A COMPREHENSIVE APPROACH FOR MEASUREMENT VALIDATION AND HEALTH STATE DETERMINATION OF GAS TURBINES: METHODOLOGY AND FIELD APPLICATION

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ABSTRACT

A reduction of gas turbine maintenance costs, together with the increase in machine availability and the reduction of management costs, is usually expected by supporting gas turbine Preventive Maintenance with On-Condition Maintenance, which requires up-to-date knowledge of the machine health state.

Gas turbine health state determination can be performed by means of Gas Path Analysis (GPA) techniques, which allow the calculation of machine health state indices, starting from measurements taken on the machine. Since the GPA technique makes use of field measurements, the reliability of the diagnostic process also depends on measurement reliability.

In this paper, a comprehensive approach for both measurement validation and health state determination of gas turbines is discussed, and its application to a 5 MW gas turbine working in a natural gas compression plant is presented.

1. INTRODUCTION

Maintaining high levels of availability and reliability is an essential objective for all production units, especially for those that are subject to high costs due to loss of production. Non-scheduled stops due to 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.

In the last decades, gas turbines have been more and more used either for power generation or as mechanical drive (e.g. in natural gas compression plants), thanks to their favorable characteristics with respect to other technologies, such as low emissions and high availability and reliability. In particular, the latter issues represent winning features of gas turbine based power plants. Hence, in order to utilize these systems as effectively as possible, the management of machine maintenance must be optimized.

The optimization of maintenance management, which should lead to cost saving and increase in machine availability, can be performed by supporting gas turbine Preventive Maintenance (which comes from manufacturer experience in terms of component life and performance degradation versus working hours and is performed according to *a priori* schedules, regardless of the effective gas turbine health state) with On-Condition Maintenance, which consists of “ad hoc” actions descending from gas turbine actual operating state [1-6]. Therefore, On-Condition Maintenance requires up-to-date knowledge of the machine health state in real time.

Gas turbine health state determination can be performed by means of several approaches which can be found in literature. One of these approaches consists of the application of Gas Path Analysis (GPA) techniques [7]. A GPA based diagnostic process uses gas turbine field measurements to determine, by means of a gas turbine thermodynamic cycle model (Cycle Program - CP), the actual values of the parameters that are indices of the gas turbine health state (Health Indices - HIs), such as efficiencies, characteristic flow passage areas and pressure drops along the gas path [8-13]. By comparing the actual and the expected values of the health indices, 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. In this paper, a GPA technique, which calculates the HIs by solving in inverse mode the CP in order to reproduce the measurements taken on the gas turbine, is adopted [9].

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 [14,15]:

- Capability of the CP to accurately reproduce the actual gas turbine thermodynamic cycle [16].
- Accuracy of field measurements. To minimize measurement error effects, it is usually advisable to support GPA techniques by means of methodologies for measurement validation [17-22]. 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 health state determination, for example by excluding such a measurement set from the diagnostic process.
- Limited availability of measured quantities on the gas turbine, which causes problems to correctly assess 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 [9]. So, only an adequate number of measured quantities can help to distinguish among different failures.
- Some of the HIs to be estimated have to be kept constant during the calculations. In fact, since the number of the available measured quantities is usually lower than the number of HIs that have to be determined, some of them have to be considered constant. This causes an estimation error on the HIs considered as problem variables, when variations due to aging or deterioration occur on the HIs which were considered as fixed HIs [14,15].

Thus, methodologies for the improvement in HI determination accuracy are required [17,18, 23-26]. In particular, since the methodology makes use of field measurements, the reliability of the diagnostic process also depends on measurement reliability. For this reason, two techniques for measurement validation are presented in the paper: the first one is based on the use of acceptability bands [17,27], while the other uses statistical-based methods for outlier identification [18]. Analytical redundancy techniques for sensor fault detection and isolation can also be used [28].

In this paper, a comprehensive methodology developed by the authors for both measurement validation and health state determination of gas turbines is presented. The methodology is applied to a 5 MW gas turbine working in a natural gas compression plant. Finally, this paper illustrates the main features of a software, which was implemented in the considered compression plant to automate the presented methodology.

2. METHODOLOGY FOR MEASUREMENT VALIDATION AND HEALTH STATE DETERMINATION OF GAS TURBINES

The methodology for measurement validation and health state determination of gas turbines requires the availability of a CP which should reproduce the particular gas turbine under consideration as accurately as possible. Two situations can occur:

1 - The Cycle Deck developed by the manufacturer is available. This CP reproduces a gas turbine-type, which presents average characteristics among gas turbine units of the same model;

2 - A generalized CP is available. In this case, the program has to be tuned to reproduce the machine type under investigation, for instance by using the performance curves supplied by the manufacturer to the user.

In any case, both the Cycle Deck and the generalized CP have to be tuned in order to represent the particular gas turbine unit under consideration. CP tuning procedure is reported in detail in [29].

A low number of measured quantities is usually available on gas turbines in field operation. This fact limits the number of HIs which can be determined through the GPA method. Therefore, the optimal set of HIs, which can be determined by the set of available measurements, has to be identified. This requires an *a priori* optimized selection of the HIs which have to be considered as problem variables and of the ones to be kept constant during the calculation [15,17,26].

Once a CP is tuned on the particular gas turbine and the optimal set of HIs is identified, the main steps of the comprehensive methodology for measurement validation and health state determination are sketched in Fig. 1 and reported below:

1 - Acquisition of field measurements and storage on a historic database, to perform off-line data processing.

2 - Measurement validation. This allows the identification of measurements which have a level of uncertainty higher than a fixed threshold. Thus, the measurement set can be excluded from the gas turbine diagnostic process, to avoid an incorrect evaluation of the machine health state.

3 - Analysis of the normalized measurement trend (Trend Analysis). This analysis is required for measurement validation and also provides useful information for the determination of gas turbine health state, so improving the results obtainable by using the GPA technique alone [17,27].

4 - Use of acceptable data to perform gas turbine health state determination, which consists in the determination of gas turbine HIs by using a GPA-based technique.

5 - Improvement of the diagnostic process through the determination of a higher number of gas turbine HIs by considering more than one operating point (multi-point analysis). In fact, the multiple operating point analysis allows the determination of a number of HIs higher than available measurements, since it compensates for the lack of measurements with the measurements taken at different operating points [10,30].

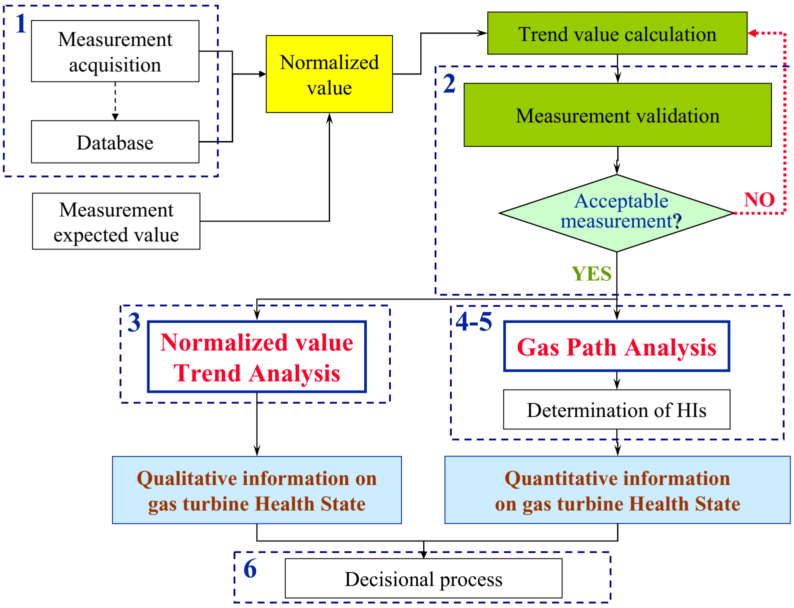

Figure 1. Comprehensive methodology for measurement validation and health state determination of gas turbines

6 - Decisional process, which consists of the identification of unacceptable measurements, the planning of the machine stop for maintenance, on the basis of the values of machine HIs, the possibility of on-line actions, such as compressor washing, the adaptation of the gas turbine control logic to its actual health state and, in the worst case, the immediate stop of the machine.

A software which automates the described methodology may be very helpful as a decision support tool for both plant director and maintenance personnel [31]. Artificial Intelligence techniques may also help in focusing on the most significant information for improving the diagnostic process and maintenance practices [32].

3. METHODOLOGY FOR MEASUREMENT VALIDATION

In this paper, two techniques are considered for measurement validation, both applied to the normalized measurement trend. Measurement normalization is performed by dividing each measured value by its expected value calculated in the same ambient and load conditions, in order to render measurements comparable each other, though collected in different ambient and load conditions. Such expected value can be calculated by using a CP or functional relations. While the CP is rarely available to gas turbine users, functional relations can be obtained by only using measurements taken along the gas path and thus the user can always apply this methodology.

The functional relations can be obtained through identification techniques, as for instance by using a linear regression procedure [27], or Neural Networks [33,34]. The tuning of the models requires the identification of a baseline condition across gas turbine life (for example, the condition after overhaul maintenance). In this condition, some measurement sets taken at different loads and ambient conditions have to be available. Starting from these sets of measurements it is possible to establish relations in the form $\boldsymbol{Q}_{m}=F(\boldsymbol{Q}_{wp})$. The relations obtained relate thermodynamic measurements $\boldsymbol{Q}_{m}$ (such as pressure and temperature at the compressor outlet) to ambient and load conditions $\boldsymbol{Q}_{wp}$ (ambient pressure and temperature, relative humidity, rotational speeds, power output) over the entire gas turbine operating range. The identification procedure has to be performed once for each $\boldsymbol{Q}_{m}$ measured quantity and has to be updated when the chosen baseline condition can be considered no longer representative for the engine. The obtained relations can be then used to normalize each measurement.

3.1 Measurement acceptability bands.

Once measurements are normalized, and the trend over time of each measured quantity is determined, measurement validation can be performed through measurement acceptability bands [17,27]: a measurement lying within these bands will be considered acceptable, otherwise not. Band amplitude can be calculated by considering the following contributions:

a - Measurement accuracy, that can be taken into account by considering band amplitude equal to measurement uncertainty.

b - An engine fault which may affect the value of the measurements along the gas path.

c - Measurements noise along the data acquisition system. This error is usually included within measurement accuracy.

d - Errors due to the CP accuracy. In fact, the CP is usually tuned on the engine type and not on the specific unit. This leads to an estimation error on the expected value of measurements and so to an error in the normalization process.

For the calculations performed in this paper, the uncertainty “d” was not considered, since the CP was tuned on the specific unit and, therefore, this source of error was considered negligible. Two bands were instead considered: the first takes into account measurements uncertainty (contribution “a”), while the second considers the variation of the measurement due to an engine fault (contribution “b”). The total band amplitude is the sum of these two contributions.

Therefore, it is possible to identify three cases to establish whether a measurement is acceptable:

- Value beyond measurements accuracy.
- Value out of measurements accuracy, but within the maximum estimated variation of the measurement due to a fault. A measurement can lie in this region either because of sensor fault or because of an incipient engine fault. In this situation, to obtain significant information, it is necessary to consider the engine behavior before and after the anomalous value and data have to be processed by the diagnostic tool.
- Value out of the maximum variation due to a fault. The measurement should not be processed by the diagnostic tool because of its unreliability.

As anticipated, the bands have to be referred to a reference value. The trend value of the normalized measurements seems a reasonable choice, since, in this manner, measurement variations due to aging can be taken into consideration.

3.2 Statistical-based method for outlier identification.

An alternative way for measurement validation is the analysis of the statistical distribution of the normalized measurement trend in order to detect outliers. A wide number of techniques for outlier detection exists in literature. In gas turbine applications, practical and easy-to-use techniques such as parametric test methodologies seem to offer a compromise solution with respect to simplicity and robustness [18].

A parametric test methodology is based on the definition of a test criterion. For any given element x_i of an N-dimension sample, a test criterion can be written as

$$\frac{|x_i - x_\mathrm{m}|}{S} \geq k, \quad i = 1,\ldots,N \qquad (1)$$

where x_m is the mean of the sample and S is the standard deviation. In the most general case, the coefficient k is a function of the sample size N and of the level of significance α. The latter parameter has to be chosen *a priori* and represents the probability of rejecting a good point. For practical purposes, three levels of significance are usually considered, namely α = 1 %, 2 % and 5 %. This means, for example, that if α = 5 % is considered, the odds against rejecting a good point are 20 to 1 (or less).

If Eq. (1) applies, x_i is to be considered an outlier. Different methods, based on Eq. (1), and characterized by different assumptions for the coefficient k, are available in literature (e.g. the Thompson method, the Grubbs method, the Chauvenet criterion).

These "traditional" methods proved only partially effective and not very robust for gas turbine data [18], in particular when data trends are not constant over time, such as in the case of measurements taken during a long period of time on a gas turbine. In order to overcome some of the limitations of these methods, a new method was developed [18]. The method is based on the application of a test criterion in the form of Eq. (1), but both the left-hand side term and the coefficient k are modified to meet the requirements that have been highlighted. The specificity of the method is that the coefficients introduced account for decreasing or increasing data trends, although they are also correctly defined when constant over time data trends are considered.

In other words, the new coefficients allow the test criterion to take the behavior-in-time of the considered quantity into account. In the new formulation, the test criterion is defined as:

$$\frac{|x_i - x_m|}{k_B S} \geq t_\alpha k_A, \quad i = 1,\ldots,N \qquad (2)$$

The coefficient k_A is defined as:

$$k_A = 1 + \frac{\lim_{N\to\infty} t_\alpha^2 + 1}{4N} \qquad (3)$$

This coefficient is defined in such a manner as to tend to one when N tends to infinity. The coefficient t_α represents the value of the quantile corresponding to a certain level of significance related to the Gaussian distribution. The coefficient k_B, defined as

$$k_\mathrm{B} = (1+N)^{\frac{1}{N}}\left(1 + |S_\mathrm{ov} - S_\mathrm{i}|\right) \qquad (4)$$

allows the scatter of the considered sample to be taken into account. In fact, a relationship between the overall standard deviation S_ov and the standard deviation calculated by considering the data range [1, i], namely S_i, where i is the current data which is under investigation, is introduced in the test criterion. In this manner, the left-hand side term of Eq. (2), instead of being constant as in the Thompson, Grubbs and Chauvenet methods, is updated at each step and, thus, the behavior-in-time of the quantity is taken into account. However, this requires the availability of all data for the time period under examination, in order to estimate data overall standard deviation S_{ov}, and, thus, k_B dependence with time can be evaluated only in the case of data off-line processing. Otherwise, if data are processed on-line, k_B only depends on sample size N, since, in this case, S_{ov} equals S_i.

4. METHODOLOGY FOR HEALTH STATE DETERMINATION OF GAS TURBINES

4.1 Single operating point analysis.

Gas turbine operating state determination consists of the assessment of the modification, due to deterioration and fault, of performance and geometric data characterizing the machine components. One of the main effects of deterioration and fault is the modification of compressor and turbine performance maps. Since detailed information about actual modification of component maps is usually unavailable, many authors simulate the effects of deterioration and fault by scaling the map itself, i.e. by multiplying the maps in *new and clean* condition by scaling factors F point by point [8,9,30]. Different scaling factors can be used; compressor and turbine maps are usually scaled by multiplying efficiency and corrected mass flow rate, at constant pressure ratio (or equivalent parameter, such as the ratio between isentropic enthalpy variation and turbine inlet temperature) and at constant corrected rotational speed [8,9,30]. The modification of compressor and turbine performance maps with respect to *new and clean* condition due to actual deteriorations and faults can be assessed by calculating the map scaling factors F in order to reproduce the measurements taken on the gas turbine [8,9,30].

Therefore, the scale factors of efficiency and corrected mass flow of compressor and turbines can be assumed as characteristic parameters of compressor and turbine health state. In addition to these parameters, two other important parameters for representing the gas turbine health state are the combustor efficiency and pressure drop. In particular, the combustor efficiency accounts for thermal losses along the gas path, which are considered as a fixed constant percentage of the thermal power introduced by the fuel, while the combustor pressure drop is usually defined as a constant percentage of the total pressure at the combustor inlet. This type of parameters is sensitive to the gas turbine health state, while it is not dependent on the gas turbine operating point. Parameters with this characteristic are usually called *Health Indices* (HIs).

The HIs can be calculated by solving in inverse mode the CP in order to reproduce the measurements taken on the gas turbine. In fact, the values of the measurable variables computed by the CP $\boldsymbol{Q}_{m,c}$ are a function of the values assumed both by the health indices $\boldsymbol{X}$ and by the variables that unequivocally determine the operating point at which the gas turbine is working $\boldsymbol{Q}_{wp}$:

$$\boldsymbol{Q}_{m,c} = f(\boldsymbol{X}, \boldsymbol{Q}_{wp}) \qquad (5).$$

By inverting Eq. (5), it is possible to calculate $\boldsymbol{X}$ starting from the measured variables:

$$\boldsymbol{X} = F(\boldsymbol{Q}_m, \boldsymbol{Q}_{wp}) \qquad (6).$$

The solution of Eq. (6), usually called "inverse" solution, has been performed by the authors through a minimization technique which determines the values of HIs that minimize the sum of the square differences, between measured and computed values of the measurable variables [9]. This problem is solved by using a non-linear algorithm which minimizes the objective function:

$$F_{ob}(X_1,...,X_{N_x}) = \sum_{i=1}^{N_m} w_i \left(\frac{Q_{m,c} - Q_m}{Q_m} \right)_i^2 \qquad (7),$$

where X_i (i=1,..,N_x) are the unknown values of HIs, $(Q_{m,c})_i$ and $(Q_m)_i$ are the computed estimates and the measured values of the measurable quantities respectively, and w_i are the weights which can be assigned to each term of the objective function.

The minimization algorithm which was used is included in the IMSL math library [35] and was successfully utilized to solve the gas turbine mathematical model [3,9,10,15,31,36-39].

Once the HIs are calculated, the gas turbine health state is determined by evaluating the variations of the HI values with respect to the expected values in the "new and clean condition". This allows the faulty component to be localized and malfunctions to be identified and quantified.

The diagnostic process was also carried out by the authors through black-box models [40,41]. This approach proved successful and robust [42].

From Eq. (6), the number and type of gas turbine HIs that can be determined for each operating point (i.e. for each set of $\mathbf{Q}_{wp}$) depend on the number and type of equations, which, in turn, depend on the number and type of the available measured quantities. In particular, the number of HIs is usually equal to the number of the $\mathbf{Q}_m$ measured variables. Thus, since the number of the $\mathbf{Q}_m$ available measured quantities is usually lower than the number of HIs to be estimated, some of them have to be kept constant during the calculations. Therefore, variations due to aging or deterioration which, in the actual machine, occur on the HIs which were considered as fixed HIs, will cause an estimation error on the HIs to be determined [14,15].

4.2 Multiple operating point analysis.

A direct consequence of Eq. (6) is that more equations can be obtained by using more than one $\boldsymbol{Q}_{wp}$ set. Thus, the number of gas turbine HIs which can be determined also depends on the number of gas turbine operating points (i.e. number of $\boldsymbol{Q}_{wp}$ sets) [10,30]. Therefore, by using multiple operating points it is possible to evaluate a number of HIs higher than the number of the available $\boldsymbol{Q}_m$ measured quantities.

Therefore, as made in the case of single operating point analysis, the solution of the system of equations obtained by using more than one $\boldsymbol{Q}_{wp}$ set in Eq. (6) was performed through a minimization technique which determines the values of HIs that minimize the sum of the square differences, between measured and computed values of the measurable variables in all the operating points considered. The objective function to be minimized becomes:

$$\mathrm{F_{ob}}(X_1,...,X_{\mathrm{N_x}}) = \frac{1}{N_{\mathrm{op}}} \sum_{\mathrm{j=1}}^{N_{\mathrm{op}}} \left[\sum_{\mathrm{i=1}}^{N_{\mathrm{m}}} w_{\mathrm{i}} \left(\frac{Q_{\mathrm{m,c}} - Q_{\mathrm{m}}}{Q_{\mathrm{m}}} \right)_{\mathrm{i}}^2 \right]_{\mathrm{j}} \qquad (8),$$

where X_i (i=1,..,N_x) are the unknown HIs, $(Q_{m,c})_i$ and $(Q_m)_i$ are the computed estimates and the measured values of the measurable variables respectively, and w_i are the weights assigned to each term of the objective function.

The main steps of the multiple operating point technique are sketched in Fig. 2. The adopted minimization algorithm is the same as for the single point analysis [35].

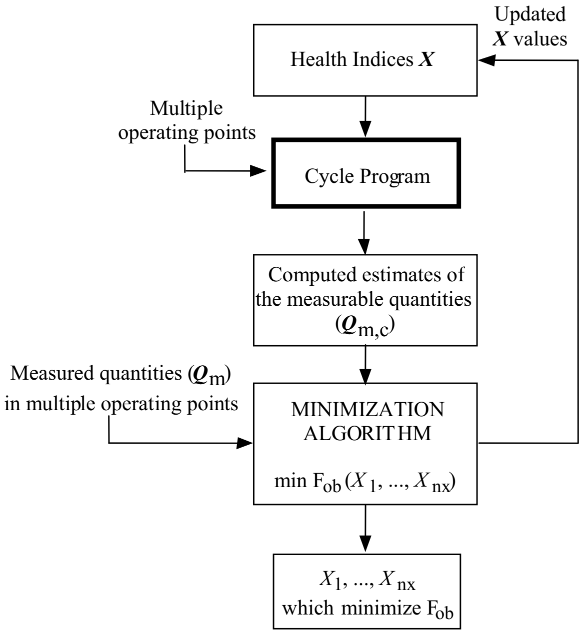

Figure 2. Multiple operating point analysis

The different operating points have to be taken within a small time interval (for instance during the same day) so that the gas turbine health state can be considered the same for all the operating points and, thus, the solution ***X*** of Eq. (6) is the same for all the operating points. The most suitable choice of the operating points to be used was analyzed in [10].

5. APPLICATION OF THE METHODOLOGY TO GAS TURBINES RUNNING IN A NATURAL GAS COMPRESSION PLANT

The comprehensive methodology for measurement validation and health state determination of gas turbines was applied to two compressor-drive gas turbines working in a natural gas compression plant. In this plant, the pressure of the gas coming from the Adriatic Sea reservoirs is raised to the value required by the Italian Gas Supply Company by using four compression systems. Two of them are driven by 5.2 MW regenerative cycle two shaft industrial gas turbines with variable power turbine nozzles (VN) and two by 1.2 MW simple cycle two shaft gas turbines. The methodology was applied to the two 5.2 MW gas turbines, whose lay out is shown in Fig. 3. In any case, the methodology is completely general. In fact, it was also successfully applied to a single shaft gas turbine working in a cogenerative combined power plant [43].

Table 1 reports the measurements available on each 5.2 MW gas turbine system. As can be seen from Tab. 1, some very important measurements for a reliable diagnosis analysis are not available. They are the fuel mass flow rate (at present, only the total fuel mass flow feeding both the 5.2 MW gas turbines is measured), the pressure and temperature between the gas generator and the power turbine (p_5, T_5), the air side and exhaust side regenerator pressure drops ($\Delta p_{2\text{-}3}$, $\Delta p_{6\text{-}7}$) and the air inlet mass flow rate (M_1).

The methodology was applied to a poorly instrumented plant, since it represents a selective test for verifying the capabilities of the proposed diagnostic system. Moreover, poor instrumented plants are highly widespread and, thus, the application to such cases seems particularly interesting.

Before applying the methodology for gas turbine health state determination, a generalized CP developed by the authors was tuned to reproduce the gas turbine under consideration. This was made by using as reference values the performance curves provided by the gas turbine manufacturer

Table 1. Available measurements

Q_{WP} MEASUREMENTS	Q_M MEASUREMENTS
T_1: COMP. INLET TEMP. P_A: AMBIENT PRESSURE *RH*: RELATIVE HUMIDITY ΔP_{A-1}: FILTER PRESSURE DROP *VN*: VAR. NOZZLE POSITION	P_2: COMP. OUTLET PRESSURE T_2: COMP. OUTLET TEMP. T_6: POWER TURB. OUTLET TEMP.
N_{GGT}: GAS GEN. TURB. ROT. SPEED	**OTHER MEASUREMENTS**
N_{PT}: POWER TURBINE ROT. SPEED	T_3: RECUPERATOR OUTLET TEMP. (AIR SIDE)
P_{PT}: POWER OUTPUT (CALCULATED FROM MEASURED T_{C1}, T_{C2} AND M_{C1})	T_7: RECUPERATOR OUTLET TEMP. (GAS SIDE)

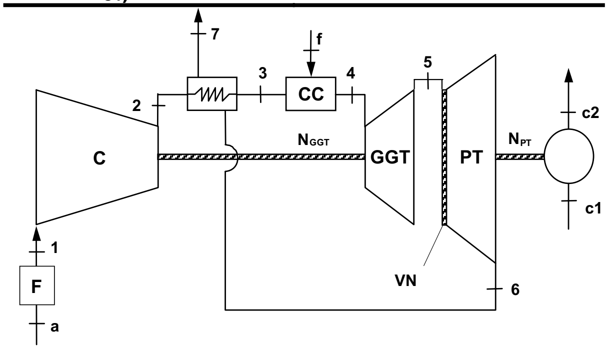

Figure 3. Lay out of the 5.2 MW two-shafts regenerative cycle gas turbine

to the user. These curves provide the compressor outlet pressure (p_2) and temperature (T_2), power turbine outlet temperature (T_6), fuel and inlet air mass flow rates (M_f and M_1) at various gas turbine working points. After the tuning, the program estimates manufacturer data with a maximum error usually lower than 1% [3].

The following step of the procedure requires the identification of the optimal combination measurements/HIs. As shown in Tab. 1, there are only three available measurements to perform the operating state determination: p_2, T_2, and T_6. In fact, the other measurements are used to define the working point. Therefore, only three HIs can be unequivocally determined. The optimal HIs set (identified according to [17,26]), which can be determined by using the set of available measurements is composed of the following HIs: compressor efficiency (η_C) and corrected mass flow (μ_C) and gas generator turbine efficiency (η_{GGT}).

Phase 1 - Acquisition and storage of field measurements.

The available data were gathered once a day manually by an operator. This caused the presence of a number of wild points originating from sources such as reading errors, data taken in unstable and/or not representative conditions, etc., which were difficult to detect. This may be a common situation in practice and thus it could represent a test bed for measurement validation techniques. The results reported refer to data acquired in the period from 2nd Nov. 1999 to 16th Jan. 2000 on one of the two gas turbines under investigation.

Phase 2 - Measurement validation.

Measurement validation was performed by means of the two previously described techniques, both applied to the normalized measurement trend. Measurement normalization was performed by dividing each measured value by its expected value calculated in the same ambient and load conditions, by using the CP tuned on the machine under consideration.

Measurement acceptability bands were applied to the normalized measurement trend and take into account both measurement uncertainty and maximum variations of measurements due to faults, according to Tab. 2 [17,27].

Measurement uncertainty bands (second column in Tab. 2) were set according to the sensor accuracy reported in [44] and by considering the case in which the measurements were taken in the field with standard machine instrumentation during normal operation and not when conducting an acceptance test. In order to establish the amplitude of the bands deriving from measurement variation due to faults, the CP tuned on the considered machine was used to simulate some of the most common faults that can occur on a gas turbine (compressor fouling, compressor mechanical damage, gas generator turbine mechanical damage, gas generator turbine erosion and power turbine erosion) [17]. Faults are to be considered as sudden faults, since measurement variations due to aging or deterioration are considered through the normalization process.

Table 2. Band amplitude: measurements accuracy and total band amplitude

Measured Quantities	Measurements accuracy [% of reference value]	Confidence band [% of trend value]
T_2	±0.85	[-1 ; + 5.5]
p_2	±1.00	[-4; + 3]
T_6	±0.75	[-1 ; + 5.5]

Figure 4 reports the normalized values of the compressor outlet pressure (p_2) and temperature (T_2) and of the power turbine outlet temperature (T_6) versus time. The solid line indicates measurement trend over time, while the dashed lines are the acceptability bands. The figure highlights:

- the decreasing trend of the outlet compressor pressure and the slightly increasing trend of the compressor outlet temperature. These symptoms may be attributed to compressor fouling The increasing trend of the power turbine outlet temperature can be also observed.
- the measurement scattering due to the uncertainties in field measurement readings;
- the unacceptable measurements according to the use of acceptability bands (white symbols). Moreover, the application of the statistical-based method for outlier identification reveals that only one measurement set (i.e. the one at day #20) can be considered unacceptable also by using this second method. Thus, the use of the statistical-based method reveals less restrictive than the use of acceptability bands.

Phase 3 – Analysis of the normalized measurement trend (Trend Analysis).

The analysis is aimed at establishing relations among performance drops and normalized measurement trends of compressor outlet pressure (p_2) and temperature (T_2) and the power turbine outlet temperature (T_6) reported in Fig. 4.

Form Fig. 4, a reduction of about 2 % in 70 days on the trend of normalized compressor outlet pressure can be noticed, while compressor outlet temperature remains almost constant. These trends highlight a normal compressor fouling. The analysis of T_6^* alone, whose trend is slightly increasing, does not provide additional diagnostic information about the two turbines.

Phase 4 – Gas turbine health state determination.

The percentage variation E between computed and reference values of compressor efficiency (η_C) and corrected mass flow (μ_C) HIs and of gas generator turbine efficiency HI (η_{GGT}) versus time are reported in Fig. 5. The black and white symbols indicate the HIs evaluated by using the acceptable and unacceptable measurement sets, respectively.

Figure 5 highlights the decreasing trends of both compressor efficiency and mass flow function HIs, which can be attributed to compressor fouling, as already highlighted by the Trend Analysis in the previous section. Over a period of two months, the trend values of η_C and μ_C HIs were reduced by 1.0 % and 2.5 % respectively, showing that fouling is not severe [45,46]. The trend of gas generator turbine efficiency HI is instead almost constant, indicating that this component is not suffering from significant changes in its health state. Figure 5 also highlights the remarkable reduction of the scattering of HI trends, obtainable by using the acceptable measurement sets only.

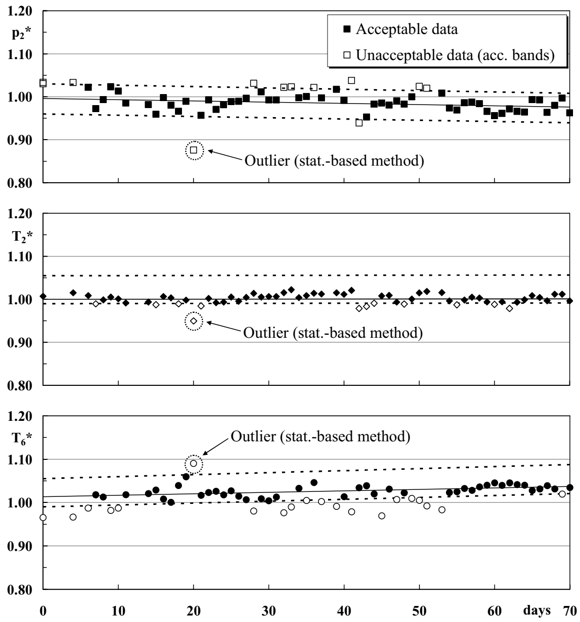

Figure 4. Normalized values of compressor outlet pressure (p_2), compressor outlet temperature (T_2*) and power turbine outlet temperature (T_6*) versus time*

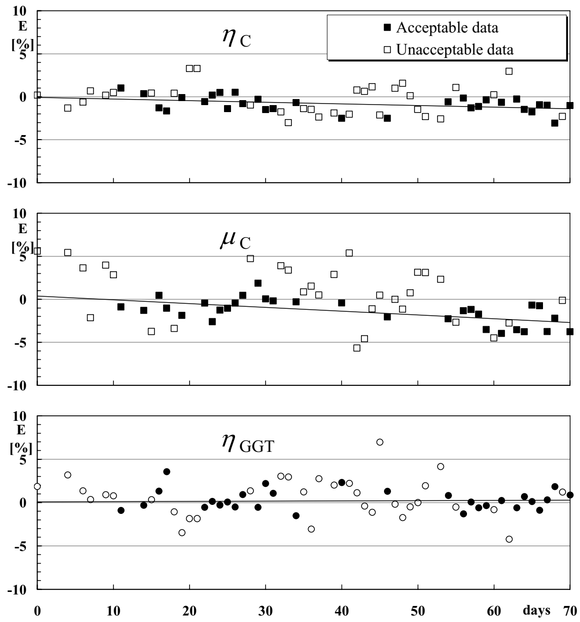

Figure 5. Computed and reference value percentage variations for compressor efficiency (η_C) and corrected mass flow (μ_C) and gas generator turbine efficiency (η_{GGT})

Phase 5 – Gas turbine health state determination on multiple operating points.

A multi-point analysis was also applied to the gas turbine unit considered by using measurements taken during special operating conditions, immediately before and after a maintenance stop. In these cases, measurements at different gas turbine loads were performed, so that it was possible to perform the multi-point analysis.

Two different calculations were performed by using different sets of variable HIs. In Fig. 6a, the normalized values of η_C, μ_C, η_{GGT} and μ_{GGT}, calculated by using the multi-point analysis with three HIs (η_C, μ_C, η_{GGT}) as problem variables, are reported. In Fig. 6b, the normalized values of η_C, μ_C, η_{GGT}, μ_{GGT}, η_{PT} and μ_{PT}, calculated by using the multi-point analysis with five HIs (η_C, μ_C, η_{GGT}, μ_{GGT}, η_{PT}) as problem variables, are shown. Black and white symbols refer to the measurements taken before and after the maintenance stop respectively. It can be highlighted how the multi-point analysis allows the determination of a number of HIs higher than available measured quantities, since it compensates for the lack of measured quantities with the measurements taken at different operating points.

The results obtained by using five HIs as problem variables (Fig. 6b) seem more convincing than the ones obtained in the case of three variable HIs (Fig. 6a). In this last case, in fact, it seems that there are no improvements due to maintenance, while, in the case of five variable HIs, an increase in the compressor and gas generator turbine corrected mass flows HIs can be noticed.

6. SOFTWARE TOOL FOR GAS TURBINE ON-CONDITION MONITORING AND DIAGNOSTICS

For the considered natural gas compression plant, a software tool was developed and implemented [31], to allow the prompt visualization of the required information by means of a user-friendly interface, so allowing gas turbine health state analysis and supporting the decision for maintenance actions.

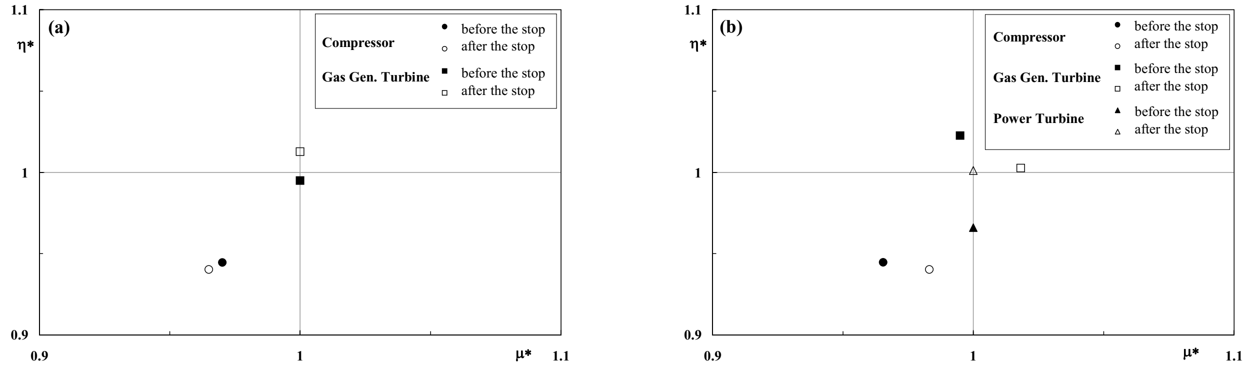

Figure 6. Normalized values of HIs in case of (a) three problem variables (η_C μ_C, η_{GGT}) and (b) five problem variables (η_C μ_C, η_{GGT}, μ_{GGT}, η_{PT}, μ_{PT}) (multiple operating point analysis)

The developed software, whose structure is sketched in Fig. 7, allows:

- the measurement normalization;
- the calculation of HIs for the evaluation of gas turbine health state;
- the comparison of the measured delivery of compressed natural gas compared with the calculated maximum possible delivery. This latter value is estimated by assuming the gas turbine in new and clean conditions.

Moreover, the software system stores all data in a database and calculates the trend line in order to perform the trend analysis for all the parameters.

The kernel of the software system consists of the subroutines which allow the manual insertion of data, data direct acquisition from the control system, the visualization of the results and the modification of calculation parameters. The user interface is provided by means of floating toolbars (buttons and/or text), as shown in Fig. 8.

Results can be displayed in form of graphs and tables which allows a user-friendly interpretation of the results. The graphical form shows plots of calculated values and the corresponding trend lines versus time; acceptability bands are visualized around the trend line to evidence unacceptable data.

The program also determines the net power output of the gas turbine starting from measurements acquired on the centrifugal compressor, the overall gas turbine efficiency and the turbine inlet temperature. The ratio between the actual and the nominal value for both the net power output and the turbine inlet temperature can be used as indices of the gas turbine overall health state.

Moreover, starting from the indices of the gas turbine health state, the software calculates the value of the production losses due to the actual health state. In fact, if M_{gasM} is the measurement of the natural gas flow rate processed by the centrifugal compressor and M_{gasC} the flow rate that the centrifugal compressor could process when the driving gas turbine is in new and clean conditions, a lost production index LPI can be calculated as:

$$\text{LPI} = \frac{M_{\text{gasC}} - M_{\text{gasM}}}{M_{\text{gasC}}} \qquad (10)$$

In Fig. 9 a sample trend of LPI is reported. The trend is increasing due to gas turbine ageing: in fact, the more the gas turbine deterioration increases (and, thus, its performances decrease), the more the gas flow rate which the centrifugal compressor can process (M_{gasM}) reduces.

In conclusion, the software can actually represent a helpful support tool for the plant operation management. The persons which can take advantage from these analyses can be:

- the plant manager. In fact LPI evaluation allows useful information on the actual economical benefit of keeping the plant in operation rather than stop it to perform maintenance actions;

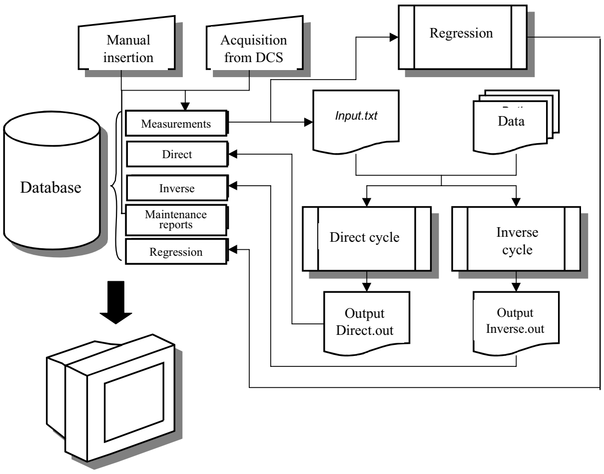

Fig. 7. Software system architecture

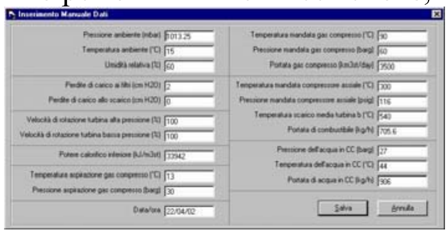

Fig. 8. Dialog box for manual data insertion

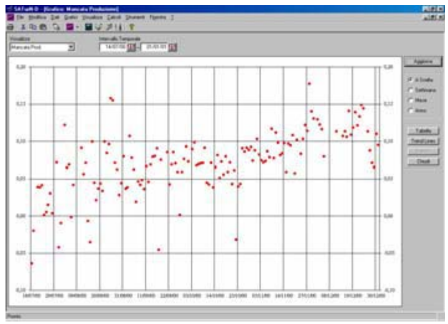

Fig. 9. Lost production index trend

- the maintenance manager, which, through the analysis of the normalized measurement and of the HIs trends, can obtain information on overall performance deterioration, on the components that are responsible of the deterioration, on the type and on the quantification of the deterioration;
- the maintenance chief engineer, which, still through the analysis of the normalized measurement and of HIs trends, can obtain information on the performance recovery after maintenance actions.

7. CONCLUSIONS

In this paper, a comprehensive methodology for both measurement validation and health state determination of gas turbines was presented, discussed and applied to a 5 MW gas turbine working in a natural gas compression plant.

The methodology demonstrated to be effective in supporting plant operation and maintenance management and some interesting results were presented. In particular:

- The application of the methodologies for measurement validation allowed the identification of unreliable measurements sets, with a remarkable reduction of the scattering of the trend-over-time of the measurements. The measurement sets identified as unreliable were not used for estimating machine health indices.
- Gas turbine health state determination, performed by applying the developed Gas Path Analysis technique over a working period of two months, highlighted that compressor fouling (though not severe) was occurring, while gas generator turbine was not suffering from significant changes in health state.
- The application of the multi-point analysis to measurements taken immediately before and after a

maintenance stop allowed a more detailed analysis of the health state of the main gas turbine components.

Finally, the main features of a software, which was implemented in the considered compression plant to automate the diagnostic process and to support plant operation and management, were presented. As a sample application, the loss of production, due to gas turbine deterioration, was reported.

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Nomenclature

E	variation
F	map scaling factors
F_{ob}	objective function
k, k_A, k_B	test criterion coefficients
LPI	Loss of Production Index
M	mass flow rate
N	sample size, rotational speed
N_m	dimension of $\mathbf{Q}_m$ vector
N_{op}	number of operating points
N_x	dimension of $\mathbf{X}$ vector
p	total pressure
P	power
$\boldsymbol{Q}_m$	vector of measured variables
$\boldsymbol{Q}_{m,c}$	vector of computed estimates of the measured variables
$\boldsymbol{Q}_{wp}$	vector of measured variables necessary to define the working point
RH	relative humidity
S	standard deviation of the sample
T	total temperature
t_α	t-Student distribution quantile
VN	variable nozzle angular position
w	weight
x	element of the sample
$\boldsymbol{X}$	$[X_1, \ldots, X_{Nx}]^T$ vector of Health Indices
α	level of significance
Δ	variation
η	efficiency
μ	$= \frac{M\sqrt{T}}{p}$ mass flow function
*	normalized value

Subscripts

a	ambient
C	compressor
f	fuel
m	mean value
GGT	gas generator turbine
gasC	compressed gas (calculated)
gasM	compressed gas (measured)
ov	overall
PT	power turbine

Acronyms

C	Compressor
CC	Combustion chamber
CP	Cycle Program
F	Filter
GGT	Gas generator turbine
GPA	Gas Path Analysis
HI	Health Index
PT	Power turbine