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Statistical Analyses to improve Gas Turbine Diagnostics Reliability

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ABSTRACT

Gas Path Analysis (GPA) based techniques allow the determination of machine health state by means of the calculation of health indices, such as efficiencies, characteristic flow passage areas and pressure drops along the gas path. One of the key aspects of these techniques is the accuracy of the information that can be obtained when they are applied in the field.

In this paper, in order to improve the reliability of the diagnostic process when GPA based techniques are used, a methodology is presented, which allows the identification of the best combination of measurements and health parameters that should be used for the determination of the gas turbine health indices with the minimum uncertainty. This methodology is based on the use of weighting factors derived from literature and databases of maintenance reports for different typologies of machines, in order to take into account the statistical occurrence and incidence of failures. In this way, the most significant measurements to be implemented in order to correctly diagnose the failures are identified.

NOMENCLATURE

M	mass flow rate
n	number of gas path measured variables and of X_v parameters
P	power
p	pressure
$\mathbf{Q}_m$	vector of measured variables
$\mathbf{Q}_{WP}$	vector of measured variables necessary to define the working point
RN	Reward Number
s	number of fixed parameters
t	number of working point measured variables
T	temperature
VN	variable nozzle angular position
w	weight
$\mathbf{X}$	$= (\mathbf{X}_f, \mathbf{X}_v)$ vector of non-dimensional characteristic parameters
$\mathbf{X}_f$	vector of fixed characteristic parameters
$\mathbf{X}_v$	vector of variable characteristic parameters
$\mathbf{Y}$	$= (\mathbf{X}_f, \mathbf{Q}_m, \mathbf{Q}_{WP})$
μ	$= \dfrac{M\sqrt{T}}{p}$ mass flow function

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Subscripts

c	compressor
cc	combustor
cool	cooling
f	fuel, fixed parameter
ggt	gas generator turbine
ic	compressor inlet section
oc	compressor outlet section
oggt	gas generator turbine outlet section
ot	power turbine outlet section
pt	power turbine
v	variable parameter

INTRODUCTION

The optimization of industrial gas turbine maintenance and operation, together with the increase in machine availability and the reduction of management costs, can be achieved through the knowledge of the gas turbine actual operating state (Hoeft, 1996; Schmitt and Petroff, 1996; Bettocchi et al., 2001).

Gas turbine non-scheduled stops, because of unforeseen faults, cause relevant costs related to the reduction or the interruption of the process, and to the consequent repairing actions. For this reason, in strategic applications, stand-by machines are usually required to ensure the desired level of availability. The optimization of gas turbine maintenance and operation can lead to a considerable reduction of these costs, since non-scheduled stops are minimized and additional economical investments for stand-by machines can be reduced (Bettocchi et al., 2001).

The predominant strategy for industrial gas turbine maintenance is the scheduled maintenance, which is performed according to *a priori* schedules, regardless of the effective gas turbine health state. An increase in machine availability and a reduction of costs can be achieved if the regular maintenance is supported by the on condition maintenance. The on condition maintenance is based on *ad hoc* actions, derived from the knowledge of the machine actual operating state.

One of the most widespread techniques for gas turbine health state determination is the Gas Path Analysis (GPA). A GPA based diagnostic process uses gas turbine field measurements to determine, by means of a gas turbine thermodynamic cycle model, the actual values of the parameters that are indices of the gas turbine health state, such as efficiencies, characteristic flow passage areas and pressure drops along the gas path (Stamatis et al., 1990; Bettocchi and Spina, 1999). By comparing the actual and the expected values of the parameters, it is possible to determine (i) how far the actual machine operating condition is from the expected one, (ii) which components are degraded and (iii) the causes of malfunctioning. Thus, the up-to-date knowledge of the gas turbine health state allows the in-advance planning of maintenance stops, depending on the actual gas turbine health state, on the availability of stand-by machines and on the production requirements. Furthermore, if the actual values of the health indices are known, it is possible to decide to perform on-line maintenance actions, to adapt the gas turbine control logic to the machine actual health state and, in the worst cases, to stop the machine to prevent from faults that may even compromise machine integrity.

One of the most critical problems that has to be faced when GPA techniques are applied is the reliability of the information that can be obtained, which depends on several factors (Stamatis et al., 1992; Pinelli and Spina, 2002):

1. Capability of the Cycle Program to accurately reproduce the actual gas turbine thermodynamic cycle.
2. Accuracy of field measurements. To minimize measurement error effects, it is usually advisable to support GPA techniques by means of methodologies for measurement validation (Bettocchi et al., 2001; Pinelli and Venturini, 2001). In this way, it is possible (i) to determine whether a measurement set is reliable and, if it is recognized as unreliable, (ii) to adapt the technique for the operating state determination, for example by excluding such a measurement set from the diagnostic process.
3. Limited availability of measured variables on the gas turbine, which causes problems to correctly detect the actual health state. In fact, for example, a single failure can lead to the same effects (same measurement variations) than those that can be induced by a series of concurrent failures. Furthermore, some typologies of failures, as clearance increase or combustor malfunctioning, are usually detectable with difficulty (Bettocchi and Spina, 1999). So, only a sufficient number of measured variables can help to distinguish among different culprits.
4. Some of the characteristic parameters to be estimated have to be kept constant during the calculations. In fact, since the number of the available measured variables is usually lower than the number of characteristic parameters that have to be determined, some of them have to be considered constant. This causes an estimation error on the characteristic parameters that are instead problem variables.

In this paper, a methodology, which takes into account the statistical occurrence and incidence of failures, has been developed, to identify the best measurement/parameter combination that should be used for the determination of the gas turbine health indices with the minimum uncertainty. This was done, by using factors related to the probability that a given failure may occur to weigh the possible solutions of the operating state determination problem. In this way, starting from the available measured variables, it is possible to establish the most significant measurements suitable to be performed in addition to the most common ones and the best parameters combination according to a given set of available measured variables, in order to improve the accuracy in gas turbine operating state determination. The weighting factors were determined starting from information derived from literature and databases containing maintenance reports and measurements taken on a large number of operating gas turbines.

GAS TURBINE FAULT INCIDENCE

In order to define a scheduled maintenance program, it is fundamental to know the component life and the rate of performance decrease as a function of running hours and type of installation (Hoeft, 1996; Ceschini and Carlevaro, 2002). This can be done by analyzing gas turbine historical data over a long period. The analysis is oriented to establish, on a statistical basis, the incidence and the severity of machine malfunctions and failures, in relation to typology (heavy-duty, aeroderivative, single or two shaft, etc.), installation site (land, off-shore) and operating regime (base load, alternate, stand-by).

The knowledge of failure incidence can be useful also for the development and application of on condition maintenance. In fact, as explained in the following paragraph, the use of indices related to the probability that a given failure may occur allows the uncertainty in gas turbine health state determination to be reduced.

Different sources of information about failure occurrence and typology are available.

Manuals for turbomachine maintenance provide information about component deterioration level as a function of machine running hours. For example, Table 1 (Sawyer and Hallberg, 1980) reports the results of the experience of one insurance company over a 10-year period with failures or incidents involving gas turbines. Blade failures (compressor and turbine) comprise the largest group of failures (35%). Next in the order are fires and explosions in the combustor and turbine sections. Information of the type reported in Table 1 is used by gas turbine manufacturers to schedule maintenance actions in order to prevent failures. This is usually done by substituting the most critical component at scheduled times.

Another source of information can be found in databases developed by gas turbine users, which deal with the operating stories of a given fleet of machines. Such information reports the malfunctions which took place *regardless* of the scheduled maintenance and so the percentage incidence is completely different from the one reported in Table 1. In fact, the scheduled maintenance plan is intended to minimize the failure typologies in Table 1, as outlined above.

One of these databases is the one developed by the OREDA consortium (1999). OREDA (Offshore REliability DAta) consortium groups a great number of companies involved in oil and gas treatment, which are also gas turbine users. In particular, the 1999 OREDA handbook edition reports data referring to 219 gas turbines working in off-shore sites for a total amount of 3.196.085 firing hours.

A statistical analysis was performed on the available data. The percentage incidence of the failures, which can affect the main components of a gas turbine (see Fig. 1, according to the scheme adopted in OREDA), was determined. This was done both for all the available machines (total amount of 219 gas turbines) and by dividing them into two main classes: aeroderivative (74) and heavy-duty (145).

Fig. 2 shows the failure percentage incidence for the considered gas turbines (off-shore installations): it can be observed that the most critical components are the monitoring and control system and the gas generator. Moreover, it can be noticed that failure incidence depends slightly from machine typology (aeroderivative or heavy-duty).

Table 1 Causes of gas turbine failures
(Sawyer and Hallberg, 1980)

Failure type	Percent of total
Turbine blade failures	25.5 %
Fires and explosions	16.0 %
Impact of loose parts	10.5 %
Compressor blade failures	9.5 %
Bearings, Lube failures	8.5 %
Blade tip rubs	5.5 %
Shaft failures	4.0 %
Turbine nozzle failures	3.0 %
Seals failures	3.0 %
Bearing support failures	3.0 %
Disk cracking	2.0 %
Combustor liner failure	2.0 %
Thrust-bearing wiping	1.0 %
Miscellaneous	6.5 %

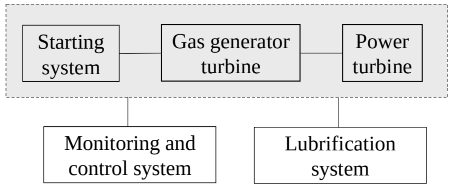

Fig. 1 Gas turbine main components (OREDA, 1999)

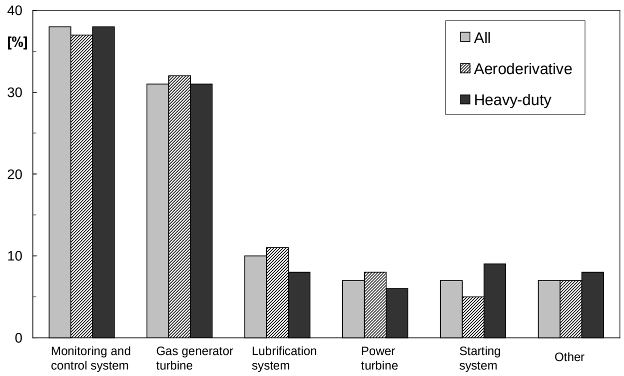

Fig. 2 Failure percentage incidence (OREDA, 1999)

Tables 2 shows in detail, for all the 219 considered gas turbines, the failure percentage incidence for the gas generator and power turbine sub-components.

From the analysis of OREDA data, gas turbine failure percentage incidence was also related to failure severity. On this basis, a failure can be classified as:

- critical, if the considered component immediately and completely loses the capability to fulfill its duty;
- performance deterioration, if component's capability to fulfill its function is altered and evolves towards a critical fault;
- incipient, when the failure, if not detected at the right time, tends to a performance deterioration or to a critical failure.

Figure 3 shows the incidence related to the three classes of failures, both for all the considered gas turbines and by distinguishing between aeroderivative and heavy-duty machines.

In order to predict gas turbine availability, two indices related to machine reliability can also be determined:

- the number of faults per machine, calculated as the ratio between the number of faults and the number of gas turbines under investigation;
- the Mean Time Between Failure (MTBF), referred to the normal operation life (i. e. excluding the burn in and wear out phases) and calculated as the ratio between the total firing hours and the number of faults.

The calculation was performed dividing the gas turbine by operating regime (base load, alternate or stand-by).

The results for the first of the two indices are shown in Fig. 4: heavy-duty gas turbines, working at base load, have the smallest number of faults per machine, while the most critical gas turbines are the aeroderivative machines with alternate operating regime.

Figure 5 reports the MTBF values for all the failure severity types, while in Figure 6 only critical faults were considered. It can be observed that MTBF values in Fig. 5 are in quite good agreement with faults per gas turbine in Fig. 4, i. e. highest reliability for heavy-duty gas turbine working at base load and high criticality for aeroderivative machines with an alternate operating regime. As regards stand-by machines, they present relatively low MTBF values since a quite high number of faults (see Fig. 4) corresponds to a low number of working hours. In Fig. 6, the highest MTBF value (i. e. higher availability) between two critical successive failures was found to be associated to heavy-duty gas turbines with an alternate operating regime. This is probably due to the fact that, for these machines, some incipient failures or degradation are removed during machine stops, before they degenerate into critical failures.

Table 2 Causes of gas generator and power turbine failures (OREDA, 1999)

Failure type	Percent of total
Gas generator turbine	
Fuel control system	10.6 %
Valves	4.3 %
Intake	3.6 %
Ducts	3.1 %
Combustor	2.4 %
Burners	1.7 %
Sensors	0.5 %
Compressor stator	0.3 %
Compressor rotor	0.2 %
HP turbine	0.1 %
Other	4.2 %
Total GGT failures	*31.0 %*
Power turbine	
Exhaust	1.7 %
Valves	1.2 %
Ducts	0.9 %
Sensors	0.7 %
Bearings and seals	0.4 %
Power turbine rotor	0.3 %
Power turbine stator	0.1 %
Other	1.7 %
Total PT failures	*7.0 %*

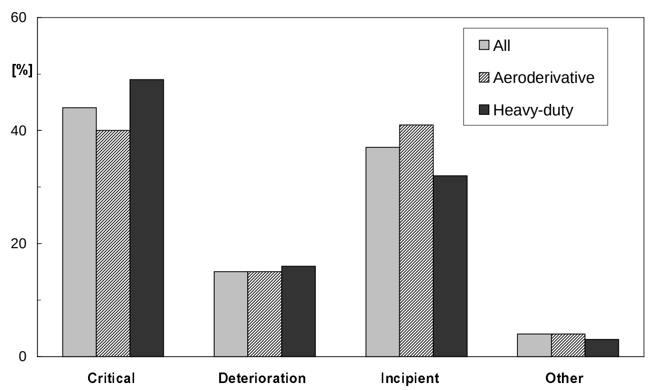

Fig. 3 Percentage incidence related to failure severity

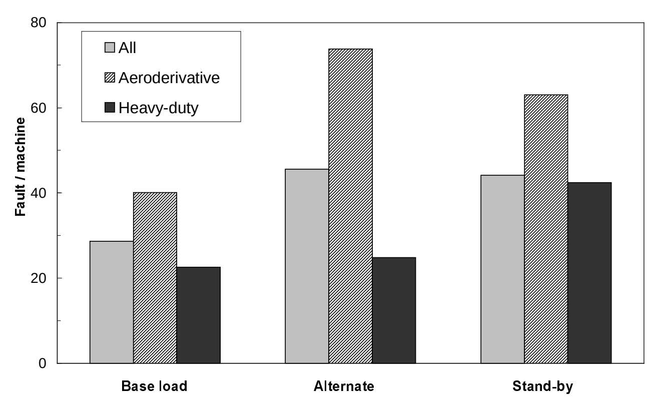

Fig. 4 Faults per gas turbine related to operating regime

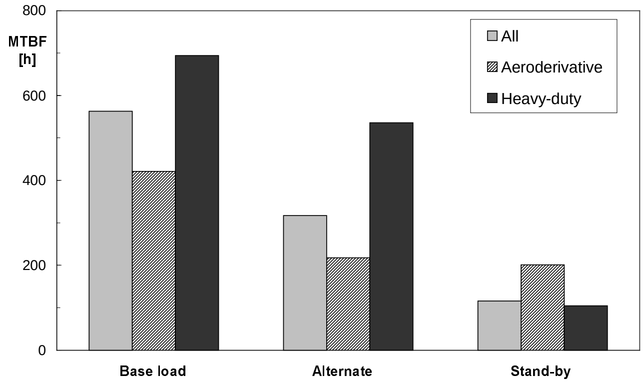

Fig. 5 Mean time between failure MTBF per gas turbine related to operating regime

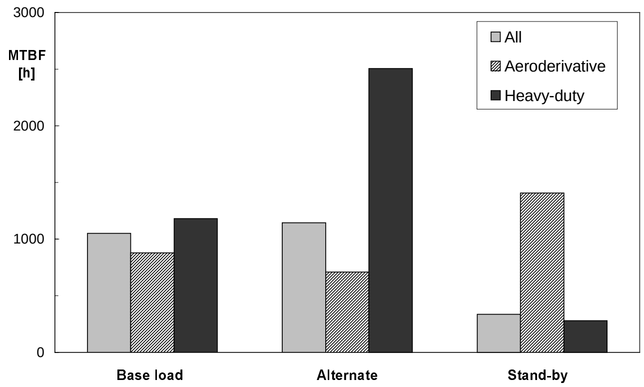

Fig. 6 Mean time between two **critical** successive failures per gas turbine related to operating regime

Table 3 Causes of gas turbine failures: ranking by forced outage (Ogaji et al., 2002)

Failure type	Percent of total
Control system	24.5 %
Fuel system	11.5 %
Compressor	2.0 %
Turbine	1.0 %
Other	60.0 %

Table 3 reports the results of a similar analysis presented by Ogaji et al. (2002). It can be observed that these results are in good accordance with the data derived from OREDA.

SELECTION OF THE BEST COMBINATION OF MEASUREMENTS AND PARAMETERS

The assessment of gas turbine operating state to perform on condition maintenance can be carried out by using Gas Path Analysis techniques. In this manner, parameters that are indices of the gas turbine health state (such as efficiencies, characteristic flow passage areas and pressure drops along the gas path) are determined by solving in inverse mode the mathematical model of the gas turbine thermodynamic cycle starting from the measurements available on the machine (Stamatis et al., 1990; Bettocchi and Spina, 1999).

In fact, the measurable variables $\mathbf{Q}_m$ are a function of the machine characteristic parameters ($\mathbf{X}$) and of the parameters that unequivocally determine the actual working point at which the gas turbine is operating ($\mathbf{Q}_{WP}$):

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

where **f** is a non-linear function that represents the mathematical model of the gas turbine. However, the number and type of gas turbine characteristic parameters that can be determined for each operating point (i.e. for each set of $\mathbf{Q}_{wp}$) depend on the number and type of the available measured variables. In particular, the number of characteristic parameters is generally equal to the number of the $\mathbf{Q}_m$ measured variables. So, since the number of the $\mathbf{Q}_m$ available measured variables is usually lower than the number of the parameters that are indices of the gas turbine health state, some of them have to be kept constant during the calculations. (Bettocchi and Spina, 1999). Therefore, the parameter vector $\mathbf{X}$ can be split into two parts, a vector of fixed parameters ($\mathbf{X}_f$) and a vector of variable parameters ($\mathbf{X}_v$). The $\mathbf{X}_v$ vector can be determined as:

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

As can be seen, the solution $\mathbf{X}_v$ of Eq. (2) is affected by variations of $\mathbf{Q}_m$ and $\mathbf{Q}_{WP}$ (due, for example, to measurement errors) and of $\mathbf{X}_f$. In fact, the parameters kept constant in the calculation, may vary in the actual machine, for instance due to the aging and deterioration of gas turbine components (Pinelli and Spina, 2002).

The relative error on each variable parameter X_{vj} of the vector $\mathbf{X}_v$ due to these variations can be expressed as (Coleman and Steele, 1989):

$$\frac{\Delta X_{vj}}{X_{vj}} = \sqrt{\sum_{i=1}^{n+t+s} \vartheta_{ij}^2 \left(\frac{\Delta Y_i}{Y_i}\right)^2} \quad , \quad j = 1,...,n \qquad (3),$$

where n is the number of the gas path measured variables and of the variable parameters, t the number of working point measured variables, s the number of the parameters kept constant and ϑ_{ij} are the sensitivity coefficients defined as $\vartheta_{ij} = (Y_i/X_{vj})(\partial X_{vj}/\partial Y_i)$.

In order to compare different measurement/parameter combinations, the authors have introduced a "Reward Number" (RN) defined as the inverse of the average-root-sum-square of the errors on all the considered variable parameters. In the calculation of RN all the relative variations $\Delta Y_i/Y_i$ were expressed in percentage and assumed equal to 1, so that RN is independent of ΔY_i amounts, and is only dependent on the considered measurement/parameter combination. Therefore, RN assumes the following expression:

$$RN = \left[\sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\frac{\Delta X_{vj}}{X_{vj}}\right)^2}\right]^{-1} = \left[\sqrt{\frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{n+t+s}\vartheta_{ij}^2}\right]^{-1} \qquad (4).$$

The measurement/parameter combination characterized by the greatest value of RN is the one for which the average-root-sum-square of the errors on all the variable parameters is minimum.

However, not all the parameters indices of the gas turbine health state have the same importance for the operating state assessment of gas turbines. In fact, as shown in the previous section, each failure presents a different probability of occurrence, and, so, the characteristic parameters associated to the most probable failures should be calculated with the highest accuracy.

To take into account this fact, a "Weighted Reward Number" (RN_w) has been introduced defined as:

$$RN_w = f_c \left[\sqrt{\frac{1}{n}\sum_{j=1}^{n} w_j^2 \sum_{i=1}^{n+t+s}\vartheta_{ij}^2}\right]^{-1}$$
$$f_c = \sum_{j=1}^{n+s} w_j \delta_j; \qquad \delta_j = \begin{cases} 0 & \text{if } X_j \notin \mathbf{X}_v \\ 1 & \text{if } X_j \in \mathbf{X}_v \end{cases} \qquad (5)$$

In the expression of RN_w:

- the weights w_j depend on the failure probability; the higher is the weight, the higher is the criticality of the corresponding characteristic parameter and, so, the higher is the desired calculation accuracy;
- the combination factor f_c is used to take into account the presence (δ_j equal to 1) or the absence (δ_j equal to 0) of each $X_{j\text{-th}}$ parameter (j= 1,…, n+s) in a given variable parameter set $\mathbf{X}_v$.

Selection of the weights. The choice of the weights is performed according to the probability that a failure may occur. The methodology for weight selection consists of four steps:

1. Statistical analysis of failure occurrence to estimate their incidence for the gas turbine under investigation, in terms of typology and percentage incidence, as done in Tables 1, 2 and 3.
2. Assignment of GPA characteristic parameters X_j to each gas turbine failure type, as shown in Table 4. Since Gas Path Analysis techniques can only detect the gas-path failures that have observable effects on the measurable variables (Ogaji et al., 2002), some of the failures reported in Tables 1, 2 and 3, may not be detected, i.e. they are not assigned to any characteristic parameter. On the contrary, since some failures may affect more than one parameter, the corresponding incidence was assigned to each parameter. The only exceptions were the case of "Blade tip rubs" reported in Table 1, for which the incidence was equally divided between compressor and gas generator mass flow functions, and the case of "Turbine" reported in Table 3, for which the incidence was equally split between the gas generator and the power turbine.
3. Calculation of total failure incidence related to each GPA characteristic parameter.
4. Calculation of the relative incidence for each characteristic parameter, by normalizing failure incidence values so that the sum makes one.

Table 5 shows the numerical results for the three analyzed situations. In Sawyer and Hallberg (1980), the sum in the first column is greater than 100 % since some failures are assigned to more than one parameter. Failure incidences reported in the third and in the fifth column of Table 5 are derived from Table 2 and 3, respectively. It is interesting to notice that the results derived from OREDA (1999) and Ogaji et al. (2002) are in good agreement each other.

Analyzed cases. The RN_w calculations performed consider seventeen possible measurement/parameter combinations, chosen among the most significant cases that can be encountered in practice for a two shaft gas turbine with variable power turbine nozzle (Pinelli and Spina, 2000; Pinelli and Venturini, 2001).

Table 4 Failure type and affected parameters

Failure type	*Affected parameter*
Sawyer and Hallberg (1980)	
Turbine blade failures	η_{ggt}, μ_{ggt}
Impact of loose parts	η_{ggt}, μ_{ggt}, η_{pt}, μ_{pt}
Compressor blade failures	η_c, μ_c
Blade tip rubs	μ_c (50 %), μ_{ggt} (50 %)
Turbine nozzle failures	η_{ggt}, μ_{ggt}
Combustor liner failure	η_{cc}
OREDA (1999)	
Compressor stator	η_c, μ_c
Compressor rotor	η_c, μ_c
Gas generator turbine	η_{ggt}, μ_{ggt}
Combustion chambers	η_{cc}
Burners/fuel nozzles	η_{cc}
Power turbine rotor	η_{pt}, μ_{pt}
Power turbine stator	η_{pt}, μ_{pt}
Ogaji et al. (2002)	
Compressor	η_c, μ_c
Gas Generator Turbine (50 % Turbine)	η_{ggt}, μ_{ggt}
Power Turbine (50 % Turbine)	η_{pt}, μ_{pt}
Fuel system	η_{cc}

These combinations are reported in detail in Table A1 in the Appendix. Table A2 in the Appendix shows the considered values for the weights used to calculate RN_w. First, a sensitivity analysis with respect to any single parameter was performed (RN_w^1 through RN_w^7). Then, the sensitivity analysis was extended to the main components: through RN_w^8, RN_w^9 and RN_w^{10}, the critical component is considered to be the compressor, the gas generator turbine and the power turbine respectively. Finally, the weights used in RN_w^{11}, RN_w^{12} and RN_w^{13} were chosen in accordance with failure occurrence estimated through the statistical analysis that was carried out above (Table 5). In particular, the weights used for RN_w^{11} calculation were derived from Sawyer and Hallberg (1980), the RN_w^{12} was referred to OREDA (1999) data and the RN_w^{13} was obtained from Ogaji et al. (2002).

Table 5 Failure incidence and its relative frequency related to the characteristic parameters

	Sawyer and Hallberg (1980)		**OREDA (1999)**		**Ogaji et al. (2002)**	
Characteristic parameter	*Failure incidence [% of total failures]*	*Failure relative frequency*	*Failure incidence [% of total failures]*	*Failure relative frequency*	*Failure incidence [% of total failures]*	*Failure relative frequency*
η_c	9.5	0.08	0.5	0.08	2.0	0.11
μ_c	12.3	0.10	0.5	0.08	2.0	0.11
η_{ggt}	39.0	0.31	0.1	0.02	0.5	0.03
μ_{ggt}	41.8	0.33	0.1	0.02	0.5	0.03
η_{pt}	10.5	0.08	0.4	0.06	0.5	0.03
μ_{pt}	10.5	0.08	0.4	0.06	0.5	0.03
η_{cc}	2.0	0.02	4.2	0.68	11.5	0.66
Total	125.6	1.00	6.2	1.00	17.5	1.00

Results and discussions. The best measurement/parameter set should be identified for any given number and kind of available measured variable set: this is the situation that can be encountered in practice when a given instrumentation set is present on the machine and the most appropriate parameter combination has to be chosen. Furthermore, the analysis that was carried out should lead to the identification of the most significant measurements which would be useful to be performed in addition to the ones that are already available.

In Figures 7 through 11, the results of the sensitivity analysis are reported. In particular, Figures 7 through 10 allow the determination of the best measurement/parameter combination in order to calculate each single characteristic parameter with the highest accuracy. In Figure 11, a similar analysis is developed on a component-basis.

From the analysis of the figures, it can be observed that

- with four available measured variables no information can be obtained about power turbine and combustor;
- when six measured variables are available, the absence of M_f measurement (Case 15) is advisable for compressor, gas generator and power turbine analysis (see Fig. 11), though combustor efficiency η_{cc} can not be determined (see Fig. 10);
- if seven measurements are available, Case 17 is recommended for the analysis of all single parameters and components.

According to failure occurrence derived from Sawyer and Hallberg (1980), OREDA (1999) and Ogaji et al. (2002), three Weighted Reward Numbers (RN_w^{11}, RN_w^{12} and RN_w^{13}) for the three weight combinations 11, 12 and 13 were calculated. For all measurement/parameter combinations (Cases 1 through 17), the results are reported in Figure 12. It can be noticed that:

- if four measured variables are available (Cases 1 and 2), Case 2 (p_{oc}, T_{oc}, T_{ot} and VN instead of M_f) is the best independently of the considered weight combination, in agreement with Pinelli and Venturini (2001);
- if five measured variables are available (Case 3 to 6), Case 3 is the best, for all the three considered weight combinations;
- if six measured variables are available (Cases 7 to 15), the best Case is 15 for all the three considered weight combinations;
- if seven measured variables are available, Case 17 is better than Case 16. So, it seems better to have the inlet mass flow rate measurement (Case 17) instead of T_{oggt} measurement (Case 16) for all the three considered weight combinations. Anyway, it should be paid attention to the fact that M_{ic} measurement accuracy may be lower than the one for T_{oggt}.

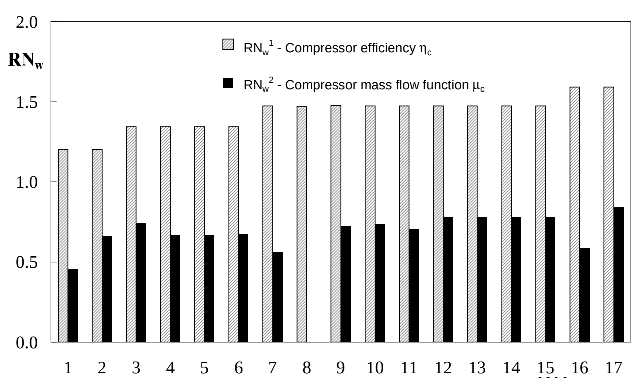

Fig. 7 "Weighted" Reward Number 1 and 2: influence of compressor characteristic parameters

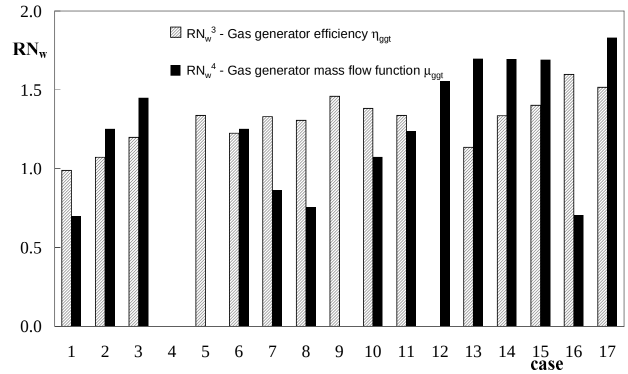

Fig. 8 "Weighted" Reward Number 3 and 4: influence of gas generator turbine characteristic parameters

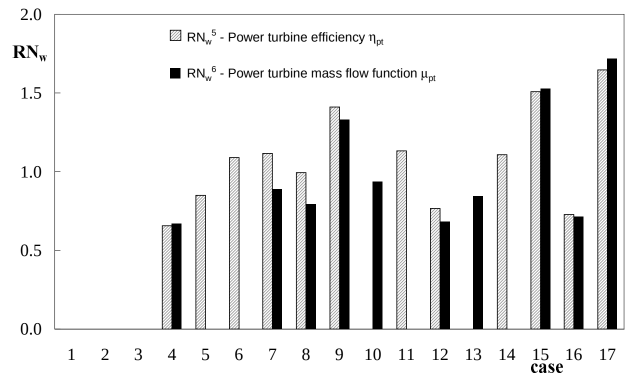

Fig. 9 "Weighted" Reward Number 5 and 6: influence of power turbine characteristic parameters

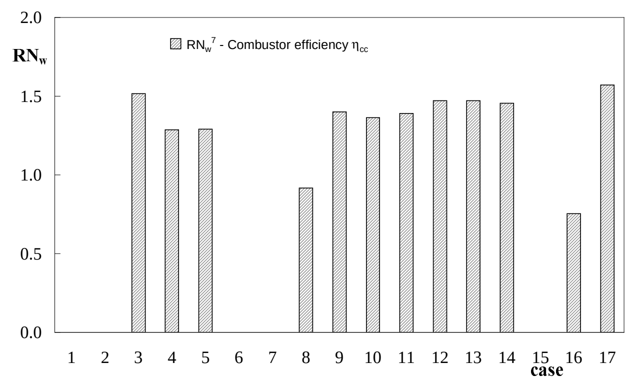

Fig. 10 "Weighted" Reward Number 7: influence of combustor efficiency

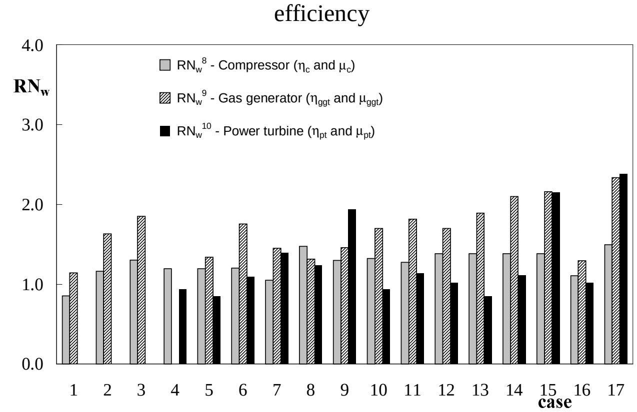

Fig. 11 "Weighted" Reward Number 8, 9 and 10: compressor (RN_w^8), gas generator turbine (RN_w^9) and power turbine (RN_w^{10}) respectively are considered the most critical components

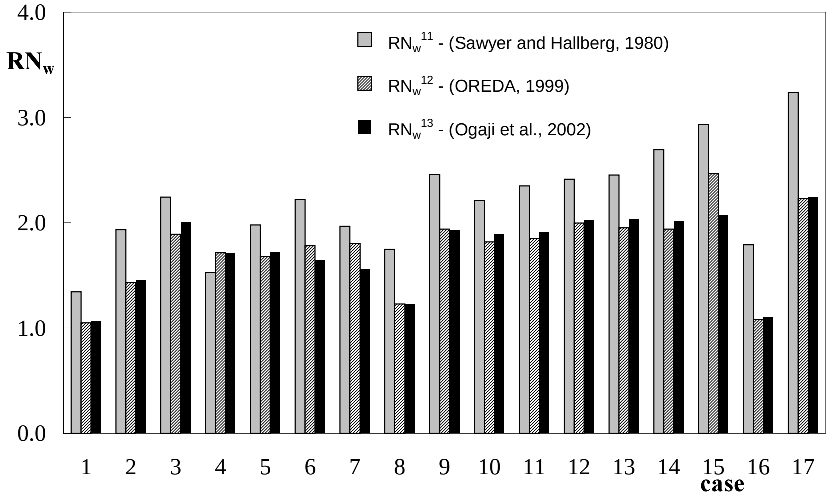

Fig. 12 "Weighted" Reward Number 11, 12 and 13: weights chosen according to failure occurrence taken from Sawyer and Hallberg (1980) (RN_w^{11}), from OREDA (1999) (RN_w^{12}) and from Ogaji et al. (2002) (RN_w^{13})

CONCLUSIONS

In this paper, a methodology to improve the reliability in gas turbine health state determination has been developed, by optimizing the choice of the best measurement/parameter combination in accordance with the incidence of failures that affect the gas turbine under investigation.

The analysis of failure incidence, performed through data which were collected from bibliography and from *ad hoc* databases, allowed the determination of factors to weigh the different possible measurement/parameter combinations.

For any given number and kind of available measured variables, the best measurement/parameter set was identified. This allows (i) the identification of the most appropriate parameter combination with respect to a given instrumentation set and (ii) the choice of the most significant measurements to perform in addition to the ones which are already available on the gas turbine.

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APPENDIX

Table A1 - Measurement/Parameter combinations

Case	Available measured variables	Variable parameters	Fixed parameter
1	p_{oc}, T_{oc}, T_{ot}, M_f	η_c, μ_c,η_{ggt}, μ_{ggt}	η_{pt}, μ_{pt}, η_{cc}, Δp_{cc}, M_{cool}
2	p_{oc}, T_{oc}, T_{ot}, VN	η_c, μ_c,η_{ggt}, μ_{ggt}	η_{pt}, μ_{pt}, η_{cc}, Δp_{cc}, M_{cool}
3	p_{oc}, T_{oc}, T_{ot}, M_f, VN	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{cc}	η_{pt}, μ_{pt}, Δp_{cc}, M_{cool}
4	p_{oc}, T_{oc}, T_{ot}, M_f, VN	η_c, μ_c, η_{pt}, μ_{pt}, η_{cc}	η_{ggt}, μ_{ggt}, Δp_{cc}, M_{cool}
5	p_{oc}, T_{oc}, T_{ot}, M_f, VN	η_c, μ_c, η_{ggt}, η_{pt}, η_{cc}	μ_{ggt}, μ_{pt}, Δp_{cc}, M_{cool}
6	p_{oc}, T_{oc}, T_{ot}, VN, p_{oggt}	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{pt}	μ_{pt}, η_{cc}, Δp_{cc}, M_{cool}
7	p_{oc}, T_{oc}, T_{ot}, M_f, VN, p_{oggt}	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{pt}, μ_{pt}	η_{cc}, Δp_{cc}, M_{cool}
8	p_{oc}, T_{oc}, T_{ot}, M_f, VN, p_{oggt}	η_c, η_{ggt}, μ_{ggt}, η_{pt}, μ_{pt}, η_{cc}	μ_c, Δp_{cc}, M_{cool}
9	p_{oc}, T_{oc}, T_{ot}, M_f, VN, p_{oggt}	η_c, μ_c, η_{ggt}, η_{pt}, μ_{pt}, η_{cc}	μ_{ggt}, Δp_{cc}, M_{cool}
10	p_{oc}, T_{oc}, T_{ot}, M_f, VN, p_{oggt}	η_c, μ_c, η_{ggt}, μ_{ggt}, μ_{pt}, η_{cc}	η_{pt}, Δp_{cc}, M_{cool}
11	p_{oc}, T_{oc}, T_{ot}, M_f, VN, p_{oggt}	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{pt}, η_{cc}	μ_{pt}, Δp_{cc}, M_{cool}
12	p_{oc}, T_{oc}, T_{ot}, M_f, VN, M_{ic}	η_c, μ_c, μ_{ggt}, η_{pt}, μ_{pt}, η_{cc}	η_{ggt}, Δp_{cc}, M_{cool}
13	p_{oc}, T_{oc}, T_{ot}, M_f, VN, M_{ic}	η_c, μ_c, η_{ggt}, μ_{ggt}, μ_{pt}, η_{cc}	η_{pt}, Δp_{cc}, M_{cool}
14	p_{oc}, T_{oc}, T_{ot}, M_f, VN, M_{ic}	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{pt}, η_{cc}	μ_{pt}, Δp_{cc}, M_{cool}
15	p_{oc}, T_{oc}, T_{ot}, VN, p_{oggt}, M_{ic}	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{pt}, μ_{pt}	η_{cc}, Δp_{cc}, M_{cool}
16	p_{oc}, T_{oc}, T_{ot}, M_f, VN, p_{oggt}, T_{oggt}	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{pt}, μ_{pt}, η_{cc}	Δp_{cc}, M_{cool}
17	p_{oc}, T_{oc}, T_{ot}, M_f, VN, p_{oggt}, M_{ic}	η_c, μ_c, η_{ggt}, μ_{ggt}, η_{pt}, μ_{pt}, η_{cc}	Δp_{cc}, M_{cool}

Table A2 - Characteristic Parameters Weights

Weight combination	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
$\mathbf{RN_w}$	$\mathbf{RN_w^1}$	$\mathbf{RN_w^2}$	$\mathbf{RN_w^3}$	$\mathbf{RN_w^4}$	$\mathbf{RN_w^5}$	$\mathbf{RN_w^6}$	$\mathbf{RN_w^7}$	$\mathbf{RN_w^8}$	$\mathbf{RN_w^9}$	$\mathbf{RN_w^{10}}$	$\mathbf{RN_w^{11}}$	$\mathbf{RN_w^{12}}$	$\mathbf{RN_w^{13}}$
w_{η_c}	1	0	0	0	0	0	0	0.5	0	0	0.08	0.08	0.11
w_{μ_c}	0	1	0	0	0	0	0	0.5	0	0	0.10	0.08	0.11
$w_{\eta_{ggt}}$	0	0	1	0	0	0	0	0	0.5	0	0.31	0.02	0.03
$w_{\mu_{ggt}}$	0	0	0	1	0	0	0	0	0.5	0	0.33	0.02	0.03
$w_{\eta_{pt}}$	0	0	0	0	1	0	0	0	0	0.5	0.08	0.06	0.03
$w_{\mu_{pt}}$	0	0	0	0	0	1	0	0	0	0.5	0.08	0.06	0.03
$w_{\eta_{cc}}$	0	0	0	0	0	0	1	0	0	0	0.02	0.68	0.66