RELIABILITY IN THE DETERMINATION OF GAS TURBINE OPERATING STATE

Pier Ruggero Spina
DIEM – University of Bologna
Viale Risorgimento, 2 – 40136 Bologna – Italy
Phone: ++39-051-2093316, Fax: ++39-051-2093313
e-mail: pierruggero.spina@mail.ing.unibo.it

Abstract

This paper analyzes the problems which arise using gas turbine Health Monitoring Systems and proposes a method of improving the reliability in gas turbine health determination. The method involves the following main steps:

- an analysis to evaluate the best measurements/parameters combination, in terms of accuracy in gas turbine health determination;
- the submission of measurements to sensor Fault Detection and Isolation (FDI) analyses, before they are used as input by the Health Monitoring System, in order to verify if there are measurements affected by errors due to faulty sensors.

Three FDI techniques are developed and compared: they use, for the residual generation, parity equations, dynamic observers or Kalman filters, respectively.

Nomenclature

e	residual vector
M	mass flow rate
m	number of models
N_s	number of samples
n_m	number of measured quantities
n_r	number of residuals
P_e	electrical power
p	pressure
$\mathbf{Q}_m$	vector of measured parameters
$\mathbf{Q}_{WP}$	vector of measurements necessary to define the working point
T	total temperature
Thr	threshold
t	time
u	measured input vector
X	vector of characteristic parameters
y	measured output vector
z	z-transform variable
α	Variable Inlet Guide Vane (VIGV) angle
μ	mean value
σ	standard deviation

Subscripts

c	compressor
f	fuel, fixed parameter
i	input, inlet section
mean	mean value
min	minimum
o	output, outlet section
v	variable parameter
t	turbine

Acronyms

C	Compressor
CC	Combustor
ED	Exhaust Duct
EG	Electric Generator
ID	Intake Duct
T	Turbine

1. Introduction

The use of “on condition” maintenance procedures in gas turbine management permits the achievement of increases in the machine availability and in the average efficiency during the gas turbine operating life. The application of the “on condition” maintenance requires the use of tools for the determination of the actual gas turbine health state.

The Gas Path Analysis (GPA) is one of the most widely used methods for the determination of the gas turbine operating state. This technique uses field measurements to estimate the characteristic geometric and performance parameters, which are indices of the gas turbine health, by solving in inverse mode linear (Urban, 1972) or non-linear models (Stamatis et al., 1990; Bettocchi and Spina, 1999a) of the gas turbine thermodynamic cycle. The analysis of the shifts between computed and expected values of the characteristic parameters allows the localization of inefficient operations.

In this paper, an analysis of the uncertainties in the determination of gas turbine health parameters, which arise by using a GPA method, was first performed.

Secondly, a method to improve the reliability in gas turbine health determination is proposed. It involves:

- an initial analysis to evaluate the best measurements/ parameters combination, in terms of accuracy in gas turbine health determination;
- the submission of measurements to sensor FDI analyses, before they are used as input by the GPA method, in order to verify if there are measurements affected by errors due to faulty sensors.

Three FDI techniques were developed and compared: they use, for the residual generation, parity equations, dynamic observers or Kalman filters, respectively.

2. Uncertainties in the determination of gas turbine operating state

A Health Monitoring System requires the evaluation of the actual values of characteristic geometric and performance parameters, which are indices of the machine operating state, such as the efficiencies and characteristic passage areas of the compressor and turbines, the combustor efficiency and the pressure drops in the gas path. The comparison between the actual parameter values and the ones in the reference conditions allows the evaluation of the shifts between the actual gas turbine operating state and the expected one, and the localization of inefficient operations due to deterioration and faults.

The GPA method developed by Bettocchi and Spina (1999a) evaluates the characteristic geometric and performance parameters by solving in inverse mode the program for gas turbine cycle calculation. It is performed by "adapting" the characteristic parameters, which are normally used as fixed inputs by the cycle program, until the computed estimates of the measurable parameters agree with the values measured on the gas turbine.

The measurable parameters $\mathbf{Q}_m$ computed by the cycle program are a function of the machine characteristic parameters ($\mathbf{X}$) and of the parameters that determine the actual gas turbine working point ($\mathbf{Q}_{WP}$), the latter being the boundary conditions and a number of operating parameters defining the gas turbine load condition (which generally are the rotational speeds of gas turbine shafts and the power output). The functional relation between the measurable parameters $\mathbf{Q}_m$, the characteristic parameters $\mathbf{X}$ and the parameters $\mathbf{Q}_{WP}$ can be expressed as follows:

$$\mathbf{Q}_m = \mathbf{f}(\mathbf{X}, \mathbf{Q}_{WP}) \quad (1),$$

where $\mathbf{f}$ is a non-linear function that represents the mathematical model of the gas turbine. Inverting Eq. 1, it is possible to calculate the characteristic parameters starting from measurements. This inverse calculation is performed by solving the system of equations obtained by equating to zero the residuals between the values measured on the machine and computed by the cycle program. Thus, the number and type of gas turbine characteristic parameters that can be determined depend on the number and type of equations, which, in turn, depend on the number and type of the available measurements. In particular, the number of characteristic parameters which can be determined is generally equal to the number of measurements, without considering the $\mathbf{Q}_{WP}$ measurements, which are used to define the machine working point. The number of measurements is generally lower than the number of characteristic parameters, so that it is necessary to select in advance the characteristic parameters that have to be investigated ($\mathbf{X}_v$ = variable parameters) and the ones which have to be kept constant during the calculation ($\mathbf{X}_f$ = fixed parameters).

In a previous paper Pinelli and Spina (2000a) showed how the measurement uncertainty and the selection of the characteristic parameters that have to be investigated affect the gas turbine operating state determination. Representing the inverse solution of the program for gas turbine cycle calculation as:

$$\mathbf{X}_v = \mathbf{F}(\mathbf{Q}_m, \mathbf{Q}_{WP}, \mathbf{X}_f) \quad (2),$$

it can be seen how measurement errors, due to the bias and non-repeatability errors of the sensors or to sensor faults, and the variations due to aging or deterioration which, in the actual machine, may occur on the characteristic parameters kept constant during the calculation ($\mathbf{X}_f$), cause an estimation error on the characteristic parameters to be determined ($\mathbf{X}_v$).

3. Methods to improve the reliability in the determination of gas turbine operating state

The sources of uncertainty listed above play a significant role on the reliability in the determination of gas turbine operating state (Urban, 1972; Stamatis et al., 1992; Bettocchi et al., 2000; Pinelli and Spina, 2000a). In fact, the alterations in the parameter estimation due to these uncertainties may be comparable with the alteration due to an actual loss in gas turbine performance.

In order to improve the accuracy in the characteristic parameter estimation different actions may be taken.

3.1. Determination of the best measurements/parameters combination

First, an analysis to evaluate the best measurements/ parameters combination should be performed. In a previous paper Pinelli and Spina (2000b) presented a method which makes it possible to identify:

- the most critical measurements for which an increase of accuracy is advisable to improve the gas turbine operating state determination;
- the most appropriate measurements to add to the standard machine instrumentation;
- the most appropriate characteristic parameters to evaluate, based on the available measurements.

The application of this method in particular highlighted the criticality of fuel mass flow rate measurement. In fact, the high influence of the fuel flow on the thermodynamic cycle model, coupled with the uncertainty of this measurement, which is generally high, introduces a large error on all the parameters to be determined. For this reason, it is advisable to increase the accuracy of this measurement.

3.2. Sensor Fault Detection and Isolation (FDI)

Secondly, the measurements should be processed, using FDI techniques, before they are used as input by the GPA. In this manner it is possible to verify whether there are measurements affected by errors due to faulty sensors.

The sensor FDI based on Analytical Redundancy is performed using model-based approaches (Willsky, 1976; Gertler, 1988; Patton et al., 1989). Usually the FDI system consists of two parts (Fig. 1): the first one produces a set of residuals $\mathbf{e}(t)$, using the input/output system measurements $\mathbf{u}(t)$ and $\mathbf{y}(t)$ as inputs, while the second is a logic device, which processes the residuals in order to detect when a fault occurs and to isolate the faulty sensor. As can be noted from Figure 1 the inputs to the FDI system $\mathbf{u}(t)$ and $\mathbf{y}(t)$ are different from the real system inputs $\hat{\mathbf{u}}(t)$ and outputs $\hat{\mathbf{y}}(t)$, due to the presence of measurement disturbances ($\tilde{\mathbf{u}}(t)$, $\tilde{\mathbf{y}}(t)$), such as the noise linked to measurement uncertainty, and sensor faults ($\mathbf{f}_u(t), \mathbf{f}_y(t)$):

$$\mathbf{u}(t) = \hat{\mathbf{u}}(t) + \tilde{\mathbf{u}}(t) + \mathbf{f}_u(t)$$
$$\mathbf{y}(t) = \hat{\mathbf{y}}(t) + \tilde{\mathbf{y}}(t) + \mathbf{f}_y(t)$$

Therefore, the produced residuals depend on:

a) the sensor faults ($\mathbf{f}_u(t), \mathbf{f}_y(t)$);
b) the measurement disturbances ($\tilde{\mathbf{u}}(t), \tilde{\mathbf{y}}(t)$);
c) the inaccuracy of the system model used in the model-based residual generators.

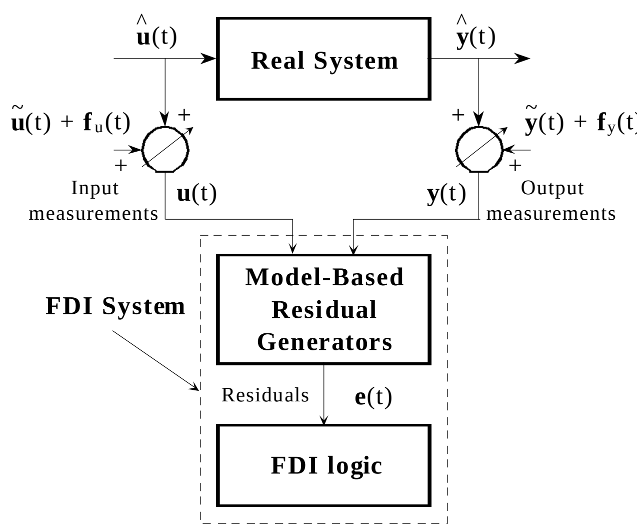

Figure 1: Logic scheme of the FDI system

Sensor fault detection and isolation by means of the residual analysis requires thresholds on the residuals to be fixed, in order to avoid false alarms due to measurement disturbances and model inaccuracy. The threshold values must be fixed by searching for a compromise between the number of false alarms and undetected faults (Patton et al., 1989).

In order to avoid incorrect fault alarms, diagnostic techniques were developed, which allow unambiguous fault detection and isolation in presence of measurement disturbances and model inaccuracy (Simani et al., 1998; Simani and Spina, 1998; Bettocchi et al., 1998, Bettocchi and Spina, 1999b). Moreover, in order to take into account gas turbine ageing, the model of the system, used to design residual generators, must be periodically identified.

Figure 2 shows the overall gas turbine diagnosis process proposed. The following phases are highlighted:

- acquisition and storage of the raw measurements on the PC of the gas turbine control system;
- generation of the data file and selection of the series of data to process;
- data processing by the FDI system to detect and isolate sensor faults;
- if there are no sensor faults, the data are used to identify the model and to perform the gas turbine operating state analysis; on the contrary, if a sensor fault is detected and isolated, the faulty sensor must be repaired or excluded from the gas turbine diagnosis process, to avoid an incorrect evaluation of the machine health state.

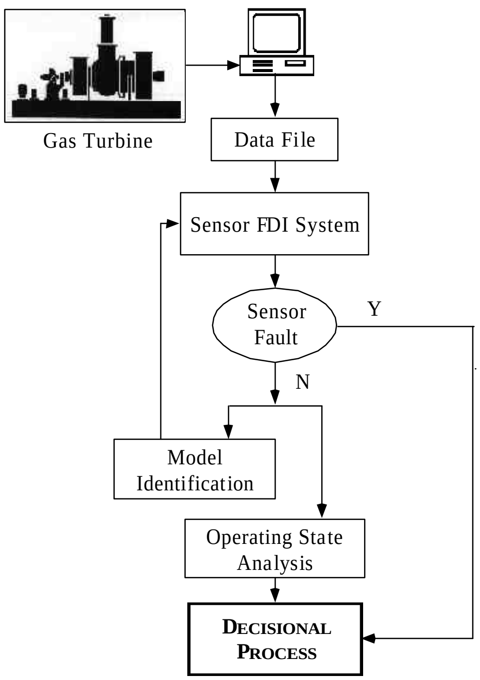

Figure 2: Overall gas turbine diagnosis process

4. Sensor fault detection and isolation techniques

The sensor FDI techniques which were developed use the following model-based approaches for residual generation:

- parity equations (Bettocchi et al., 1996a, 1998; Bettocchi and Spina, 1999b);
- dynamic observers (Simani et al., 1998);
- Kalman filters (Simani and Spina, 1998).

4.1. Parity equations

The parity equations use models of the system to calculate the residuals between computed and measured values of the same quantity. The analysis of residuals allows the detection of faults.

A number of ARX (Auto Regressive eXogenous) MISO (Multi-Input/Single-Output) models equal to the number of gas turbine measured outputs was used. Each model allows the estimation of the value of a measurable output starting from other selected inputs and outputs measured on the machine. The general form of a MISO linear model in z-domain is the following:

$$y_i(z) = \sum_{j=1}^{i-1} f_{ij}(z)\, y_j(z) + \sum_{j=i+1}^{m} f_{ij}(z)\, y_j(z) + \sum_{j=m+1}^{n_m} f_{ij}(z)\, u_j(z)$$

i=1,...,m

Therefore, the parity equations assume the following expression (Gertler and Singer, 1990):

$$\mathbf{e}(z) = \mathbf{F}(z)\,[\mathbf{y},\mathbf{u}](z) \qquad (4),$$

where $\mathbf{e}(z)$ is the residual vector, $[\mathbf{y}, \mathbf{u}](z)$ is the input/output combined vector, and the matrix $\mathbf{F}(z)$ is the transfer function of the system.

The expanded form of the relation (4) is:

$$\begin{bmatrix} e_1 \\ \dots \\ e_m \end{bmatrix} = \begin{bmatrix} 1 & \dots & -f_{1m} & -f_{1\,m+1} & \dots & -f_{1\,n_m} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ -f_{m\,1} & \dots & 1 & -f_{m\,m+1} & \dots & -f_{m\,n_m} \end{bmatrix} \cdot \begin{bmatrix} y_1 \\ \dots \\ y_m \\ u_{m+1} \\ \dots \\ u_{n_m} \end{bmatrix}$$

When a fault on a sensor occurs, the elements of the residual vector, which are linked to the signal of the faulty sensor by **F** matrix coefficients different from zero, assume values different from zero. The fault signature is the vector obtained from **e**, by substituting the **e** elements with values 0 or 1 on the basis of whether they are lower or higher than fixed thresholds.

Fault isolation is performed by comparing the fault signature with the columns of the "incidence" (or "fault") matrix, which is obtained from **F** matrix by substituting the **F** coefficients with values 0 or 1 on the basis of whether they are zero or not.

In order to set-up a technique which is robust with respect to measurement disturbances and model inaccuracy, an incidence matrix with column-canonical structure was used (Bettocchi et al., 1998; Bettocchi and Spina, 1999b). This matrix structure, characterized by the same number of zeroes in each matrix column, allows the determination of a fault signature degradation avoiding an incorrect fault alarm (Gertler, 1988; Gertler and Singer, 1990). Indeed, minor faults may produce some residuals which remain under the threshold, generating an incorrect fault signature, that, if equal to another fault signature, generates an incorrect fault alarm. The use of an incidence matrix with column-canonical structure highlights the occurrence of a fault signature degradation, since, in this case, the number of zeroes in the actual fault signature is higher than the number of zeroes common to all the incidence matrix columns. Therefore, it is possible to detect a minor fault, whereas the fault isolation is possible only when the seriousness of the fault is greater than the one generating the fault signature degradation.

The set-up parity equation-based technique allows the unambiguous isolation of single faults occurring in the input and output sensors.

4.2. Dynamic observers

The observer-based sensor FDI was performed designing two different types of dynamic observers for isolating faults in output and input sensors (Simani et al., 1998).

The unambiguous isolation of faults occurring on output sensors was performed using a number of classical dynamic observers (Luenberger, 1971) equal to the number *m* of output sensors, each observer being driven by a single output and all the inputs of the system. Figure 3 shows the basic scheme used for output sensor fault detection and isolation.

The unambiguous isolation of faults occurring on input sensors was performed using a number of Unknown Input Observers (UIO) equal to the number n_m-m of input sensors. The *i*-th UIO is driven by all but the *i*-th input sensor and all the outputs of the system. Figure 4 shows the basic scheme used for input sensor fault detection and isolation.

Table 1 shows the fault signatures which, in case of single faults, are obtained using the set-up observer-based sensor FDI technique, by substituting the residuals which are lower or higher than the fixed thresholds with 0 or 1, respectively. This technique allows the unambiguous isolation of multiple faults in the output sensors and of single faults in the input sensors. In fact, a fault on the *i*-th output sensor affects only the residual function of the output observer driven by the *i*-th output and all the UIO residual functions. In contrast, a fault on the *i*-th input sensor affects all the input/output observer residual functions, except that of the UIO which is insensitive to the *i*-th input.

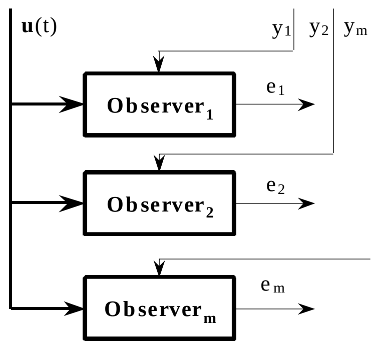

Figure 3: Output sensor FDI

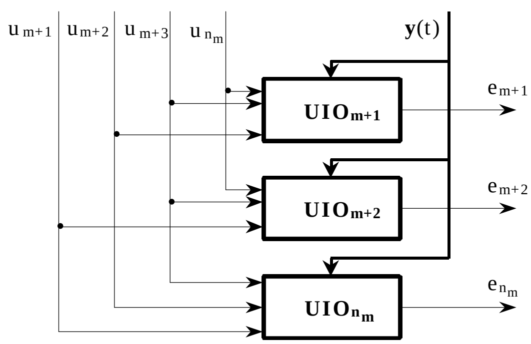

Figure 4: Input sensor FDI

Table 1: Fault signatures obtained using the observer-based sensor FDI

	y_1	y_2	…	y_m	u_{m+1}	u_{m+2}	…	u_{n_m}
e_1	1	0	…	0	1	1	…	1
e_2	0	1	…	0	1	1	…	1
…	…	…	…	…	…	…	…	…
e_m	0	0	…	1	1	1	…	1
e_{m+1}	1	1	…	1	0	1	…	1
e_{m+2}	1	1	…		1	0	…	1
…	…	…	…	…	…	…	…	…
e_{n_m}	1	1	…	1	1	1	…	0

4.3. Kalman filters

The performances of the observer-based sensor FDI technique may be improved by substituting the dynamic observers with Kalman filters (Kalman, 1960; Willsky, 1976). The use of Kalman filters requires however that the statistical characteristics of measurement disturbances ($\tilde{\mathbf{u}}(t), \tilde{\mathbf{y}}(t)$) are known. Generally it can be assumed that $\tilde{\mathbf{u}}(t)$ and $\tilde{\mathbf{y}}(t)$ are white, zero-mean, uncorrelated Gaussian noises. Under these hypotheses two different Kalman filter configurations were designed for isolating faults in output and input sensors (Simani and Spina, 1998). The basic schemes used for output and input sensor fault detection and isolation are equal to that of Figure 3 and 4, respectively, where, in the former, the observers were substituted with classical Kalman filters (Kalman, 1960), while in the latter the UIO were substituted with Kalman filters with unknown inputs (Hayar et al., 1996).

The fault signatures obtainable, in case of single faults, using the set-up sensor FDI technique which uses Kalman filters are the same as in Table 1. So, this technique also allows the unambiguous isolation of multiple faults in the output sensors and of single faults in the input sensors.

5. Comparison among the FDI techniques

The three different sensor FDI model-based approaches were compared in terms of minimal sensor faults which can be isolated. The comparisons were performed with reference to a single-shaft industrial gas turbine, with Variable Inlet Guide Vane (VIGV) angle, working in parallel with the electrical mains.

The machine lay-out is shown in Figure 5, where the output (y_i) and input (u_i) monitored sensors are highlighted. These are for the measurement of:

- pressure at the compressor inlet "p_{ic}" (y_1);
- pressure at the compressor outlet "p_{oc}" (y_2);
- pressure at the turbine outlet "p_{ot}" (y_3);
- temperature at the compressor outlet "T_{oc}" (y_4);
- temperature at the turbine outlet "T_{ot}" (y_5);
- electrical power at the generator terminals "P_e" (y_6);
- VIGV angular position "α" (u_7);
- fuel mass flow rate "M_f" (u_8).

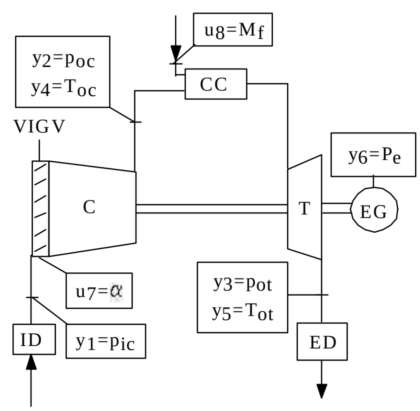

Figure 5: Lay-out of the single-shaft gas turbine

The first step was, in each case, the identification of a number of ARX MISO models equal to the number of the output variables (m = 6) (Simani and Spina, 1998; Simani et al., 1998; Bettocchi and Spina, 1999b). These six models were then used to build the incidence matrix with column-canonical structure (parity equation-based technique), or to design dynamic observers (observer-based technique), or Kalman filters (Kalman filter-based technique). The ARX models were identified (Ljung, 1987) using time series of data generated with a non-linear dynamic gas turbine model (Bettocchi et al., 1996b). The time series of data, generated with the non-linear dynamic model, simulate measurements taken on the machine with a sampling rate of 0.1 s and without measurement disturbances, such as the noise due to measurement uncertainty which is, instead, always present in real measurement systems. Measurement noises $\tilde{\mathbf{u}}(t)$ and $\tilde{\mathbf{y}}(t)$ with standard deviation reported in Table 2 were then added to the input/output time series generated with the non linear model, assuming zero-mean white Gaussian sequences.

Table 2: Measurement noise standard deviations

Measured quantities	σ_{noise} [% of ref. value]	Measured quantities	σ_{noise} [% of ref. value]
p_{ic} (gauge)	0.20	T_{ot}	0.30
p_{oc} (gauge)	0.20	P_e	0.25
p_{ot} (gauge)	0.20	α	0.50
T_{oc}	0.25	M_f	1.00

For the determination of the minimal faults which can be isolated, simulations of step faults of different amounts were performed, fixing the following fault detectability thresholds on the residuals:

$Thr_i = \mu_i \pm 3 \times \sigma_i\big|_{mean}$, i= 1,…, n_r,

where: $\mu_i = \frac{1}{N_s}\sum_{j=1}^{N_s} e_{ij}$ is the residual mean value,

and: $\sigma_i\big|_{mean} = \sqrt{\frac{1}{N_s - 1}\sum_{j=1}^{N_s}\left(e_{ij} - \mu_i\right)^2}$

is the standard deviation of the residual referred to the mean value, both evaluated in fault-free conditions.

The faults were simulated during transients, since this is the worst case for isolating a fault. In fact, the residuals in fault-free conditions due to model approximation during transients are much higher than in steady state conditions (Bettocchi et al., 1996a).

The best results obtained using the parity equation-based technique were achieved by using an incidence matrix with three zeroes per column, and by applying a digital filter to the time series of data used in the model identification phase, in the simulations and to the residuals obtained by the simulations (Bettocchi and Spina, 1999b). The obtained incidence matrix with column-canonical structure with three zeroes per column is the following:

$$
\begin{array}{c}
 \\ e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \\ e_6
\end{array}
\begin{array}{c}
\begin{array}{cccccccc} p_{ic} & p_{oc} & p_{ot} & T_{oc} & T_{ot} & P_e & \alpha & M_f \end{array} \\
\begin{pmatrix}
1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 \\
1 & 1 & 1 & 1 & 0 & 1 & 0 & 0 \\
0 & 1 & 1 & 0 & 0 & 0 & 1 & 1 \\
0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\
0 & 0 & 1 & 0 & 1 & 1 & 0 & 1
\end{pmatrix}
\end{array}
$$

Tables 3, 4 and 5 show the standard deviations and the mean values of the residuals in fault-free conditions obtained by using the parity equation-based, the observer-based and the Kalman filter-based techniques, respectively, while Tables 6, 7 and 8 show the minimal faults to be isolated for the same cases.

Figure 6 shows the values of the ratios between minimal faults to be isolated and noise standard deviations for the three set-up techniques.

The comparison between the three sensor FDI techniques shows how the best results, in terms of minimal faults which can be isolated, are obtained using the parity equations. The use of Kalman filters, however, allows the unambiguous isolation of multiple faults in output sensors. Moreover, the Kalman filter-based technique may be improved by monitoring the residual whiteness, but this involves an increase in computational costs and in technique complexity. (Simani and Spina, 1998).

The minimal sensor faults which can be isolated appreciably decrease using the three sensor FDI technique only during steady-state operation. In this case, in fact, the residuals in fault-free conditions due to model approximation are much lower than in transient conditions and, thus, it is possible to reduce the fault detectability thresholds on the residuals (Bettocchi et al., 1996a).

Table 3: Residual standard deviations and mean values in fault-free conditions (parity equations)

Model	$\sigma_i\|_{mean}$	μ_i
p_{ic}	7.636 x 10^{-6}	- 8.551 x 10^{-6}
p_{oc}	6.033 x 10^{-4}	4.084 x 10^{-5}
p_{ot}	6.946 x 10^{-6}	- 7.438 x 10^{-6}
T_{oc}	7.745 x 10^{-4}	9.860 x 10^{-4}
T_{ot}	9.217 x 10^{-4}	- 5.159 x 10^{-4}
P_e	1.699 x 10^{-3}	2.892 x 10^{-3}

Table 4: Residual standard deviations and mean values in fault-free conditions (observers)

Observer	$\sigma_i\|_{mean}$	μ_i
p_{ic}	2.41 x 10^{-2}	4.70 x 10^{-3}
p_{oc}	4.66 x 10^{-2}	3.50 x 10^{-3}
p_{ot}	2.41 x 10^{-2}	- 5.00 x 10^{-3}
T_{oc}	3.45 x 10^{-1}	- 9.45 x 10^{-4}
T_{ot}	2.16 x 10^{-1}	1.30 x 10^{-3}
P_e	2.67 x 10^{-2}	3.60 x 10^{-3}
α	3.47 x 10^{-1}	- 9.80 x 10^{-4}
M_f	3.59 x 10^{-2}	4.00 x 10^{-3}

Table 5: Residual standard deviations and mean values in fault-free conditions (Kalman filters)

Kalman filter	$\sigma_i\|_{mean}$	μ_i
p_{ic}	6.51 x 10^{-1}	3.40 x 10^{-3}
p_{oc}	1.98 x 10^{-1}	2.48 x 10^{-2}
p_{ot}	6.37 x 10^{-1}	- 8.20 x 10^{-3}
T_{oc}	6.63 x 10^{-1}	- 5.69 x 10^{-4}
T_{ot}	4.93 x 10^{-1}	1.85 x 10^{-2}
P_e	6.62 x 10^{-2}	1.25 x 10^{-2}
α	6.64 x 10^{-1}	- 6.80 x 10^{-4}
M_f	6.23 x 10^{-2}	1.26 x 10^{-2}

Table 6: Minimal faults to be isolated (parity equations)

Measured quantities	Minimal faults to be isolated [% of ref. value]	Measured quantities	Minimal faults to be isolated [% of ref. value]
p_{ic} (gauge)	2	T_{ot}	3
p_{oc} (gauge)	1.1	P_e	1.5
p_{ot} (gauge)	2.5	α	3
T_{oc}	1.5	M_f	8

Table 7: Minimal faults to be isolated (observers)

Measured quantities	Minimal faults to be isolated [% of ref. value]	Measured quantities	Minimal faults to be isolated [% of ref. value]
p_{ic} (gauge)	8	T_{ot}	20
p_{oc} (gauge)	6	P_e	2
p_{ot} (gauge)	8	α	15
T_{oc}	17	M_f	2

Table 8: Minimal faults to be isolated (Kalman filters)

Measured quantities	Minimal faults to be isolated [% of ref. value]	Measured quantities	Minimal faults to be isolated [% of ref. value]
p_{ic} (gauge)	5.5	T_{ot}	3.5
p_{oc} (gauge)	1.3	P_e	0.8
p_{ot} (gauge)	5	α	3
T_{oc}	3.5	M_f	0.7

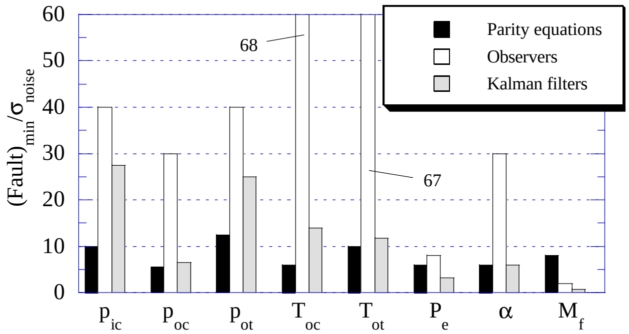

Figure 6: Ratios between minimal faults to be isolated and noise standard deviations for the three set-up sensor FDI techniques

6. Conclusions

The problems which arise by using gas turbine Health Monitoring Systems have been analyzed in this paper. They concern inaccuracy in the gas turbine operating state determination due to the measurement errors and the *a priori* selection of the characteristic parameters that have to be investigated.

The method proposed for improving the reliability in gas turbine health determination involves:

- an initial analysis to evaluate the best measurements/ parameters combination, in terms of accuracy in gas turbine health determination;
- the submission of measurements to sensor FDI analyses, before they are used as input by the Health Monitoring System. In this manner it is possible to verify whether there are measurements affected by errors due to faulty sensors.

Three FDI techniques were developed and compared. They use for the residual generation parity equations, dynamic observers or Kalman filters, respectively.

The comparison between the three techniques shows how the best results, in terms of minimal faults which can be isolated, are obtained using the parity equations. The use of Kalman filters, however, allows the unambiguous isolation of multiple faults in output sensors. Moreover, the Kalman filter-based technique may be improved by exploiting special testing methods of residuals, but this involves an increase in computational costs and in technique complexity.

Finally, the minimal sensor faults which can be isolated appreciably decrease using the three sensor FDI technique only during steady-state operation. In this case, in fact, the residuals in fault-free conditions due to model approximation are much lower than in transient conditions, allowing the reduction of the fault detectability thresholds on the residuals.

References

Bettocchi, R., Spina, P. R., 1999a, "Diagnosis of Gas Turbine Operating Conditions by Means of the Inverse Cycle Calculation", ASME Paper 99-GT-185.

Bettocchi, R., Spina, P. R., 1999b, "A Method for the Diagnosis of Gas Turbine Sensor Faults in Presence of Measurement Noise", ASME Paper 99-GT-303.

Bettocchi, R., Spina, P.R., Azzoni, P.M., 1996a, "Fault Detection for Gas Turbine Sensors Using I/O Dynamic Linear Models - Methodology of Fault Code Generation", ASME Paper 96-TA-002.

Bettocchi, R., Spina, P.R., Bedeschi, A., 1998, "Incidence Matrix with Canonical Structure in Gas Turbine Sensor Fault Diagnosis", *Proceedings, 6th IEEE Mediterranean Conference on Control and Automation,* Alghero, Italy.

Bettocchi, R., Spina, P. R., Benvenuti, E., 2000, "Set-Up of an Adaptive Method for the Diagnosis of Gas Turbine Operating State by Using Test-Bench Measurements", ASME Paper 2000-GT-0309.

Bettocchi, R., Spina, P. R., Fabbri, F., 1996b, "Dynamic Modeling of Single-Shaft Industrial Gas Turbine", ASME Paper 96-GT-332.

Gertler, J., 1988, "Survey of model-based failure detection and isolation in complex plants", *IEEE Control Systems Magazine*, December, 3-11.

Gertler, J., Singer, D., 1990, "A New Structural Framework for Parity Equation-Based Failure Detection and Isolation", *Automatica*, Vol. 26, No. 2, pp. 381-388.

Hayar, M., Zasadzinsky, M., Darouach, M., 1996, "Robust Kalman Filtering for Uncertain System Subject to Unknown Inputs: The Discrete-Time Case", *Proceedings, 13th IFAC World Congress*, San Francisco, CA, USA, pp. 55-58.

Kalman, R. E., 1960, "A New Approach to Linear Filtering and Prediction Problems", *Transaction of the ASME - Journal of basic engineering*, pp. 35-45.

Ljung, L., 1987, "System Identification: Theory for the User", Prentice-Hall International, Englewood Cliffs, N.J., U.S.A..

Luenberger, D. G., 1971, "An Introduction to Observers", *IEEE Transaction AC*, AC-16, pp. 596-602.

Patton, R.J., Frank, P., Clark, R., 1989, "Fault diagnosis in dynamic systems. Prentice-Hall International, U.K..

Pinelli, M., Spina, P. R., 2000a, "Gas Turbine Field Performance Determination: Sources of Uncertainties", ASME Paper 2000-GT-0311.

Pinelli, M., Spina, P. R., 2000b, "Influence of Different Sets of Measurements on Gas Turbine Field Performance Determination", *Proceedings, International Mechanical Engineering Congress and Exposition of ASME*, Orlando, FL, USA, 5 - 10 Novembre.

Simani, S., Spina, P. R., 1998, "Kalman Filtering to Enhance the Gas Turbine Control Sensor Fault Detection", *Proceedings, 6th IEEE Mediterranean Conference on Control and Automation,* Alghero, Italy.

Simani, S., Spina, P. R., Beghelli, S., Bettocchi, R., Fantuzzi, C., 1998, "Fault Detection and Isolation Based on Dynamic Observers Applied to Gas Turbine Control Sensors", ASME Paper 98-GT-158.

Stamatis, A., Mathioudakis, K., Papailiou, K.D., 1990, "Adaptive Simulation of Gas Turbine Performance", ASME *Journal of Engineering for Gas Turbines and Power,* Vol. 112, pp. 168-175.

Stamatis, A., Mathioudakis, K., Papailiou, K., 1992, "Optimal Measurement and Health Index selection for Gas Turbine Performance Status and Fault Diagnosis", ASME *Journal of Engineering for Gas Turbines and Power,* Vol. 114, pp. 209-216.

Urban, L. A., 1972, "Gas Path Analysis Applied to Turbine Engine Condition Monitoring", *Proceedings, AIAA/SAE 8th Joint Propulsion Conference,* New Orleans, USA.

Willsky, A.S., 1976, "A survey of design methods for failure detection in dynamic systems", *Automatica*, 12, pp. 601-611.

Acknowledgments

The work was carried out with the support of the M.U.R.S.T. (Italian Ministry of University and Scientific & Technological Research).