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# PARAMETRIC IDENTIFICATION FOR ROBUST FAULT DETECTION

**Cesare Fantuzzi** * **Silvio Simani** **

* *Dipartimento di Scienze e Metodi per l'Ingegneria. Università di Modena e Reggio Emilia. Via Allegri 15, 42100 Reggio Emilia - ITALY. Tel: +39 0522 496466. Fax: +39 0522 430632. E-mail:* `cesare.fantuzzi@ieee.org`
** *Dipartimento di Ingegneria, Università di Ferrara. Via Saragat 1, 44100 Ferrara - ITALY. Tel: +39 0532 293839. Fax: +39 0532 768602. E-mail:* `ssimani@ing.unife.it`

Abstract: The work presents some simulation results concerning the application of robust model–based fault diagnosis to an industrial process by using identification and disturbance de–coupling techniques. The first step of the considered approach identifies several equation error models by means of the input–output data acquired from the monitored system. Each model describes the different working conditions of the plant. In particular, the equation error term of the identified models takes into account disturbances (non–measurable inputs), non–linear and time–invariant terms, measurement errors, etc. The next step of this method exploits state–space realization of the input–output equation error models allowing to define several equivalent disturbance distribution matrices related to the error terms. Moreover, in order to achieve good robustness properties for a process normally working at different operating points, a single optimal equivalent disturbance distribution matrix is selected. Finally, eigenstructure assignment method for robust residual generation and disturbance de–coupling can be successfully exploited for the fault diagnosis of the dynamic process. The fault diagnosis procedure is applied to a benchmark simulation of a gas turbine process.

Keywords: Model–Based Approach, Fault Diagnosis, System Identification, Eigenstructure Assignment, Industrial Process.

## 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 malfunctions regarding the system under investigation (Isermann and Ballé, 1997).

Recently, different methods based on analytical redundancy have been developed to diagnose faults in linear, time–invariant, dynamic systems and a wide variety of model-based approaches has been proposed (Frank *et al.*, 2000; Patton *et al.*, 2000). There are different model–based approaches to the FDD problem, namely parameter identification (Willsky, 1976), parity equations (Gertler, 1998), 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).

Although the analytical redundancy method has been recognised as an effective technique for detecting and isolating faults, the critical problem of unavoidable modelling uncertainty has not been fully solved. The main problem regarding the reliability of FDD schemes is the modelling uncertainty which is due, for example, to process noise, parameter variations and non–linearities.

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 modelling uncertainty is unavoidable. The design of an effective and reliable FDD scheme should take into account of the modelling uncertainty with respect to the sensitivity of the faults.

Several papers addressed this problem. For example, optimal robust parity relations were proposed in (Chow and Willsky, 1984; Lou *et al.*, 1986), and the threshold selector concept was introduced in (Emami-Naeini *et al.*, 1988).

One other promising approach is the decoupling between disturbances and residuals achieved by means of a proper observer eigenstructure assignment (Chen and Patton, 1999, chapt. 4). This approach requires the knowledge of the system model and, in particular, of the estimation of the *disturbance distribution* matrix (i.e. the structure of the disturbance entry points) (Chen and Patton, 1999, chapt. 5). Thus, some procedures can be defined to model correctly the disturbance matrix (Patton *et al.*, 2000).

In this paper, an identification approach is suggested, in which a family of equation error (EE) models are derived from input–output data acquired from the monitored system. A set of models is here considered, since the operating point of the monitored system may vary according to the different plant conditions (Simani *et al.*, 2000*b*; Patton *et al.*, 2001). In particular, in each EE model, the error term takes into account any causes of mismatch between model and real process (disturbances, measurement noise and modelling errors). Under this assumption, it is supposed that EE terms may change in connection with the different working conditions.

On the other hand, a state–space realization of such models leads to define a structure indicating how non–ideal terms act on the system by means of a disturbance distribution matrix (Simani *et al.*, 2000*a*).

In the design of the model–based FDD scheme, instead of using a multiple model–based approach, a single model for ease of implementation can be exploited. However, when using a single model in this way, it is supposed that different modelling errors can arise corresponding to different operating points. Therefore, different operating points correspond to different disturbance distribution matrices. One way to achieve good robustness is to satisfy the disturbance de–coupling conditions for all the identified disturbance distribution matrices (Chen and Patton, 1999, chapt. 5). This can be done by using an equivalent disturbance distribution matrix (Fantuzzi *et al.*, 2001) which approximates all disturbance distribution matrices.

The paper is organised as follows. In Section 2 the problem statement is given and it is described from a mathematical point of view. The robust fault diagnosis scheme is also presented in Section 2 considering the varied operating point. In Section 3 the characteristics of a gas turbine model used to test the proposed methodology are presented and the results regarding the diagnosis of simulated faults are also reported. Finally, conclusions and open problems reported in Section 4 end the paper.

## 2. ROBUST RESIDUAL GENERATION

A typical description for the system uncertainty make use of the concept of unknown inputs $\mathbf{d}(t)$ acting upon a nominal linear discrete–time model of the monitored system as described by

$$\begin{cases} \mathbf{x}(t+1) = \mathrm{A}\mathbf{x}(t) + \mathrm{B}\mathbf{u}(t) + \mathrm{R}_1\mathbf{f}(t) + \mathrm{E}\mathbf{d}(t) \\ \mathbf{y}(t) = \mathrm{C}\mathbf{x}(t) + \mathrm{R}_2\mathbf{f}(t) + \mathbf{d}(t)\ ,\ t = 1, 2, \dots \end{cases} \tag{1}$$

where $\mathbf{y}(t) \in \Re^m$ is the system output vector and $\mathbf{u}(t) \in \Re^r$ is the control input vector. The vector $\mathbf{x}(t) \in \Re^n$ represents the system state, whilst the term $\mathbf{d}(t) \in \Re^q$ takes into account the modelling non–ideal terms, such as measurement noise, real system non–linear terms, etc. The vector $\mathbf{f}(t) \in \Re^p$ represents the faults affecting the process (Simani *et al.*, 2000*a*).

In the general framework of linear system and assuming fault free system operation, the system matrices $\mathrm{A}_{(n\times n)}$, $\mathrm{B}_{(n\times r)}$ and $\mathrm{C}_{(m\times n)}$ can be obtained by modelling or proper identification procedures (Simani *et al.*, 2000*a*). Moreover, when the unknown vector $\mathbf{d}(t)$ is considered as a disturbance and the matrix $\mathrm{E}_{(n\times q)}$ describes its distribution, the terms E $\mathbf{d}(t)$ represent uncertainties acting upon the system. Fault matrices $\mathrm{R}_{1\,(n\times p)}$ and $\mathrm{R}_{2\,(m\times p)}$ are assumed to be known (Chen and Patton, 1999).

In fault free conditions ($\mathbf{f}(t) = \mathbf{0}$), under the assumption that the dynamic process works at different operating point, the modelling error may vary according to different plant conditions. Hence, the system (1) can be rewritten as

$$\begin{cases} \mathbf{x}(t+1) &= \mathrm{A}\mathbf{x}(t) + \mathrm{B}\mathbf{u}(t) + \mathrm{E}^{(i)}\mathbf{d}(t) \\ \mathbf{y}(t) &= \mathrm{C}\mathbf{x}(t) + \mathbf{d}(t) \ , \ t = 1, 2, \ldots \end{cases} \tag{2}$$

where $\mathrm{E}^{(i)}$, with $i = 1, \ldots, M$, represents the different unknown input distribution matrices corresponding to $M$ operating points of the system. It is attractive to be able design a single robust FDD scheme (i.e. for the A, B, C, $\mathrm{R}_1$ and $\mathrm{R}_2$ system matrices) for the whole range of operating points $M$. Therefore, in order to achieve a robust model–based FDD, the "optimal" distribution matrix E, which is unknown, has to be estimated by means identification procedure.

The problem of the estimation of the disturbance distribution matrices $\mathrm{E}^{(i)}$ can be approached from an identification point of view using input–output data.

The mathematical description of the system under diagnosis for the $i^{\text{th}}$ working condition can be performed by means of a discrete–time equation error linear model in polynomial form

$$\mathrm{Q}(z)\mathbf{y}(t) = \mathrm{P}(z)\mathbf{u}(t) + \mathrm{D}^{(i)}(z)\mathbf{d}(t) \tag{3}$$

where $z$ is the unitary advance operator. $\mathrm{Q}(z)$, $\mathrm{P}(z)$ and $\mathrm{D}^{(i)}(z)$ are polynomial matrices with maximal order $n$ and whose coefficients have to be identified. When identifiability conditions are fulfilled for the *ARMAX* (Auto-Regressive Moving Average eXogenous) model described by Eq. (3), a minimal parametrisation of $(\mathrm{Q}(z), \mathrm{P}(z), \mathrm{D}^{(i)}(z))$ can be successfully estimated (Guidorzi, 1996; Ljung, 1999).

As an example, assuming fault–free system operation, ARMAX model structure and parameters can be estimated using a Prediction Error Method (PEM) procedure in each $i^{\text{th}}$ working condition. In particular, a Maximum Likelihood (ML) (Ljung, 1999) technique can be exploited to estimate the $(\mathrm{Q}(z), \mathrm{P}(z))$ coefficients and then the $\mathrm{D}^{(i)}(z)$ parameters of the ARMAX model in each $i^{\text{th}}$ working point.

The identification method used in this work for the computation of the minimal parametrisations in the multivariable ARMAX identification relies on iterative algorithms like Newton–Raphson or Gauss–Newton numerical procedures (Guidorzi, 1996).

Concerning the determination of the plant working points and the clustering of the data $\{\mathbf{u}(t), \mathbf{y}(t)\}$ into $M$ regions, the related works (Simani *et al.*, 2000*b*; Patton *et al.*, 2001) by the same authors could be referred.

However, for diagnosis purposes, a state–space realization of the model (3) is needed. It can be therefore proved (see, e.g., (Ljung, 1999)) that a state—space minimal form (A, B, C, $\mathrm{E}^{(i)}$) can be obtained from the input–output EE model (3) for the $i^{\text{th}}$ working point. Once a suitable state–space representation of the system model (3) is achieved, there different approaches to generate the residual for the system (1).

In this work, the observer–based method is used to estimate the outputs of the system from the input–output measurements. In model–based FDD, the state estimation is not necessarily needed, because the required information is in the diagnostic signal (the residual). So direct approach to de–couple residual to disturbance can be used, even if state estimation error still coupled with disturbance.

This approach is detailed in (Chen and Patton, 1999, chapt. 4). However, that procedure should be modified to take into account the different plant working conditions according to Eq. (2). The following fault $\mathbf{f}(t)$ to residual $\mathbf{r}(t)$ transfer matrix is obtained:

$$\begin{aligned} \mathbf{r}_f(t) &= \mathrm{Q}\mathrm{R}_2\mathbf{f}(t) + \\ &+ \mathrm{H}(z\mathrm{I} - \mathrm{A} + \mathrm{KC})^{-1}(\mathrm{R}_1 - \mathrm{K}\mathrm{R}_2)\mathbf{f}(t) \end{aligned} \tag{4}$$

where $\mathrm{H} = \mathrm{QC}$.

On the other hand, the *disturbances* $\mathbf{d}(t)$ to residual $\mathbf{r}(t)$ transfer matrix is

$$\begin{aligned} \mathbf{r}_d(t) &= \mathrm{QI}\mathbf{d}(t) + \\ &+ \mathrm{H}(z\mathrm{I} - \mathrm{A} + \mathrm{KC})^{-1}\left(\mathrm{E}^{(i)} - \mathrm{KI}\right)\mathbf{d}(t). \end{aligned} \tag{5}$$

It is worthwhile noting how the disturbance $\mathbf{d}(t)$ acts either on system state and output (see Eq. 1), but it can not be completely rejected. Only the dependence of $\mathbf{d}(t)$ on system state can be eliminated with a proper choice of matrix H (Chen and Patton, 1999, chapt. 4). In such way, only the disturbance term (6) in Eq. (5) can be deleted, i.e.

$$\mathrm{H}(z\mathrm{I} - \mathrm{A} + \mathrm{KC})^{-1}\mathrm{E}^{(i)}\mathbf{d}(t) = 0. \tag{6}$$

In particular, concerning a *dead–beat* design for robust residual generation (Chen and Patton, 1999, chapt. 4), in order to make the disturbance de–coupling hold for all operating points, the following relation should be satisfied

$$\mathrm{HE}^{(i)} = 0 \text{ for } i = 1, \ldots, M. \tag{7}$$

The relation (6) is nulled when the following condition is satisfied

$$\mathrm{HA}_c = 0 \tag{8}$$

where $\mathrm{A}_c = \mathrm{A} - \mathrm{KC}$. Matrices H and K have to be designed in such a way that rows of H are left eigenvectors of $\mathrm{A}_c$ corresponding to zero–valued eigenvalues, Eq. (8) then holds true.

On the other hand, the Eq. (7) means that the left eigenvectors to be assigned are orthogonal to the disturbance directions, and the residual weighting matrix Q is therefore computed using this equation.

Finally, according to the system (1), in order to choose the "optimal" disturbance distribution de–coupling matrix $\mathrm{E}^{(i)}$, the problem could be solved by defining the following optimisation procedure

$$\min_{\mathrm{E}^{(i)}} \| \mathbf{r}_d(t) \| \quad \text{s.t.} \quad \max_{\mathrm{E}^{(i)}} \| \mathbf{r}_f(t) \| \qquad \text{for } i = 1, \ldots, M \tag{9}$$

or

$$\min_{\mathrm{E}^{(i)}} \frac{\| \mathbf{r}_d(t) \|}{\| \mathbf{r}_f(t) \|} \qquad \text{for } i = 1, \ldots, M. \tag{10}$$

Under the previous assumptions, in connection with a dead–beat observer, the optimal E is selected among all disturbance distribution matrices $\mathrm{E}^{(i)}$ for $i = 1, \ldots, M$ in order to minimise disturbance effects and to maximise residual sensitivity to faults.

In the formulation of the problem (9), the infinity norm of the matrices may be used. However, other matrix norms (such as the Frobenius norm) can be also exploited (Frank *et al.*, 2000).

## 3. GAS TURBINE MODEL DESCRIPTION

The process under investigation is a simulated model of a single–shaft industrial gas turbine. The block structure of the plant is depicted in Figure (1) and more detail about the process can be found in (Bettocchi *et al.*, 1996; Simani *et al.*, 1998).

The actuator control inputs are $u_1(t)$, representing the Inlet Guide Vane (IGV) angular position $\alpha(t)$ and $u_2(t)$, corresponding to the fuel mass flow rate, $M_f(t)$.

The output sensors are those used for the measurement of $y_1(t)$, the pressure at the compressor inlet $p_{ic}(t)$, $y_2(t)$, the pressure at the compressor outlet $p_{oc}(t)$, $y_3(t)$, the pressure at the turbine outlet $p_{ot}$, $y_4(t)$, the temperature at the compressor outlet $T_{oc}$, $y_5(t)$, the temperature at the turbine outlet $T_{ot}$ and $y_6(t)$, the electrical power at the generator terminal $P_e$.

The process operates at different working conditions and 8 noisy process measurements, including temperatures, flow rates, pressures, control signals, turbine speed and torque can be acquired with a sampling rate of 0.1 s. Due to the presence of sensors, actual measurements $\mathbf{u}(t)$ and $\mathbf{y}(t)$ are affected by noise (Simani *et al.*, 1998).

A pressure sensor bias (abrupt fault on the $p_{ot}$ pressure sensor signal) and an actuator failure (abrupt fault on the $\alpha(t)$ signal) have been simulated to experiment with both the identification and the fault diagnosis methods.

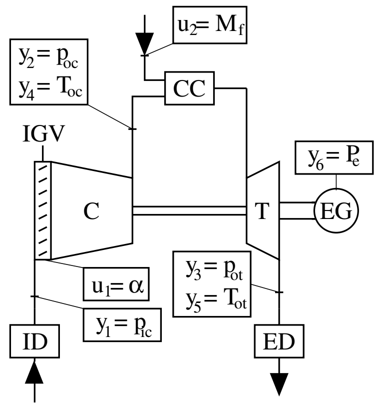


Fig. 1. Layout of the turbine model.

Because of the underlying physical mechanisms and because of the modes of the control signals, the process has non–linear steady state as well as dynamic characteristics (Simani *et al.*, 1998).

A clustering algorithm was used with $M = 3$ clusters (operating conditions) (Julián, 1999*b*; Julián, 1999*a*). After clustering, the ARMAX (3) model order $n = 2$ and structure $(\mathrm{Q}(z), \mathrm{P}(z), \mathrm{D}^{(i)}(z))$ have been estimated using PEM and ML identification method in each region with $i = 1, 2, 3$.

The model has been then validated on a separate data set. Therefore, model (2) matrices (A, B, C, $\mathrm{E}^{(i)}$) have been estimated with $i = 1, \ldots, M$ and $M = 3$.

In fault–free conditions, Table (1) reports the mean square values of the output estimation errors $\mathbf{r}(t)$ given by classical observers for all operating conditions without de–coupling properties (Simani *et al.*, 1999; Simani *et al.*, 2000*a*). These values are large and they cannot be used to detect faults reliability.

A meaningful improvement has been obtained by using the identification technique presented in Section 2 when the process disturbances are described by means of different $\mathrm{E}^{(i)}$ matrices, with $i = 1, 2, 3$.

The mean square errors of the residuals $\mathbf{r}(t) = \mathbf{r}_d(t)$, are also collected in Table (1), under no–fault conditions. The results indicate that the residuals obtained using a dead–beat observer when optimisation procedure (9) is performed can serve as reliable fault symptoms. Hence, using these diagnostic signals, the observer–based approach for fault diagnosis can be exploited and applied to the power plant.

Table 1. Residual $\mathbf{r}_d(t)$ values with and without the de–coupling approach.

| **Outputs** | $p_{ic}$ | $p_{oc}$ | $p_{ot}$ |
|---|---|---|---|
| **Classical Observer** | 13.29 | 7.56 | 15.34 |
| **Dead–Beat Observer** | 1.04 | 1.22 | 0.67 |
| **Outputs** | $T_{oc}$ | $T_{ot}$ | $P_e$ |
| **Classical Observer** | 20.22 | 21.57 | 19.70 |
| **Dead–Beat Observer** | 1.55 | 1.58 | 0.70 |

The fault $\mathbf{f}(t)$ occurring on $\alpha(t)$ actuator or $p_{ot}(t)$ sensor causes alteration of the signals $\mathbf{u}(t)$, $\mathbf{y}(t)$ and of the residuals $\mathbf{r}(t) = \mathbf{r}_f(t) + \mathbf{r}_d(t)$ corresponding to Equations (4) and (5). Residuals should then indicate fault occurrence whether their values are lower or higher than thresholds fixed in fault-free conditions (residual geometrical analysis).

To summarise the performance of the whole FDD technique, the minimal detectable faults on the $m = 6$ output sensors and $r = 2$ actuators, expressed as per cent of the mean values of the relative signals, are collected in Table (2). The results were obtained by using Luenberger observers for all operating conditions without disturbance de–coupling.

An improvement of the FDD performance has been obtained by using the presented de–coupling algorithm. Table (2) summarises also the performance of the enhanced FDD technique and collects the minimal detectable faults on the various sensors and actuators. The fault sizes are expressed as per cent of the signal mean values.

Table 2. Minimal detectable faults with and without de–coupling approach.

| **Meas.** | $\alpha$ | $M_f$ | $p_{ic}$ | $p_{oc}$ |
|---|---|---|---|---|
| **Classical Obs.** | 4% | 4% | 5% | 7% |
| **Dead–Beat Obs.** | 0.8% | 1.3% | 0.08% | 0.08% |
| **Measurements** | $p_{ot}$ | $T_{oc}$ | $T_{ot}$ | $P_e$ |
| **Classical Obs.** | 5% | 5% | 2.5% | 1.7% |
| **Dead–Beat Obs.** | 0.8% | 0.7% | 0.05% | 0.2% |

The residuals $\mathbf{r}(t)$ obtained by using the presented de–coupling approach are more sensitive to faults. Noise rejection is, in fact, almost achieved by means of the optimisation method here developed. Moreover, smaller thresholds can be placed on the residual signals to declare the occurrence of faults.

As an example, fault–free and faulty residuals $\mathbf{r}(t)$ regarding the $\alpha(t)$ signal are reported in Figures (2) and (3). They were generated by using a classical observer approach and the presented de–coupling method, respectively. Fault-free thresholds were marked by using '−' and '+'.

Finally it is worthwhile noting how the values of the faults, reported in Table (2), obtained by using the enhanced FDD technique are lower

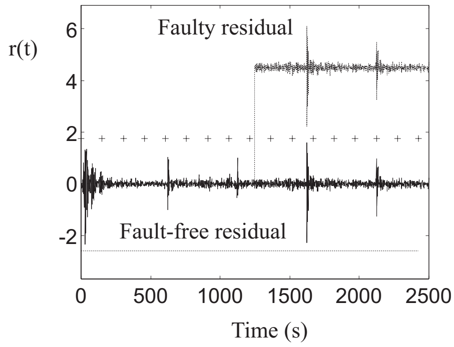


Fig. 2. Residuals for the actuator signal $\alpha(t)$ without de–coupling procedure

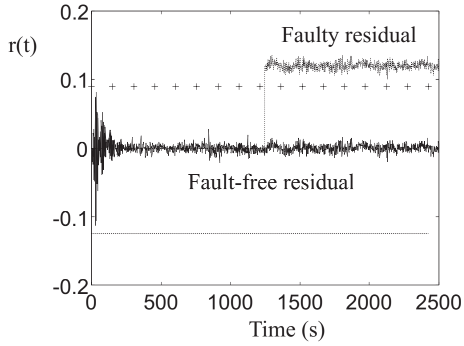


Fig. 3. Residuals for the signal $\alpha(t)$ with de–coupling approach

than the ones corresponding to classical observers. Moreover, the minimal detectable faults on the various sensors and actuator seem to be adequate to the industrial diagnostic applications. However, these improvements are not free of charge: they have been obtained with a procedure of greater complexity.

## 4. CONCLUSIONS AND FURTHER WORKS

This paper concerned the identification of models suitable for fault diagnosis purpose. The structure of equation error models (ARMAX) are derived from an identification procedure. In this manner, state–space realizations of such models lead to estimate a set of disturbance distribution matrices related to the error terms. Different operating points correspond to different disturbance distribution matrices.

The state–space models are successfully exploited for the design of a robust fault diagnosis schemes, once the single disturbance distribution matrix approximating all disturbance distribution matrices is estimated.

Finally, the paper reports a eigenstructure assignment procedure for a dead–beat observer, which is applied to the robust fault diagnosis of a non–linear model of a turbine model working at different operating points.

Open problems regard the isolation of the different fault occurring on the monitored process as well as the application of the proposed FDD procedure to real data acquired from the actual plant.

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