RESEARCH ARTICLE

An artificial neural network-based diagnostic methodology for gas turbine path analysis—part I: introduction

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Abstract The reliability of gas path components (compressor, burners and turbines) of a gas turbine is generally high, when compared with those of other systems. However, in case of forced stops, downtime is usually high, with a relatively low availability. The purpose of condition monitoring and fault diagnostics is to detect, isolate and evaluate (i.e., to estimate quantitatively the extent) defects within a system. One effective technique could provide a significant improvement of economic performance, reduce operating costs and maintenance, increase the availability and improve the level of safety achieved. However, conventional analytical techniques such as gas path analysis and its variants are limited in their engine diagnostic, due to several reasons, including their inability to effectively operate in the presence of noise measures, to distinguish anomalies of component from a failure sensor, to preserve the linearity in the relations between parameters of gas turbines and to manage the sensors range to achieve accurate diagnosis. In this paper, the approach of a diagnostic scenario to detect faults in the gas path of a gas turbine has been presented. The model provides a large-scale integration of artificial neural networks designed to detect, isolate and evaluate failures during the operating conditions. The engine measurements are considered as input for the model, such as the speed, pressure, temperature and fuel flow rate. The output supplies any changes in the sensor or in the efficiency levels and flow rate, in the event of fault components. The diagnostic method has the ability to evaluate anomalies of both multiple components and multiple sensors, within the range of operating points.

In the case of components failures, the system provides diagnostic changes in efficiency and flow rate that can be interpreted to determine the nature of the physical problem. The technique has been applied in different operating conditions by comparing the results obtained with the solutions provided by linear and nonlinear analysis.

Keywords Gas turbine diagnostic · Gas path analysis · Neural network

List of symbols

a	Correction exponent for δ
a	Prediction of a network performance parameter
ADT	Advanced diagnostic techniques
ANN	Artificial neural network
b	Correction exponent for θ
c	Correction exponent for γ
CoC	Coefficient of correlation
DOD	Direct object damage
DSA	Double-step analysis
FL	Fuzzy logic
FMF	Fuel mass flow rate
FOD	Foreign object damage
GG	Gas generator
GPA	Gas path analysis
GPF	Gas path failure
GPFD	Gas path fault diagnosis
GT	Gas turbine
HCF	High-cycle fatigue
KF	Kalman filter
LCF	Low-cycle fatigue
MBD	Model-based diagnostic
MMKF	Multimodeling Kalman filter

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n	Number of engine measurements
N	Relative velocity, number of tests
p	Pressure
P	Power turbine
r	Number of measurements that can be considered as disturbed measurements
RNA	Ribonucleic acid
SF	Sensor fault
SL	Sea level
SP	Shaft power
T	Temperature
TBO	Time between overhaul
TSA	Triple step analysis
TIT	Turbine inlet temperature
X, Z, z	Input parametrs

Greek symbol

η	Efficiency
Γ	Flux capacity of the function/component
σ	Standard deviation
γ	Power ratio between shaft power and reference/design power
δ	Pressure ratio at suction side
ρ_m	Measured parameter value at environmental pressure, temperature and rated power
θ	Temperature ratio between the environmental temperature and reference temperature
Δ	Difference

Subscripts

a	Ambient
bki	Corrected reference for sensor “i” on “k” model
C	Compressor
cki	Network prevision for sensor “i” on “k” model
CT	Compressor driven by turbine
i	Sensor
ki	K model sensor
PT	Power turbine
T	Turbine

1 Introduction

The turbine plays an increasingly important role in the energy generation and distribution. This aspect leads to improve economic performance, by improving the efficiency of components, extending the periods between maintenance (TBOS) and increasing the overall performance. The cost per kilowatt value produced by a GT (€/kW) is one of the most aspect in the plant management and includes all necessary costs to maintain the turbine operational. The efficiency variation should be considered in the calculation of the plant life cycle. The availability of gas

path components might be relatively low because high downtime is normally associated with forced stops (Agrawal et al. 1978). A possible solution to increase the availability is to improve the maintenance operations, based on monitoring conditions (CBM). Before the advent of the GPA (gas path analysis) tools, the gas path failures have been diagnosed mainly by means of quality tools, by matching symptoms to pre-established patterns (to identify the tendency to the variation in the engine measurements and then isolate a failing module or component). This approach does not consider that the apparent fault could be due to measurement noise. The solutions cannot be provided by qualitative approaches, both conventional and evolutionary. GPA and its variants, as well as some artificial intelligence techniques, are able to provide quantitative results for the breakdowns in the gas path.

2 Methodology briefings

2.1 Gas path fault

A GT plant is exposed to several failures as reported in Table 1 (Agrawal et al. 1978; Aker and Saravanamuttoo 1989; Anderson and McNeill 1992). A failure in the gas path (GPF) can be described by directional changes in the size or can be diagnosed by their effect on performance independent variables. It is not possible to describe all possible defects that affect the GT gas path. Table 1 reports the most common failures that can produce a significant efficiency loss or dangerous stops, during the operational duty.

2.2 Conventional approaches

The classification of conventional approaches includes all diagnostic techniques that compare the symptoms with pre-established models (Agrawal et al. 1978; Aker and Saravanamuttoo 1989; Ali and Gupta 1990; Allwood et al. 1996; Anderson and McNeill 1992), to identify the tendency to the variation in the measurements of the engine and isolate a faulty module or component.

2.3 Analytical approaches

This method uses gas path engine detectable data (dependent variables) to determine the variations of component characteristics and the flow rate (independent variable/primary performance). This change in operating characteristics can be caused by a failure of a component or a module. Consequently, a potential source of mismatch is the “not repeatability of the measure,” due to the operating environment noise. The primary use of dependent

parameters, for isolating GPF, is based on the fact that the primary performance parameters or independent variables are not directly measurable. They are related to the thermodynamically dependent variables, so that changes in the latter ones are induced by changes in independent variables, with the possibility to identify the failing component. The implementation of the GPA as analytical system has been limited by the component sensors that intrinsically lack of strength. In fact, their positions inside the turbine, often, are not optimal. Their selection is ineffective compared to the failures matrix (Agrawal et al. 1978; Barschdorff 1991). This interconnection matrix is required to identify the various failures (Agrawal et al. 1978). In response to some of these sensor problems, GPA programs, designed to operate with large performance deviations, have been realized.

2.4 Evolutionary approaches

To create possible functions with some degrees of freedom, and develop high-level systems, researchers have adopted some tools related to the biological sciences. Artificial intelligence (AI) is divided into several areas such as expert systems, fuzzy logic, genetic algorithm and artificial neural networks (Ali and Gupta 1990; Angelakis et al. 2001; Barschdorff 1991). Among these, the artificial neural networks (ANNs) have been shown to respond to the needs by offering the “quasi-optimal” interpretation of symptoms. The possibility of integrating the artificial neural networks (ANNs) in plant monitoring has recently been investigated by several researches (Bakal et al. 1995; Barlett and Uhrig 1992; Shalan et al. 2010; Hajagos and Bérubé 2001; Centeno et al. 2005). It can be remembered that an artificial neural network is described as a schematic representation of a mathematical equation that receives values (inputs) and generates results (output). The nonlinearity in the performance of the GT and limits of GPA analytical

techniques-based model makes inevitable the need for interpretation by ANN model. The basic steps needed to obtain a typical supervised feed-forward ANN include:

1. Evaluate the problem to be solved, in an attempt to verify the possibility of discretization.
2. Generation of test data and training.
3. Definition and formation of various network architectures, to obtain the optimum one. The training process disrupts the weights and variations, to generate the collection that optimizes the system performance, with reduced errors and good generalization. The “Weight adjustment” for the case of a counter reaction network, which operates on the gradient decrease techniques, is achieved by:

$$\Delta w_{ij} = \eta \left(-\frac{\partial E(n)}{\partial w_{ij}} \right) + \alpha \Delta w_{ij}(n-1) \quad (1)$$
4. Try the ANN with enough data, to determine the generalization ability.

3 Advanced diagnostic methodology

3.1 Advanced diagnostic techniques (ADT) for gas path fault diagnosis (GPFd)

In this research, an engine model operating in steady-state conditions will be considered. For the GT presented, a non-linear simulation package to assemble the models is used. The engine decreasing performance is modeled by scale factor adjustments of efficiency and flow rate of the considered component (ith). The aim is to use these templates to generate data for networks training and testing. An effective application of the developed method should avoid the use of engine model, once completed the networks training, because the parameters have been already fixed. In this situation, our

Table 1 Gas turbine fails and failures

Compressor	Turbine	Combustor	Filter	Mechanical problems
Fouling	Fouling	Corrosion	Fouling	Bearings problems
Blade fatigue	Corrosion	Cracking	Clogging	Critical speeds
Blade pitting, blade corrosion	Hot corrosion, sulfidation	Nozzle imbalance	Icing	Unbalance
surge	FOD/DOD	Fuel quality	Airflow distortion	Looseness and misalignment
Corrosion, erosion	Excessive back pressure	Vibration and pulsation	Humidity effects	Foundations
LCF/HCF	Creep	Clogging	Loss of airtightness	Rotor bows
FOD	Nozzle bowing	Leaks		
	Bearings distress	Fretting corrosion		
	HCF/LCF			
	Blade coating			

application of ANN can be seen as based on learning from examples, rather than based on diagnostics (MBD).

3.2 Sensors

The system performances are detected by sensors. These are usually smaller than the number of variables to be monitored. As a result, computational level, the system possesses infinite degrees of freedom to obtain the solution. In order to reach a solution “correct and probable,” it is important to establish boundary conditions. Also the choice of sensor type and its placement is fundamental in the creation of the array. Therefore, the operating conditions must be “observed” unambiguously. One possible method for choice of sensors and their location may be to simulate a fault and collect data from the instruments. In this way, it is possible to determine the optimal combination, able to measure the dependent variables that describe the phenomenon or failure. In general, this generates a number of possible combinations of measure sets, with each series that can diagnose similar failures in gas path. In Table 2, a list of proposed sensors for a GT system is given. In addition, each sensor and device has its reference line (operation line under varying inlet conditions). The variation of the measured values from this reference line is calculated by Eq. (2). The equation is applicable to both independent and dependent variables.

$$\Delta\% = \frac{Z - Z_{\text{estbaseline}}}{Z_{\text{estbaseline}}} \cdot 100 \quad (2)$$

$Z_{\text{estbaseline}}$ is the basic condition set, and Z is the measured or calculated value.

The non-repeatability of the instrument is excluded, that is applied as white noise with a Gaussian distribution, to generate the engine data in the range of three standard deviations (3σ) of the mean value.

3.3 Parameters correction

To evaluate the corrections, several systems have been simulated. The operating point is determined by three parameters, as well as the shaft power (P), the ambient temperature (T_a) and pressure (p_a). These parameters can vary during the plant

operation. The aim is to obtain reference measurements, to generate the reference line. It can be noticed that a diagnostic program should require that the engine data are generated whenever a fault diagnosis is carried out, or find alternative methods to obtain these reference lines (Bakal et al. 1995; Hajagos and Bérubé 2001; Centeno et al. 2005). In addition, an analytical approach, derived by the TSA procedure (triple-step analysis), has been used. The approach utilizes a database of various operating points (available in literature and by experimental tests (Capata 2015)) on which a three-dimensional interpolation can be realized, to determine the baseline for each engine measures, after setting the current value to the environment conditions and power (Allwood et al. 1996; Bakal et al. 1995; Barschdorff 1991). A correct definition and positioning of the reference line is a step toward obtaining a sufficiently accurate value for the deviations of each measurement (Allwood et al. 1996). The results show that this process is fast and reliable for regions with operational points distributed on the component operative maps. Moreover, a relationship between the engine measurements and the operating point parameters is derived, if any. So, the region where to concentrate the TSA data correction is obtained, and finally, the TSA method for parameters correction is described (Anderson and McNeill 1992) and shown in Fig. 1. In fact, for each obtained engine measure, and for each point on the surface obtained from various combinations of temperature (T_a) and pressure (P_a), it can define some relationships, such as to transform that base point to another reference point, arbitrarily and previously defined. By extension, any surface, defined by a different engine conditions, probably caused by the deterioration of a component or system, can be sufficiently described by relations developed to the reference line. Since the surfaces are irregular, it is reasonable to consider the fact that different points on the surface would require several exponents of correction, a high exponent value for a positive slope and a lower value for a negative slope.

3.4 Relationship between operating point parameters and engine data

In order to make the corrections, different configurations of GT plant were simulated. Among these, the simulations

Table 2 Sensors, identity and accuracy

Sensor	Identity	Unit	(%) Required accuracy over span
n_1	Speed	RPM or 1/s	± 0.03
p_2	Compressor outlet pressure	Atm.	± 0.1
T_2	Compressor outlet temperature	K	± 0.4
FMF	Fuel flow	kg/s	± 1.0
p_4	Exhaust pressure	Atm.	± 0.1
T_4	Exhaust temperature	K	± 0.4

low temperatures and high pressures (Anderson and McNeill 1992; Angelakis et al. 2001). The reason for this is that the compressor work varies with environmental conditions, because it is easier to compress the cold air than hot air. Moreover, in hot conditions, the density varies and the only way to produce the same power level is to increase the mass flow rate through the motor shaft, which rotates faster. Besides, the various surfaces in the figure represent varying levels of power setting.

The regression analysis conducted to map points on these surfaces failed. In fact, it was necessary to apply separate coefficients for each surface. So, the approach with adaptive TSA coefficients was considered and designed. The TSA approach determines, first of all, the exponents for each measurements of the base surface and then applies these exponents to calculate the surface deterioration. Final step is the needed data correction.

3.5 Basic assumption

Table 3 GT operational parameters

Mass flow rate [kg/s]	75
Pressure ratio	8.5
TIT [K]	1350

Fig. 2 Gas path principles (Agrawal et al. 1978)

Fig. 3 Comparison between component/engine reference line and measured parameters

Fig. 4 Effect of p_a , T_a and SP variation on the shaft relative speed

conditions” can be represented by this new surface. Analyzing both figures, it can reasonably consider valid the precondition on the various surfaces similarity, at different failure levels within the operating range. Repeating the construction for all parameters, it can be notice that, once again, the surface curvature similarity is clear and seems to validate our assumptions. A method to validate our assumptions is to determine the percentage deviation between the scenarios, obtained in the presence of an engine fault, with that in the absence of failure, through a given operating range for each parameter ρ (Ogaji 2003).

In this case, Eq. (3) is applied.

$$\% \text{Deviation} = \frac{\rho_{\text{measured}} - \rho_{\text{baseline}}}{\rho_{\text{baseline}}} \cdot 100 \quad (3)$$

Fig. 5 Operational and affected system surfaces

The equation provides a relative comparison, which allows to verify the consistency changes throughout the range adopted.

4 The proposed “ANN” methodology

The processes, used for performing the parameters corrections, can be basically divided into two levels:

- Level 1: Determine the correction exponents from the reference surface in ambient conditions and the rated power. This multidimensional problem requires three steps.
- Level 2: Use the exponents obtained for correct engine measures at sea level—reference point specified.

4.1 Level 1

The TSA approach can actually be carried out in any of six possible routes of which we introduce one, i.e., from point K to L and then to M, which is a gradual correction of pressure, temperature, and then finally to shaft power (note that the MN is not indicated for simplicity). This is shown in Fig. 5.

Consider the surface in Fig. 3, and report it in Fig. 6. The details are:

1. Given a point K with environmental pressure and temperature p_{ak} and T_{ak} , respectively, it generates a calculated value of the parameter considered ρ_c , through an interpolation from a database or from an

Fig. 6 DSA approach on a reference surface (Ogaji 2003)

accurate thermodynamic engine model (previously mentioned), in relation to environmental temperature and pressure. Both approaches should give roughly the same results because the database was obtained from engine model. However, any difference between the results could be due to errors of approximation.

- From the surface, using a 2D interpolation, it obtains a value for the parameter in section L $(\rho_b)_p$, for example, the pressure value SL but the temperature remains at T_{ak} .
- Subsequently, with the same technique as described above, a reference value for M (ρ_b) is obtained. It is the value of the parameter with environmental temperature and pressure at the reference point.
- In the transition from K to M, there is an influence of temperature and pressure on the parameter.

A relationship that could be applied to correct the variation in p_a , T_a and SP in the measurements is defined as:

$$(\rho_m)_{SL} = \frac{\rho_m}{\delta^a \theta^b \gamma^c} \quad (4)$$

where $(\rho_m)_{SL}$ is the correct parameter at reference point, ρ_m the measured parameter value at environmental pressure, temperature and rated power, δ pressure ratio at suction side, γ power ratio between shaft power and reference/design power, θ temperature ratio between the environmental temperature and reference temperature, a δ correction exponent, b θ correction exponent, and c γ correction exponent.

In our approach,

$$\begin{aligned} \theta &= T_a/288.15 \\ \delta &= p_1/0.99 \\ \gamma &= SP/28601640 \end{aligned} \quad (5)$$

It should be noted that the reference value for the power is equal to 90 % of maximum rated power. To obtain values for the exponent, a , b and c , the TSA has been adopted. In fact, first the influence of the environmental pressure drop is evaluated, then the influence of environmental temperature is considered and finally, the influence of shaft power variation. This process was used to determine the values for the exponents a , b and c .

Phase 1: pressure correction exponent a

From equation:

$$(\rho_b)_p = \frac{\rho_c}{\delta^a} \quad (6)$$

solving:

$$a = \frac{\ln \left[\frac{\rho_c}{(\rho_b)_p} \right]}{\ln(\delta)} \quad (7)$$

Phase 2: temperature correction exponent b

From equation:

$$(\rho_b)_{PT} = \frac{(\rho_b)_p}{\theta^b} \quad (8)$$

Analogously:

$$b = \frac{\ln \left[\frac{(\rho_b)_p}{(\rho_b)_{PT}} \right]}{\ln(\theta)} \quad (9)$$

Phase 3: power correction exponent c

From equation:

$$(\rho_b)_{SL} = \frac{(\rho_b)_{PT}}{\gamma^c} \quad (10)$$

Solving by c :

$$c = \frac{\ln \left[\frac{(\rho_b)_{PT}}{(\rho_b)_{SL}} \right]}{\ln(\gamma)} \quad (11)$$

4.2 Level 2

Once obtained the exponents, the parameter measured, ρ_m , has been corrected, by the equation,

$$\Delta \rho = [(\rho_m)_{SL} - (\rho_b)_{SL}] / (\rho_b)_{SL} \cdot 100 \quad (12)$$

The levels 1 and 2 are performed for all measured parameters. The correct parameters are then normalized, as shown in Eq. (12).

5 Conclusions

An ANN model has been exposed. It can be used to perform four basic functions in a gas turbine plant: to generate performance parameters, estimate the plant/process operating conditions, estimate the sensor data and, finally, validate sensors data using the separation of incorrect/noise measurements from good ones.

The various types of ANN currently available are various types of RNA, and some of the most popular include multilayer perceptions, perceptions, radial basis functions, learning vector quantization. Networks can be classified into controlled and uncontrolled or feed forward or feedback based on how the data are processed through the network.

At the end of this first phase, the “correction factors” for the proposal ANN method have been calculated. The next step will be to apply this methodology and calculated correction factors in gas turbine plant, to evaluate the choices and verify the correction introduced, with the aim to separate the noise/incorrect measures from the correct ones.

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