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A METHOD FOR THE DIAGNOSIS OF GAS TURBINE SENSOR FAULTS IN PRESENCE OF MEASUREMENT NOISE

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ABSTRACT

This paper presents a method for the detection and isolation of single gas turbine sensor faults, in presence of model inaccuracy and measurement noise.

The method uses a fault matrix with a column-canonical structure (i.e., each matrix column having the same number of zeroes, but in different positions), in order to obtain the unambiguous fault isolation.

The fault matrix was obtained by using a number of ARX (Auto Regressive eXogenous) MISO (Multi-Input/Single-Output) models equal to the number of measured gas turbine outputs, each model calculating an estimate of one measurable output as a function of other inputs or outputs measured on the machine.

Moreover, in order to reduce the threshold of fault detection and, therefore, the minimal detectable faults, digital filters were used, applied to the time series of data measured on the machine and computed by the models.

Finally, tests were performed in order to find the minimal sensor faults that can be detected and isolated.

NOMENCLATURE

e	$= [e_1,..., e_n]^T$	residual vector
e_i	$= (y^*_{meas} - y^*_{comp})_i$	
F	matrix of transfer function of the system	
M	mass flow rate	
m	number of measured quantities	
N_s	number of samples	
n	number of models	
n_r	number of matrix rows	
n_z	number of zeroes per column	
P	power	
p	pressure	
std	standard deviation	
T	total temperature	
Thr	threshold	
t	time	
u	$= [u_{n+1},..., u_m]^T$	system input vector
x	$= [\mathbf{u}^*, \mathbf{y}^*]^T$	input-output combined vector
y	$= [y_1,..., y_n]^T$	system output vector
z	z-transform variable	
α	Variable Inlet Guide Vane (VIGV) angle	
μ	mean value	
τ	sampling rate	

Superscripts and Subscripts

*	normalized value with respect to reference value
a	ambient
c	compressor
comp	computed value
e	electric
F	filtered quantity
f	fuel
i	input, inlet section
mean	mean value
meas	measured value
min	minimum
o	output, output section
t	turbine

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INTRODUCTION

In order to maximize the availability and therefore the overall benefit of a gas turbine plant it is possible to substitute the on-condition maintenance for the scheduled maintenance. This substitution requires the updated knowledge of the gas turbine operating state and the determination of the causes of performance degradation with respect to the expected ones.

The determination of the machine operating state requires the use of reliable measurements. Moreover, as gas turbine plants are more and more complex and depend on instrumentation (sensors), the occurrence of sensor failures is more frequent. Therefore, for fail-safe operating conditions, it is necessary to diagnose sensor faults.

The use of model-based techniques for sensor fault diagnosis in presence of both model inaccuracy and measurement noise leads to the search for a compromise between the number of false alarms and undetected faults (Patton et al., 1989). A method to reduce the number of false alarms may be the use of high threshold values of fault detection. This causes, however, a fault insensitivity which, in turn, may lead to a high number of undetected faults or, in the worst case, to incorrect fault alarms. They occur when, for a small fault, the resulting fault signature is different from the correct one, but it is equal to the signature of another fault. In literature this phenomenon is called "fault signature degradation" (Gertler, 1988; Gertler and Singer, 1990). In order to avoid incorrect fault alarms diagnostic techniques have been developed, which allow unambiguous fault detection and isolation in presence of model inaccuracy and measurement noise (Isermann, 1997; Patton, and Chen, 1997).

This paper presents a parity equation-based diagnostic technique, which uses a fault matrix with a column-canonical structure (i.e., each matrix column having the same number of zeroes, but in different positions) in order to obtain the unambiguous isolation of single gas turbine sensor faults in presence of model inaccuracy and measurement noise (Bettocchi et al., 1998; Gertler, 1988; Gertler and Singer, 1990). Moreover, in order to reduce the thresholds of fault detection and, therefore, the minimal detectable faults, it is advisable to use digital filters applied to the time series of data measured on the machine and computed by the models.

With respect to previous Author's papers (Bettochi et al., 1996b; Bettocchi and Spina, 1997) the technique presented in this work is more reliable towards false alarms due to fault signature degradation in presence of model inaccuracy and measurement noise.

SENSOR FAULT DIAGNOSIS METHOD

In the model-based diagnostic techniques, the fault detection and isolation is performed by analyzing the residuals obtained from the comparison between values measured on the machine and values estimated by models of the same quantities.

The residual calculation was performed in this paper using the parity equations (Bettocchi and Spina, 1997), whose expression is shown in Appendix. These equations link the residuals to the measured values on the machine by means of a model coefficient matrix.

A number of ARX (Auto Regressive eXogenous) MISO (Multi-Input/Single-Output) models equal to the number of machine measured outputs was used, each model allowing the estimation of the value of a measurable output starting from other selected inputs or outputs measured on the machine.

The matrix obtained from the model coefficient matrix by substituting the coefficients with values 0 or 1 on the basis of whether they are zero or not is called "incidence" or "fault" matrix. Each fault matrix column represents the fault signature of the corresponding sensor, and so the condition for obtaining the zero-threshold fault isolation in the case of single faults is that the fault matrix columns are linearly independent.

Fault isolation in presence of model inaccuracy and measurement noise

The presence of model inaccuracy and measurement noise requires that thresholds on the residuals must be fixed in order to minimize the occurrence of false alarms. In this case, when a fault occurs, the fault signature is obtained by substituting the residuals with values 0 or 1 on the basis of whether they are lower or higher than fixed thresholds.

For small amount faults, one or more residuals may remain under the threshold: this causes the fault signature degradation phenomenon (Gertler, 1988; Gertler and Singer, 1990).

If the degraded fault signature is equal to another fault signature (i.e., to one of the fault matrix columns), an incorrect fault alarm occurs.

So, the condition for obtaining an unambiguous isolation of single faults also in presence of model inaccuracy and measurement noise (high-threshold fault isolation) is that no fault matrix column can be obtained from another one by means of a degradation (i.e., that 1 turns into 0).

This fault matrix characteristic can be obtained by selecting the inputs to each model in order to build a fault matrix with column-canonical structure, i.e., in which each matrix column has the same number of zeroes, but in different positions (Bettocchi et al., 1998; Gertler, 1988; Gertler and Singer, 1990).

This type of matrix structure allows the determination of a fault signature degradation avoiding an incorrect fault alarm. Indeed, if the number of zeroes in the actual fault signature is higher than the number of zeroes common to all the fault matrix columns, it highlights that a fault signature degradation occurred. A small amount fault is therefore detected, whereas the fault isolation is possible only when the fault amount is higher than the one generating the fault signature degradation. So, an analysis should be performed on the minimal faults which can be isolated.

In order to build a fault matrix with column-canonical structure it was decided to use models of the system having the inputs ordered based on their influence on the model output accuracy (Bettocchi et al., 1998). Once the models with ordered inputs were built, the inputs are eliminated starting from the less influential one, until a fault matrix with column-canonical structure is obtained.

The elimination of the less influential inputs from the models consequently increases the residual sensibility to the faults.

In order to take into account the gas turbine ageing the models can be periodically identified in automatic way, maintaining the same set of model inputs. In this manner the model orders and the model parameters change, while the structure of the models remains the same.

MINIMAL SENSOR FAULT TO BE ISOLATED FOR A GAS TURBINE APPLICATION

The diagnosis method which make use of a fault matrix with column-canonical structure was applied to the sensors of a single-shaft industrial gas turbine, with Variable Inlet Guide Vane (VIGV) angle, working in parallel with electrical mains.

The input (u_i) and output (y_i) monitored sensors on the machine are for the measurement of:

- VIGV angular position "α" (u_1);
- fuel mass flow rate "M_f" (u_2);
- 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);

The gas turbine rotational speed measurement sensor was not considered since the operation of the machine in parallel with electrical mains ensures a constant rotational speed.

The measurements of ambient temperature and relative humidity were also not considered, since they are not directly used by the gas turbine control system. The ambient temperature in particular is taken into account by the machine control system by means of the measurement of compressor outlet pressure.

A number of ARX MISO models equal to the number of machine measured outputs was built, each model calculating the value of a measurable output starting from all the inputs and outputs measured on the machine. The models have the inputs ordered based on their influence on the model output accuracy, as shown below, where the inputs of each model are arranged in decreasing order of influence:

1) $p_{ic} = f_1(\alpha, M_f, p_{oc}, T_{ot}, p_{ot}, T_{oc}, P_e)$

2) $p_{oc} = f_2(p_{ot}, M_f, P_e, p_{ic}, \alpha, T_{oc}, T_{ot})$

3) $p_{ot} = f_3(p_{oc}, M_f, p_{ic}, P_e, \alpha, T_{oc}, T_{ot})$

4) $T_{oc} = f_4(p_{ot}, M_f, p_{oc}, \alpha, T_{ot}, p_{ic}, P_e)$

5) $T_{ot} = f_5(M_f, \alpha, P_e, p_{ic}, T_{oc}, p_{oc}, p_{ot})$

6) $P_e = f_6(M_f, p_{oc}, T_{ot}, p_{ot}, \alpha, T_{oc}, p_{ic})$

The six models were identified (i.e., the model orders and the model parameters were determined) (Ljung, 1987, 1988; Norton, 1986; Söderström and Stoica, 1987; Van den Bosch and Van den Klauw, 1994) using time series of data generated with a non-linear dynamic gas turbine model. It was previously developed and validated by means of measurements taken during transients on a gas turbine in operation, and presents an accuracy better than 1 % for all the measured quantities, in the range of ambient temperature 0-40 °C and load conditions 70-100 % (Bettocchi et al., 1996a).

The time series of data, generated with the non-linear dynamic model, simulate measurements taken on the machine with a sampling rate τ = 0.1 s and without noise due to measurement uncertainty which is, instead, always present in the real measurement systems.

Measurement noises, with standard deviations reported in Table 1, were therefore added to the input and output time series generated with the non linear model. The measurement noises were assumed to be zero-mean white Gaussian processes and were generated by "randn" function in MATLAB environment (MathWorks, 1990).

Tab. 1: Noise standard deviations in percent of the reference value and reference values.

Measured quantities	Noise standard deviations [% of reference value]	Reference values	
p_{ic} (gauge)	0.4	- 0.5	[kPa]
p_{oc} (gauge)	0.4	769.7	[kPa]
p_{ot} (gauge)	0.4	0.9	[kPa]
T_{oc}	0.5	598	[K]
T_{ot}	0.6	811	[K]
P_e	0.5	4473	[kW]
α	1.0	90	[°]
M_f	2.0	0.3636	[kg/s]

The model coefficient matrix related to models 1 to 6 has a dimension 6x8 and, therefore, the corresponding fault matrix with column-canonical structure requires a minimum of two zeroes per column. Indeed the number of matrix rows (n_r), the number of zeroes per column (n_z) and the number of measured quantities ("m", which is equal to the number of matrix columns) must satisfy the following inequality (Gertler and Singer, 1990):

$$\binom{n_r}{n_z} = \frac{n_r!/(n_r - n_z)!}{n_z!} \geq m$$

In the following the obtained fault matrix with canonical structure is shown. This was built by eliminating the model inputs starting from the less influential ones, but with the condition for obtaining two zeroes per column in different positions. The initial matrix, from which the process elimination starts, is the 6x8 fault matrix related to models 1 to 6 in which all the elements are equal to 1.

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

Once the inputs to the six models were determined, the models were identified again in order to build the most accurate structures.

In order to determine the minimal faults to be isolated, simulations of step faults of different amounts were performed, fixing fault detectability thresholds for each model as follows:

$Thr_i = \mu_i \pm 3 \times std_i|_{mean}$, $i = 1,...,6$, where:

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

$std_i|_{mean} = \sqrt{\frac{1}{N_s - 1}\sum_{j=1}^{N_s}(e_{ij} - \mu_i)^2}$ is the standard deviation of the residual referred to the mean value.

The faults were simulated during transients different from the ones relative to the time series of data used in the model identification phase, since this is the worse case to isolate a fault. In particular the residuals in fault-free conditions due to ARX model approximation during transients are higher than the ones in steady state conditions (Bettocchi et al., 1996b).

Table 2 shows, for each model, the residual standard deviation referred to mean value and the residual mean value in a fault-free condition, which are due both to ARX model approximation and noise.

Table 3 shows the minimal faults, as percent of the reference value, which can be detected, without fault signature degradations, using a column-canonical matrix with two zeroes per column. They are very large and cannot be accepted. It is therefore necessary to adopt methods to reduce the minimal faults to be isolated.

Tab. 2: Standard deviations of residuals referring to mean value and residual mean values in fault-free conditions.

Model	$std_i\|_{mean}$	μ_i
p_{ic}	1.227×10^{-5}	6.620×10^{-6}
p_{oc}	1.825×10^{-3}	-4.904×10^{-5}
p_{ot}	1.855×10^{-5}	2.863×10^{-6}
T_{oc}	2.541×10^{-3}	3.858×10^{-4}
T_{ot}	3.162×10^{-3}	2.898×10^{-4}
P_e	3.127×10^{-3}	-7.152×10^{-4}

Tab. 3: Minimal faults to be isolated [% of reference value] with a column canonical matrix with two zeroes per column.

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}	18
p_{oc} (gauge)	1.4	P_e	7
p_{ot} (gauge)	5.7	α	90
T_{oc}	20	M_f	22

REDUCTION OF THE MINIMAL SENSOR FAULT TO BE ISOLATED

In order to reduce the minimal sensor faults which can be isolated two different actions can be taken.

The first is the reduction of the fault detectability thresholds, while the second is the increase of residual sensitivities with respect to faults.

In order to reduce the fault detectability thresholds, the residuals in fault-free conditions due both to ARX model approximation and noise should be reduced. This was done by filtering:

- the time series of data used in the model identification phase,
- the time series of data used for the simulations,
- the residuals obtained by the simulations.

The filter used is a first order digital filter, whose expression is the following (Gertler, 1988):

$x_{Fi}(t) = p\, x_{Fi}(t-\tau) + (1-p)x_i(t)$,

where "p" is a parameter characterizing the filter, and i=1,...,6, in the case of residual filtering, and i=1,...,8 when the input time series of data are filtered.

Increasing the "p" value from zero to one the residual standard deviations decreases, but the fault detection promptness also decreases. The "p" value was fixed at 0.8, since this value allows the obtainment of a good compromise between reduction of residual standard deviation and detection promptness.

Tables 4 and 5 show the residual standard deviation referring to mean value and the residual mean value in fault-free conditions which were obtained in the following two cases respectively:

1) by filtering only the residuals obtained by the simulations (Table 4);
2) by filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations (Table 5).

Tab. 4: Standard deviations of residuals referring to mean value and residual mean values in fault-free conditions (case of residual filtering).

Model	$std_i\|_{mean}$	μ_i
p_{ic}	9.229×10^{-6}	-1.650×10^{-5}
p_{oc}	6.372×10^{-4}	5.471×10^{-4}
p_{ot}	7.248×10^{-6}	-2.089×10^{-5}
T_{oc}	8.936×10^{-4}	2.792×10^{-3}
T_{ot}	1.105×10^{-3}	-2.984×10^{-4}
P_e	1.961×10^{-3}	2.670×10^{-3}

Tab. 5: Standard deviations of residuals referring to mean value and residual mean values in fault-free conditions (case of filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations).

Model	$std_i\|_{mean}$	μ_i
p_{ic}	5.648×10^{-6}	-3.484×10^{-6}
p_{oc}	4.953×10^{-4}	2.727×10^{-4}
p_{ot}	4.994×10^{-6}	3.455×10^{-8}
T_{oc}	6.628×10^{-4}	3.549×10^{-4}
T_{ot}	7.622×10^{-4}	1.448×10^{-4}
P_e	1.471×10^{-3}	-6.644×10^{-4}

Note how the residual standard deviations in Tab. 5 are lower than residual standard deviations in Tab. 4, and how these last values are lower, in turn, than residual standard deviations in Tab. 2. This highlights how the use of filters permits the reduction of fault detectability thresholds.

In the second case, in which the time series of data used in the model identification phase were also filtered, a new series of models was obtained, whose fault matrix with column-canonical structure is the following:

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

Table 6 shows the values of the minimal faults to be isolated, which were obtained using the filters.

Tab. 6: Minimal faults to be isolated [% of reference value] with a column canonical matrix with two zeroes per column and by filtering:
1) the residuals obtained by the simulations
2) the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations.

Measured quantities	1 [% of reference value]	2 [% of reference value]
p_{ic} (gauge)	4	1.5
p_{oc} (gauge)	1.1	2.3
p_{ot} (gauge)	2.5	2
T_{oc}	10	2
T_{ot}	6	3
P_e	3	1.5
α	30	9
M_f	9	9

A further reduction in the minimal faults to be isolated can be obtained by using a series of models characterized by a fault matrix with column-canonical structure with three zeroes per column. The models were identified starting from the filtered time series of data with the procedure of the previous paragraph. The elimination of the less influential model inputs to obtain a column-canonical matrix with three zeroes per column leads to residuals having a higher sensitivity with respect to faults than in the case of a fault matrix with two zeroes per column. The obtained fault matrix with column-canonical structure with three zeroes per column is the following:

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

Table 7 shows the minimal faults to be isolated by using the column-canonical matrix with three zeroes per column and by filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations.

The comparison between the minimal faults to be isolated (Tab. 7) and the standard deviation of the relative measurement noise (Tab. 1) highlights how, in this case, it results: $(\text{fault})_{min} < 6.3\ (\text{std})_{noise}$. These values may be acceptable in many industrial applications, which actually are without any sensor control devices.

Tab. 7: Minimal faults to be isolated [% of reference value] with a column canonical matrix with three zeroes per column and by filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations.

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

Figure 1 shows the values of the ratios between minimal faults to be isolated and noise standard deviations (Tab. 1) for the four cases analyzed:

1) column canonical matrix with two zeroes per column without the use of filters (Tab. 3);
2) column canonical matrix with two zeroes per column and filtering the residuals obtained by the simulations (Tab. 6 – column 1);
3) column canonical matrix with two zeroes per column and filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations (Tab. 6 – column 2);
4) column canonical matrix with three zeroes per column and filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations (Tab. 7)

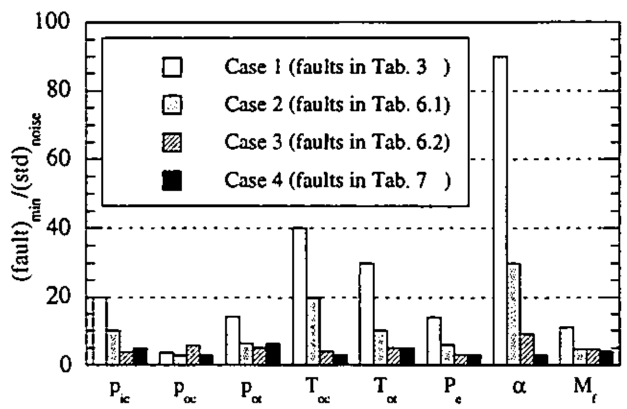

Fig. 1: Ratios between minimal faults to be isolated and noise standard deviations (Tab. 1) for the four cases analyzed.

The technique, even if, in the best case, allows the isolation of minimal faults which are from three to six times the standard deviation of the measurement noise, presents a good reliability towards false alarms due to fault signature degradation.

Further reductions in the minimal faults to be isolated may be obtained by using series of models characterized by a fault matrix with column-canonical structure with more than three zeroes per column. However, if the number of zeroes per column of the fault matrix increases, the number of inputs to each model decreases, increasing the residual sensitivity with respect to fault, but also increasing the residual standard deviations due to model approximation and so the fault detectability thresholds to be fixed. This leads to the search for a compromise between the increase in the residual sensitivity with respect to fault and the increase in the residual standard deviation. The best compromise is that in which faults to be isolated are minimum.

Table 8 shows the residual standard deviation referring to mean value and the residual mean value in fault-free conditions which were obtained with the column canonical matrix with three zeroes per column and by filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations. The values of residual standard deviations in Tab. 8 are slightly higher than the ones in Tab. 5, since, as mentioned above, if the number of zeroes per column of the fault matrix increases, the residual standard deviations also increase.

Tab. 8: Standard deviations of residuals referring to mean value and residual mean values in fault-free conditions (case of a column canonical matrix with three zeroes per column and of filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations).

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

Another method to reduce the minimal faults to be isolated may be the use of statistical tests on the residual whiteness, instead of comparing the residual amounts with fixed thresholds (geometrical analysis of residuals) (Simani and Spina, 1998).

CONCLUSIONS

The analysis performed in the paper shows how the use of a parity equation-based diagnostic technique, utilizing a fault matrix with a column-canonical structure, allows the unambiguous isolation of single gas turbine sensor faults, in presence of model inaccuracy and measurement noise.

Values of the minimal faults to be isolated acceptable for industrial applications can however be obtained only by using fault matrices with more than two zeroes per column and by filtering the time series of data used in the model identification phase, in the simulations and the residuals obtained by the simulations.

Improvements may be obtained by increasing the number of zeroes per column of the fault matrix and by using statistical tests on the residual whiteness instead of geometrical analysis of residuals.

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APPENDIX

Residual calculations

In order to estimate a machine measurable output "$(y_{comp})_i$" starting from other inputs or outputs measured on the machine a MISO model can be used.

The general form of a MISO linear model in z-domain is the following:

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

$i=1,\ldots,n$

The residual between measured and computed value of the same variable is the difference between the measured value and the value estimated by the MISO model, which uses the other inputs or outputs measured on the machine as inputs:

$$e_i = (y^*_{meas} - y^*_{comp})_i$$

The equations which express these differences and, so, which allow the residual calculation are called "parity equations". Their expression in z-domain is the following (Bettocchi and Spina, 1997):

$$e(z) = F(z)\, x(z)\,,$$

where:

$e(z) = [e_1, \ldots, e_n]^T$ is the residual vector,

$x(z) = [y^*_1, \ldots, y^*_n, u^*_{n+1}, \ldots, u^*_m]^T$

is the input-output combined vector,

$$F(z) = \begin{bmatrix} 1 & \ldots & -f_{1n} & -f_{1\,n+1} & \ldots & -f_{1m} \\ \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\ -f_{n1} & \ldots & 1 & -f_{n\,n+1} & \ldots & -f_{nm} \end{bmatrix}$$

is the transfer function of the system (the diagonal terms "$-f_{ii}$" are equal to 1).

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 zero or not.

The fault isolation is performed by comparing the fault signature with the columns of "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. So the condition for obtaining the zero-threshold fault isolation in the case of single faults is that the fault matrix columns are linearly independent.