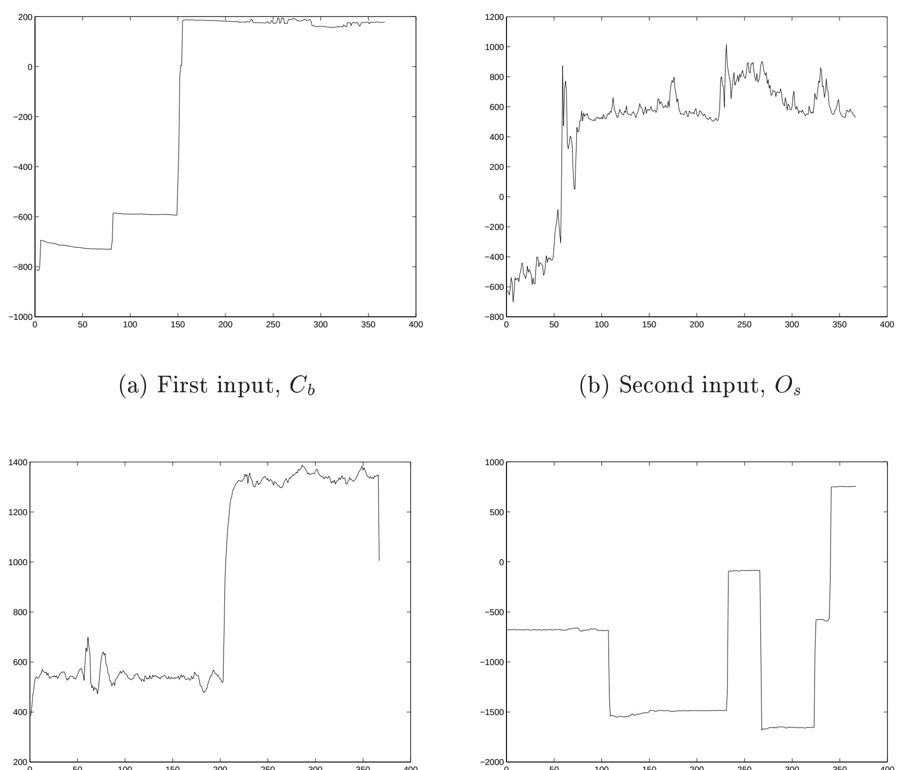


Figure 3: The structure of the power plant.



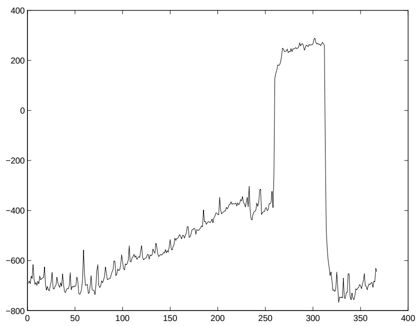
(a) First input, C_b

(b) Second input, O_s

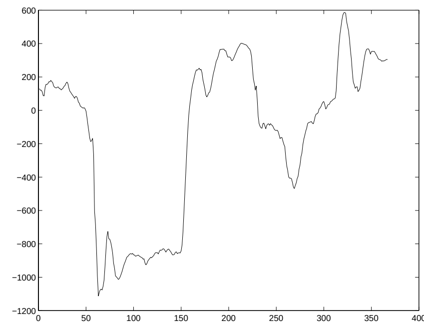
(c) Third input, Q_d

(d) Fourth input, R_y

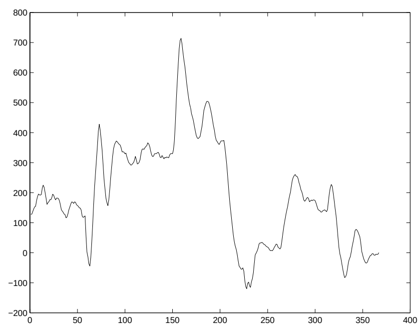
Figure 4: First four input of the power plant.



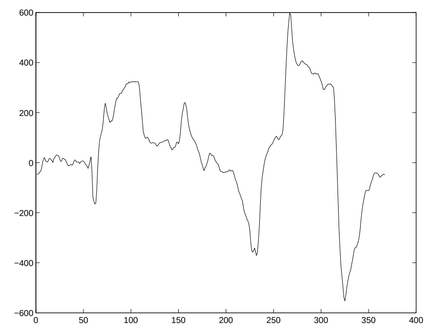
(a) Fifth input, Q_a



(b) First output, P_v



(c) Second output, T_s



(d) Third output, T_{rs}

Figure 5: Last input and three output of the power plant.

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.

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. These thresholds were settled on the basis of fault-free residuals. A margin of 10% between the thresholds and the residual values was imposed.

To summarize the performance of the FDD technique using classical observers without disturbance decoupling, the minimal detectable faults on the various output sensors referred to the mean signal values are collected in Table (1), in case of step and ramp faults.

The fault sizes are expressed as per cent of the mean signal values. Table (2) reports the mean square values of the output estimation errors given by the FDD observers without disturbance decoupling. These values are very large and they cannot be used to detect faults reliability.

Slight better results (Table 3) than the previous ones have been obtained by using a technique presented in a related work (Simani and Spina, 1998) where the process was described as an errors-in-variables model and a well-established procedure (Frisch Scheme) for dynamic system identification was performed (Frisch, 1934; Beghelli *et al.*, 1990). A Kalman filter was exploited to detect faults.

Sensor	P_v	T_s	T_{rs}
Step	18%	4%	20%
Ramp	75%	60%	25%

Table 1: Minimal detectable step and ramp faults.

P_v	T_s	T_{rs}
581.25	51.46	55.88

Table 2: The three output estimation errors without disturbance de-coupling.

Sensor	P_v	T_s	T_{rs}
Step	8%	2%	10%
Ramp	35%	55%	15%

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

The mean square errors of the output estimation errors obtained by using the Kalman filter are collected in Table (4).

Output	P_v	T_s	T_{rs}
Kalman filter	181.92	28.42	33.69

Table 4: The three output estimation errors with Kalman filters.

A meaningful improvement on the performance of the FDD device was obtained by using the UIO exploiting the disturbance decoupling technique presented in this paper.

Table (5) shows the minimal detectable faults in case of disturbance decoupling.

Sensor	P_v	T_s	T_{rs}
Step	5%	1%	1.7%
Ramp	20%	6.5%	4.7%

Table 5: Minimal detectable step and ramp faults with UIO.

Table (6) reports the mean square values of the output estimation errors when UIO is used.

Compared with the ones concerning classical observers, residuals are very small because disturbance decoupling is achieved, and consequently, their increase can be significantly detected when a fault occurs on the sensors. Moreover, smaller thresholds can be placed on the residual signals to declare the occurrence of faults. This demonstrates the improved efficiency of the FDD technique when de-coupling of disturbances is performed.

Output	P_v	T_s	T_{rs}
UIO	20.45	12.24	15.55

Table 6: The three output estimation errors with disturbance de-coupling.

5 Conclusion

The design procedure for FDD in output sensors of an industrial process is also described in this paper. 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 equation error models.

In such a way, the distribution matrix of the disturbances acting upon the system is obtained, so that the FDD is performed by using UIO.

Such a procedure has been applied to a model of a real 120MW power plant of Pont sur Sambre. In order to analyze the diagnostic effectiveness of the FDD system in the presence of abrupt changes or drifts in measurements, faults modeled by step and ramp functions were 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.

This procedure can be generalized to diagnose faults regarding also the sensors which measure the input variables of the process.

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