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EXPERIENCE WITH CONDITION-BASED MAINTENANCE RELATED METHODS AND TOOLS FOR GAS TURBINES

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ABSTRACT

This paper presents methods and tools related to condition-based maintenance (CBM) and their application on a number of real cases for gas turbine health assessment based on the experience gained over the last two decades by the research group of the Laboratory of Thermal Turbomachines at the National Technical University of Athens (LTT/NTUA).

First, the general layout of a CBM system and its constituent parts are presented, followed by a description of several related methods that have been developed by LTT/NTUA. In addition to engine performance modeling techniques, these methods incorporate model-based, stochastic and artificial intelligence approaches that can be used for sensor validation, engine component fault diagnosis and compressor washing optimization. Many of these methods have been integrated into stand-alone, customized diagnostic tools in-service today featuring – among others –hot section monitoring, performance data analysis and vibration monitoring.

These techniques have been tested and validated against benchmark cases and implemented in a number of operating gas turbine engines that are presented in the paper.

The examined case studies demonstrate that advanced diagnostic methods can efficiently detect gas turbine malfunctions in an automated way and at an early stage of their appearance, both essential features in real-world applications.

NOMENCLATURE

CBM	condition-based maintenance
PNN	Probabilistic Neural Networks
P3	Compressor delivery pressure
CDP	Compressor delivery pressure
T2	Engine Inlet Temperature
T3	Compressor delivery temperature
CDT	Compressor delivery temperature
W	Air flow rate
EGT	Exhaust Gas Temperature
Ngen	Gas Generator rotational speed
VSV	Variable Stator Vanes
IGV	Inlet Guide Vanes
Wf	Fuel flow rate
N	Compressor Speed
TET	Engine Load
fi	i-th health parameter
ΔX	Percentage deviation (delta) of quantity X from its nominal value
ACC	Active Clearance Control
SVA	Stator Vane Actuator
dT_i	normalized temperature difference at i-th burner circumferential position
HPT	High Pressure Turbine
HP	High Pressure
q_c	corrected compressor flow rate
q_{CT}	corrected core turbine flow rate
n_{pc}	compressor polytropic efficiency

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n_{isCT} core turbine isentropic efficiency
n_{isPT} power turbine isentropic efficiency
q_{PT} corrected power turbine flow rate
X_{ref} Reference value of quantity X

INTRODUCTION

One of the major challenges for Gas Turbine users is to ensure high level of engine availability and reliability, and efficient operation during their complete life-cycle. For this purpose, various maintenance approaches have been introduced over the years.

Historically, the earliest maintenance approach of machinery equipment is the so-called *Breakdown Maintenance* or *Run to Failure*, according to which maintenance actions are taken only after breakdown. A later and more advanced maintenance approach, the *Preventive Maintenance* or *Scheduled Maintenance*, involves maintenance actions after specific time intervals of operation, regardless the condition of the engines. Nowadays, due to increased complexity of Gas Turbine plants along with higher safety standards and lower profit margins, a move from traditional maintenance approaches to more reliable and cost-effective maintenance approaches, is required. This leads to *Condition-Based Maintenance (CBM)*, where maintenance actions are taken according to the actual condition of the operating engines, which is assessed through appropriate condition monitoring procedures.

According to Jardine et al. (2006): *"CBM is a maintenance program that recommends maintenance actions based on the information collected through condition monitoring. CBM attempts to avoid unnecessary maintenance tasks by taking maintenance actions only when there is evidence of abnormal behaviors of a physical asset"*.

An overview of the CBM approach is shown in Figure 1. In general, it consists of three main parts (Jardine et al. 2006, Vachtsevanos et al. 2006): The Data Acquisition part, where data are acquired from the engines under monitoring; The Data Processing part, where the acquired data are validated, corrected and transformed properly according to the requirements of the decision-making techniques that follow; The Decision Making part, where diagnostic and prognostic methods and techniques are applied to available data to analyse the current health condition of the engines, estimate the potential future development of the degradations and recommend maintenance plans.

In the heart of a CBM tool lies a model. The presence of a model, well adapted to the engine at hand, is vital for efficient CBM.

Over the years, many researchers have proposed and developed methods and techniques covering all these aspects of CBM. A good review of the topic can be found in Jardine et al. (2006), Vachtsevanos et al. (2006), Li (2002) and Marinai et al. (2004).

In this paper, a number of CBM related methods, techniques and tools, developed over the last two decades by the research group of the Laboratory of Thermal Turbomachines at the National Technical University of Athens (LTT/NTUA), are presented along with a number of case studies, where these methods were implemented in a number of gas turbine engines in the field.

CBM RELATED TECHNIQUES AND TOOLS DEVELOPED BY LTT/NTUA

The research group of the Laboratory of Thermal Turbomachines of the National Technical University of Athens (LTT/NTUA) is active for more than 25 years in the field of gas turbines condition monitoring and diagnostics. The research activities of LTT/NTUA group expand to the whole range of the CBM area and have resulted in the development of a large number of methods and techniques, as well as complete monitoring and diagnostic systems that are in use.

Starting from the front end of a diagnostic system, methods allowing sensor validation and sensor fault diagnosis have been developed. Among them, there are Pattern Recognition Methods (Aretakis et al., 2004), Model-based methods through appropriate optimization techniques (Kamboukos and Mathioudakis, 2006) and Probabilistic Neural Network based methods (Romessis and Mathioudakis, 2003) that allow the detection, isolation and identification of sensor faults, even at the simultaneous presence of engine component faults.

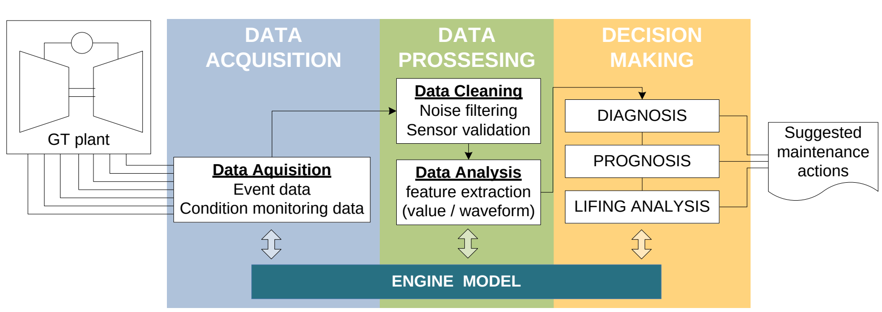

Figure 1. Overview of CBM approach

Further, a number of model-based diagnostic methods have been introduced by the group, varying from Adaptive Performance Modeling methods (Stamatis et al., 1990), Deterioration Tracking methods (Mathioudakis et al., 2002) allowing the estimation of engine health parameters during gradual deterioration of its components performance, a combinatorial approach (Aretakis et al., 2003) and an optimization technique (Kamboukos et al., 2004) that both handle efficiently the problem of estimating engine health parameters from a limited set of measurements, along with a performance model 'zooming' for in-depth component fault diagnosis (Aretakis et al., 2011). A number of developed diagnostic methods have been applied in cases where Waveform Type data were available, including Pattern recognition Methods (Aretakis and Mathioudakis, 1998), Wavelet analysis (Aretakis and Mathioudakis, 1997) and Stochastic approaches (Kyriazis et al., 2006).

A wide range of developed methods falls into the category of Artificial Intelligence approaches, such as methods based on Bayesian Belief Networks (Romessis and Mathioudakis, 2006), Probabilistic Neural Networks (Romessis et al., 2001), Fuzzy Logic (Kyriazis et al., 2011) and Neural networks based methods for diagnosis through engine emissions (Romessis and Mathioudakis, 2007). In recent years fusion approaches have also been developed incorporating principles of the Dempster-Schafer theory (Romessis et al., 2007), Probabilistic Neural Networks and Fuzzy logic (Kyriazis and Mathioudakis, 2009). In the area of prognostics incorporating maintenance policies, LTT/NTUA has recently proposed a procedure for compressor washing economic analysis and optimization (Aretakis et al., 2012).

These methods and techniques support a number of CBM software that have been developed so far. A typical example is EGEFALOS software (Tsalavoutas et al., 2000) that allows condition monitoring and fault diagnosis on Gas Turbines and so far is in operation on a FIAT TG-20 and an ABB-GT10 gas turbine.

Currently, a package allowing condition monitoring, diagnosis and prognosis for a 334MW CCGT comprising two PG9171 GE gas turbines and one SST-900 Siemens steam turbine, is under development.

This is a software tailored to the needs of the users, with a Graphical User Interface (GUI) familiar to them. Among other things, this software allows:

- Online plant overview
- Gas turbines and Steam turbine simulation and diagnosis (Figure 2)
- EGT monitoring (Figure 3)
- Compressor washing optimization
- Sensor fault diagnosis

APPLICATION EXAMPLES

The aforementioned methods and tools have been tested and validated against benchmark cases and implemented in a number of operating gas turbine engines. Cases representative of the potential of the methods developed are presented below.

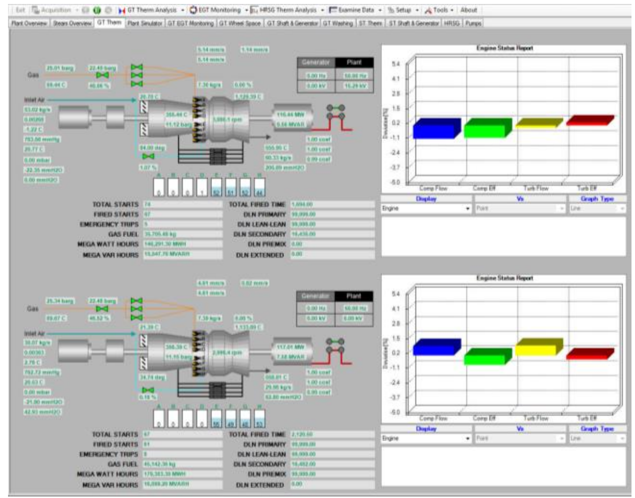

Figure 2. Gas turbines diagnostic feature of the CCGT condition monitoring software

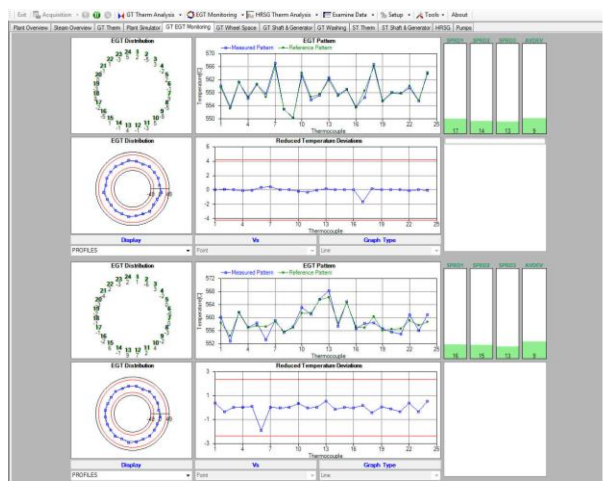

Figure 3. EGT monitoring feature of the CCGT condition monitoring software

Sensor fault diagnosis using Probabilistic Neural Networks

The method of Probabilistic Neural Networks (PNN) for the diagnosis of engine sensors malfunctions, introduced by Romessis and Mathioudakis (2003), has been applied in data acquired by a 16MW Sulzer Type-10 industrial gas turbine. This is a twin shaft engine with one 10-stage axial compressor and two 2-stages axial turbines.

The examined data consists of a series of measurements acquired during a period of one month of operation at thirty minute intervals. Right at the beginning of this period, the engine has followed scheduled maintenance and, thus, the engine was considered to operate in its reference fault-free condition.

Measurements available for condition monitoring are: Compressor delivery pressure (*P3*), Compressor delivery temperature (*T3*), Air flow (*W*), Exhaust Gas Temperature

(*EGT*) and Gas Generator rotational speed (*Ngen*). Input to the PNN is the percentage deviations (also called 'deltas') of these measurements from their nominal value, which are shown in Figure 4.

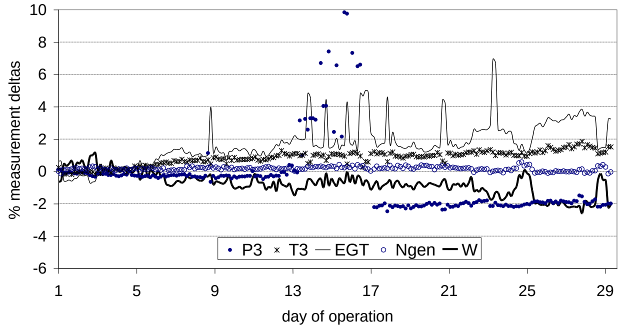

Figure 4. Deviations of a series of acquired measurements (Romessis and Mathioudakis, 2005)

From this figure, one can see that the deviation of the measurements increases with operation time, due to the growing fouling on the blades, while there is a significant deviation of *P3* from the 13th to the 17th day of operation of the engine. (for clarity, only deviations that lie within the limits of -6% up to +10% are shown. However, there are a few points, from the 13th to the 17th day, where the deviation of *P3* exceeds the limit of +10%).

Given the input information described above, the PNN method estimates which deviations of the measurements are due to sensor fault. In Figure 5 both the estimated biases of *P3* sensor and the deviations of its measured values are shown.

From this figure it can be concluded that the PNN method indicates that from the first day of operation and until the 13th day, there is no fault on the P3 sensor. From the 13th day and until the 17th day of operation, however, a bias varying between +4% and +40% is detected. After the 17th day and until the end of the period of measurements, the deviation of -2% of the *P3* measurement has been detected as a bias of -2% and -1% on the *P3* sensor.

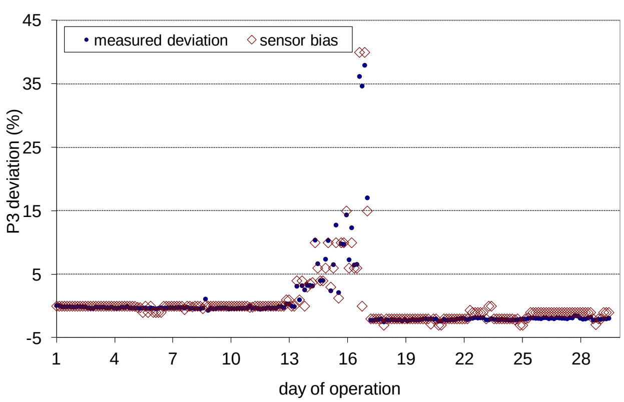

Figure 5. Estimated biases of *P3* sensor and deviations of its measured values (Romessis and Mathioudakis, 2005)

For the remaining four measurements used for monitoring no sensor bias has been detected. For instance, Figure 6 shows the estimated biases of *W* measurement and the deviations of its measured values.

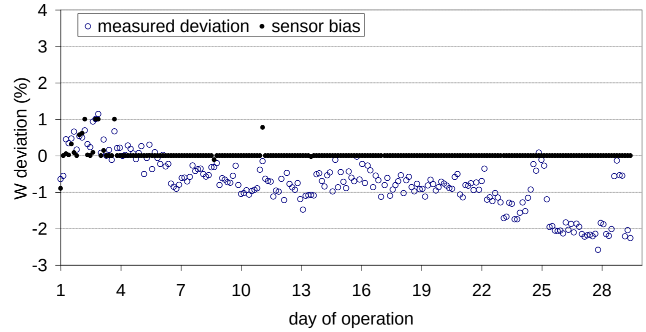

Figure 6. Estimated biases of W and deviations of measured values (Romessis and Mathioudakis, 2005)

This figure shows that although there is a deviation of the measured values of the air flow (*W*), caused by a growing compressor fouling, the PNN method correctly concludes that there is no bias.

This case study demonstrates that the specific method allows sensor malfunctions diagnosis, even at the simultaneous presence of engine components performance degradation. The specific application has been described in more detail by Romessis and Mathioudakis (2005).

Variable geometry system fault diagnosis using adaptive performance modeling

The influence of faults in the variable geometry (variable stator vanes - VSV) system of a multistage axial compressor, on the performance of an industrial gas turbine and the possibility of their diagnosis has been investigated by Tsalavoutas et al. (2000). The TORNADO gas turbine was the engine used as the test vehicle. The engine consists of 4 main modules, a compressor, a combustor, a core turbine and a power turbine. In the current series of tests the engine was operated in the single shaft configuration.

The test program was performed on an engine development test bed. For the aerothermodynamic-performance measurements, the standard instrumentation of the test bed was used. The data have been acquired with the engine data logging system. Locations at which measurements were performed are shown in Figure 7.

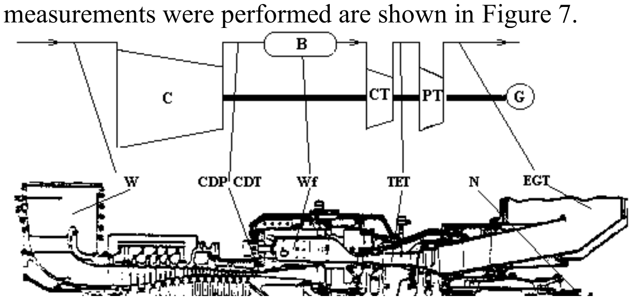

Figure 7. TORNADO engine layout and measured quantities

An investigation has been conducted, in which several variable guide vane faults were implanted into the engine by making adjustments to the linkages of one or more vanes. The performed adjustments were restricted in magnitude to be within operational limits.

The location and the magnitude of the implanted fault was selected in such a way that the performed tests are representative of faulty cases that were either reported by engine users or are very possible to occur. A list of the performed tests is given in the Table 1.

Test No.	Description	Details
1	Datum Test	Healthy Engine
2	IGV Fault	1 vane mistuned by 10°
3-5	Stage-1 Fault	1 vane mistuned by 5°, 10°, 15°
6-8	Stage-1 Fault	3 vanes mistuned by 5°, 10°, 15°
9	Stage-4 Fault	1 vane mistuned by 10°
10	Stage-4 Fault	2 vanes mistuned by 10°
11	Datum Test	Healthy Engine

Table 1. List of performed tests of VSV faults

An analysis of the obtained measurement sets was performed by employing the adaptive performance modeling method introduced by Stamatis et al. (1990), for fault detection and identification. This method considers an engine model that utilizes a set of health parameters that characterize the performance of engine components. The considered health parameters are the following:

Compressor: $f1 = \frac{q_c}{q_{cref}}$, $f2 = \frac{n_{pc}}{n_{pcref}}$ (1)

Burner: $f3 = \frac{BPL}{BPL_{ref}}$, $f4 = \frac{n_b}{n_{bref}}$ (2)

Power Turbine: $f5 = \frac{q_T}{q_{Tref}}$, $f6 = \frac{n_{isT}}{n_{isTref}}$ (3)

In the above relations, q_c and q_T are the corrected compressor and turbine flow rate, respectively, n_{pc}, n_b and n_{isT} is the compressor polytropic efficiency, burner efficiency and the turbine isentropic efficiency, respectively. *BPL* is the burner pressure loss which is defined as the ratio of burner's output pressure to the pressure on its input, while the *ref* subscript refers to reference values.

Available measurements are air flow rate (*W*), compressor delivery pressure (*CDP*) and temperature (*CDT*), fuel flow rate (*Wf*) and exhaust gas temperature (*EGT*). Compressor speed (*N*) and engine load (*TET*) defines the engine operating point.

Diagnosis of a fault existence and possible identification of its kind is facilitated if factors *f1* and *f2*, estimated by the adaptive performance modeling method, are cross-plotted on compressor diagnostic plane (plane that characterizes the compressor condition). A cross plot of the evaluated deviations of the factors *f1* and *f2* is given on Figure 8.

All points move in the same direction away from the nominal point (point [0,0]), while the distance from the origin reflects the fault severity.

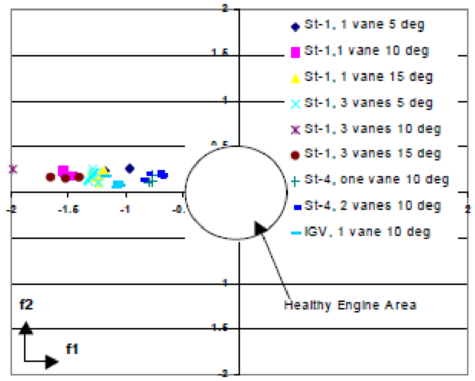

Figure 8. TORNADO compressor diagnostic plane (Tsalavoutas et al., 2000)

All faults are manifested as a decrease in pumping capacity of the compressor, while its efficiency remains practically unaltered. Looking at the turbine diagnostic plane presented in Figure 9 we can see that the points are much closer to the origin while there is no visible trend of displacements.

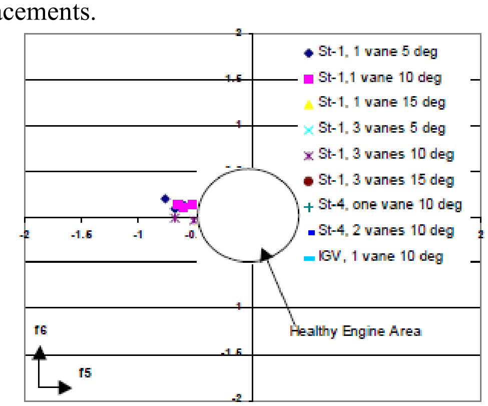

Figure 9. TORNADO turbine diagnostic plane (Tsalavoutas et al., 2000)

Thus we can state that in all cases there is a clear fault signature that can be used for fault identification. It is difficult however to distinguish the particular faulty vane configuration. The implanted faults belong to the class of compressor fault and thus, as it was expected only the compressor modification factors exhibit a systematic change.

Burner malfunctions identification using a pattern recognition approach

A method for analyzing the circumferential temperature pattern measured at the turbine exit has been developed and applied to data acquired from the TORNADO gas turbine mentioned in the previous case study, for the detection of burner malfunctions. Available data represent cases of implanted burner faults and cases of fault free operation of the burner, as well. The implanted fault was a restriction of fuel flow in individual burners, representing a realistic undesirable burner fault. The faults were implanted by acting on the fuel supply of each burner, at three levels of Severity, namely by blocking (a) the primary fuel nozzle (approximately 7% of fuel), (b) the main fuel nozzle, (c) both nozzles, with the engine operating at a specific load. Temperature patterns are measured by 16 thermocouples placed in the duct between the two turbines.

The main techniques currently employed for temperature profile monitoring are: temperature spread monitoring and deviations from average monitoring. However, both parameters constitute a global index and do not necessarily reflect pattern changes. They are, therefore, unable to give any indication of the presence of a fault causing this deviation. This can be seen in Figure 10, where the temperature spread modification due to the introduction of the burner faults is shown. We notice that in the two more severe faulty cases, there is a significant increase of temperature spread, which is in proportion to the fault severity. On the contrary, in the case where the primary fuel nozzle is blocked, there is no change in the spread. This last case constitutes an actual example of a situation where monitoring the spread cannot provide information for the detection of a fault.

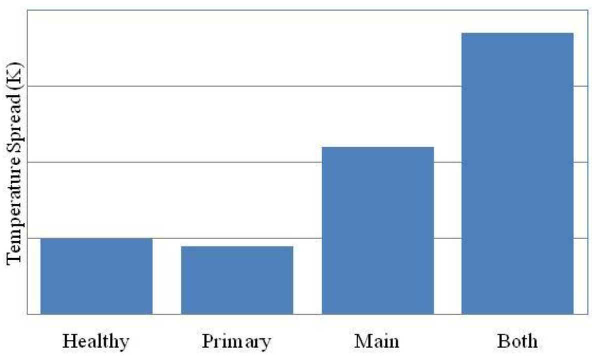

Figure 10. Normalized temperature profile deviations for all examined cases (Tsalavoutas et al., 1996)

In order to identify burner faults, a pattern recognition approach has been introduced by Tsalavoutas et al. (1996).

According to this method, temperature patterns are obtained from sensors placed at certain circumferential locations that correspond to a discrete spatial sampling of the continuous temperature distribution. Changes of this distribution will produce changes of the pattern. The distribution can change due to two reasons: (a) change of operating condition, mainly determined by power output requirements, (b) engine faults. At defined operating conditions, the temperature pattern has a specific form for a particular engine. When a burner fault occurs, the temperature pattern will be distorted at the exit of the combustion chambers, due to the geometrical changes imposed by the fault occurrence. The effect will be localized mainly at the exit of the burner influenced, and the differentiation caused will propagate through the turbine, subjected to its filtering effect. Detection and identification of the burner fault would then be possible from appropriate observation of the change in the pattern itself.

The temperature registered by each sensor is normalized by the average temperature and then compared to a reference one, representing healthy operation of the engine, giving thus a pattern of normalized temperature differences (dT_i). A burner fault occurs when this pattern exceeds a predefined threshold.

The results of the application of the pattern recognition method are presented in Figure 11. As we can see, in all examined faulty cases a number of evaluated differences exceed the threshold, resulting in a correct detection of a fault occurrence.

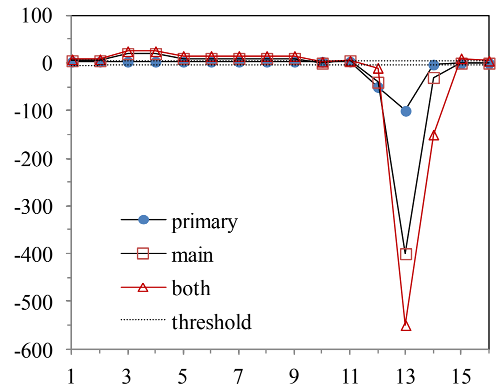

Figure 11. Normalized temperature profile deviations for all examined cases (Tsalavoutas et al., 1996)

This case study is described in more detail by Tsalavoutas et al. (1996), where it is further documented that by applying pattern processing techniques, it is possible to identify burner faults even of a small extent, which would remain unnoticed when using traditional approaches.

Turbine fouling diagnosis using adaptive performance modeling

The diagnosis of turbine fouling in a twin-shaft industrial gas turbine with 21 Mw nominal output, used for electricity production in a power station, is demonstrated (Stamatis et al., 1999). The turbine suffered from the formation of deposits on gas generator and power turbine blades, very soon after it was put on operation, as shown for example in Figure 12. A remedy action taken by the manufacturer was a small restaggering (opening) of power turbine stationary blades.

In Figure 13 corrected EGT is plotted versus corrected load. Data points corresponding to operation with compressor turbine and power turbine blades covered with deposits are clearly out of the band within which data points for clear condition lay. This figure indicates abnormal operation, but gives no information at all, about what the nature or reason of the abnormality is.

An easy and reliable way of identification of the malfunction of the engine is provided by the method of adaptive modeling. The technique has been applied to the available test data and it gave a clear picture of the problem.

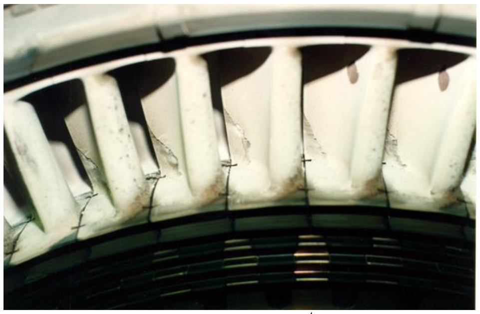

Figure 12. High Pressure Turbine 1st rotor blades (Stamatis et al., 1999)

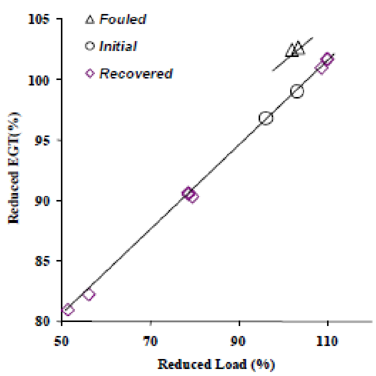

Figure 13. Corrected EGT vs Corrected Load –Before and after intervention (Stamatis et al., 1999)

For the application of the adaptive modeling method, the following health parameters related to main engine components condition can be introduced:

Compressor: $f\,1 = \dfrac{q_c}{q_{c\,ref}}$, $f\,2 = \dfrac{n_{pc}}{n_{pcref}}$ (4)

Core Turbine: $f\,3 = \dfrac{q_{CT}}{q_{CTref}}$, $f\,4 = \dfrac{n_{isCT}}{n_{isCTref}}$ (5)

Power Turbine: $f\,5 = \dfrac{q_{PT}}{q_{PTref}}$, $f\,6 = \dfrac{n_{isPT}}{n_{isPTref}}$ (6)

In the above relations, q_c, q_{CT} and q_{PT} are the corrected compressor, core turbine and power turbine flow rates, respectively, n_{pc}, n_{isCT} and n_{isPT} is the compressor polytropic efficiency and the core and power turbine isentropic efficiency, respectively. The *ref* subscript refers to reference values.

Comparison of health parameters deviation obtained from data from the initial condition of the engine and after the presence of the problem was detected, is shown in Figure 14. It is clearly shown that the swallowing capacity of both turbines has been significantly reduced, as factor *f3* shows a reduction of more than 1,5% and *f5* more than 3%. The reduction in *f1* (of ~0,8%) indicates that the compressor has also suffered some deterioration.

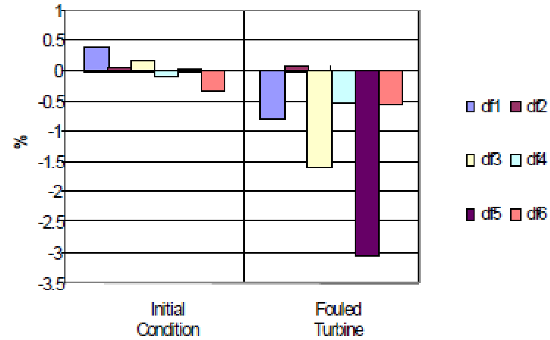

Figure 14. Health Indices Percentage deviation, for a gas turbine, which has suffered severe turbine fouling (Stamatis et al., 1999).

It was further possible to analyze the rate of deterioration, by processing data over the first month of operation. The evolution of the power turbine swallowing capacity factor *f5* is shown in Figure 15. The data points on this figure are produced by applying the adaptive model to each data set available. A trend line is drawn through these points. It is observed that deterioration has happened very fast, during the first month of operation.

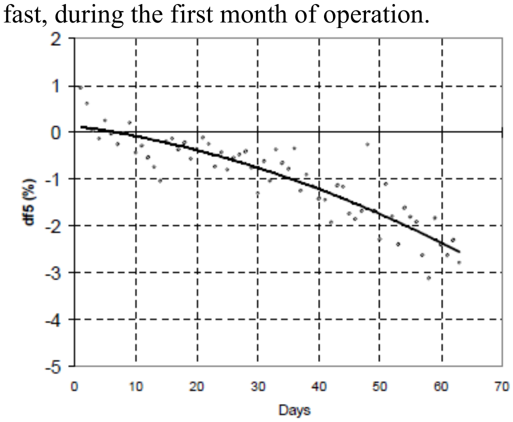

Figure 15. Evolution of power turbine degradation over the initial period of engine operation (Stamatis et al., 1999)

Compressor fouling diagnosis using adaptive performance modeling

Detection of compressor fouling and assessment of cleaning effectiveness is described (Mathioudakis et al., 2001). This case refers to a twin shaft gas turbine similar to the one presented in the previous test case, operating in a distillery, moving an electricity generator, while feeding flue gas to a steam generator, producing process steam. A typical problem for such an engine is compressor fouling, which is being taken care of through regular compressor washing.

A way to detect compressor fouling is through monitoring compressor efficiency that can be estimated by adaptive modeling. This approach has the advantage –over other methods of estimating compressor efficiency over time– that is not affected by load variations (Mathioudakis et al., 2001). Compressor efficiency versus time is presented in Figure 16. The gradual drop of efficiency over time is attributed to compressor fouling. Application of a compressor wash is seen to restore compressor efficiency.

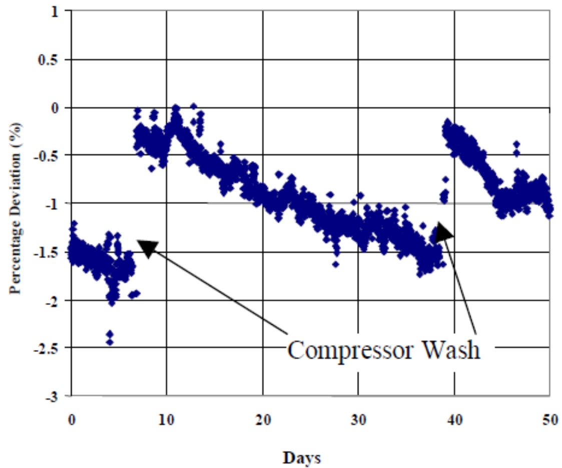

Figure 16. Example of the variation of compressor efficiency, derived by employing adaptive modeling. (Mathioudakis et al., 2001)

Aretakis et al. (2012) go one step further, where adaptive performance modeling is coupled with a detailed cost analysis module to predict the impact of the compressor washing process on the power plant revenue, allowing for the optimization of the process with regards to power plant specific data. This approach is applied for the case of an aeroderivative gas turbine of 42 MW.

In Table 2 the economic comparison among the proposed (optimized) approach and other approaches usually followed for compressor washing is presented for the reference case, assuming varied degradation rate throughout the year.

A/A	Washing strategy	No. of washings	Total profit (M$)	Change (%)	Change (k$)
1	Optimized	14	2.559	0	0
2	Typical equidistant	12	2.550	−0.359	−9.2
3	5% Power loss	15	2.553	−0.250	−6.4
4	4% Power loss	19	2.540	−0.752	−19.2
5	10% Power loss	7	2.475	−3.320	−85.0

Table 2. Comparison of different washing strategies (Aretakis et al., 2012)

Besides the proposed optimized approach, other approaches involve a predetermined limit on the allowable power loss prior to washing, while another approach is the utilization of washing once per month, independently of the economics and the power loss.

From the economic figures it is evident that the washing strategy adopted can have an impact on the plant revenue. Specifically the loss of potential gain varies from 6400$ in the case that the predetermined power loss criterion results to a number of washings close to the optimum, to 85,000$, when the power loss criterion results to a number of washings far from the optimum one.

Turbine subsystem malfunction identification from on-wing data

In this case study, presented by Aretakis et al. (2014), different approaches to engine health assessment are applied on on-wing data obtained from a commercial aircraft engine. This is a high bypass ratio turbofan engine of a commercial short-range aircraft, equipped with a set of measurements that can be used for condition monitoring. The engine stations and the available measurement set are depicted in Figure 17. The number of engine cycles (a cycle is one flight from take-off to landing), Active Clearance Control (*ACC*) valve position and Stator Vane Actuator (*SVA*) position are also available. The available measurements cover almost a year of operation, corresponding to 1100 cycles.

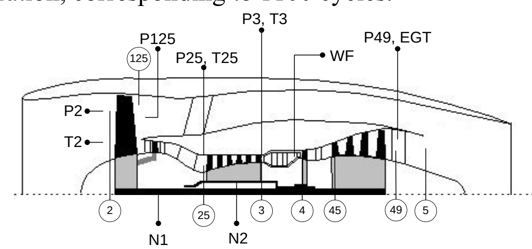

Figure 17. On-wing available measurements

The simplest approach that can be followed for engine health assessment is to use available measurements in order to acquire measurement trends. For our case, firstly, the measurements are corrected for the inlet conditions to reduce the variation in the raw data information stream. Indicatively, the Exhaust Gas Temperature (*EGT*) value changes throughout operation is presented in Figure 18, corrected and uncorrected.

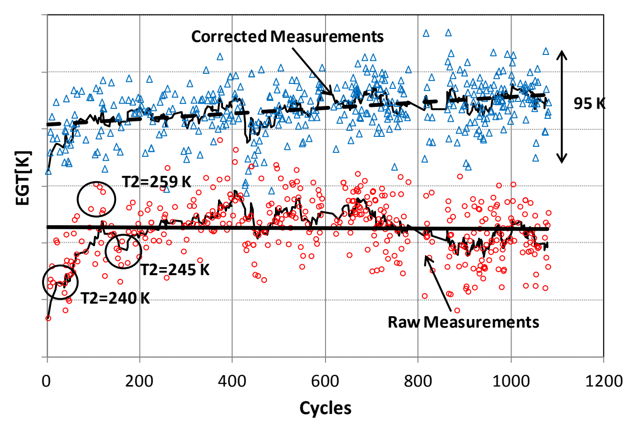

Figure 18. Raw and corrected EGT variation with engine flight cycles (Aretakis et al., 2014)

It is evident that raw measurements do not provide any information since they include both operating point and ambient conditions effects as can be seen from the indicative values of engine inlet temperature (*T2*) in the figure. Measurement correction enhances measurement quality and a deterioration trend is observable. Although corrections improve measurement quality by reducing the ambient conditions effect, the operating condition effect is still present in the engine health parameters.

For this reason, the change of each measurement against a reference value of the corresponding parameter at the same operating point should be calculated. This reference value can be obtained from an engine model representing "healthy" operation.

The corrected engine measured parameters are correlated with the corrected fan rotational speed using the data from the first 50 flight cycles. In this way, a linear "model" is created for each operating condition and measured parameter. Having established a suitable reference, the percentage deviation (deltas) of the measurements from their reference value can be computed.

In Figure 19, the *EGT* deltas (ΔEGT) are depicted, along with its exponential average. It is apparent that the deltas contain information that was not visible when only measurement correction was applied. Specifically, there are three sudden shifts on the observed parameter. The deterioration rate appears unaffected by the cause of these shifts while shift 2 indicates an improvement in engine performance (decrease of *EGT*). The sudden shifts may indicate a single component fault.

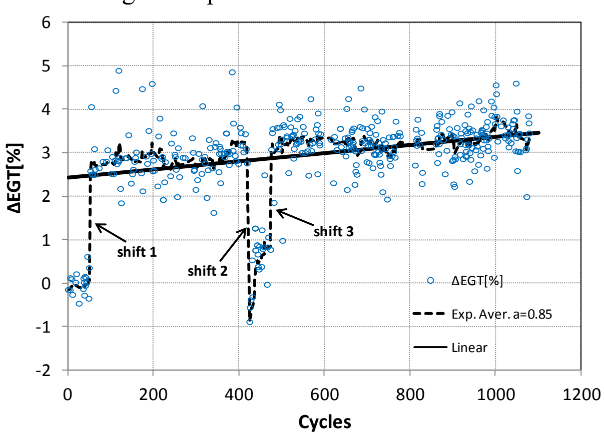

Figure 19. ΔEGT vs. flight cycles (Aretakis et al., 2014)

Although a potential component fault is detectable with this health parameters based type of analysis, neither the cause of performance trend shifts can be identified nor information about the deteriorated components can be determined.

For this reason, existing model-based methods can be used. The methods used are the Probabilistic Neural Network (PNN) method already mentioned before in a previous test case and the Deterioration Tracking Method introduced by Mathioudakis et al. (2002) and allows estimation of health parameters deviation, through an appropriate optimization approach. Both methods are supported by an engine performance model adapted to the specific engine using as additional off-design points in the calculations the cruise data from the first 50 cycles (representing healthy engine condition). The use of an engine specific model, as opposed to a generic model, leads to more accurate engine condition assessment, as stated by Aretakis et al. (2014).

The results of the PNN method are presented in Figure 20. In this figure, the estimated by the PNN probability that an HPT fault occurs for each engine cycle is shown. Figure 21 shows the estimated deviations of engine health parameter *SE4* (representing the HP turbine efficiency) for each engine cycle, provided by the Deterioration Tracking method. From these figures and regarding the sudden performance shifts, we note that both methods give a clear indication of High pressure (HP) turbine fault.

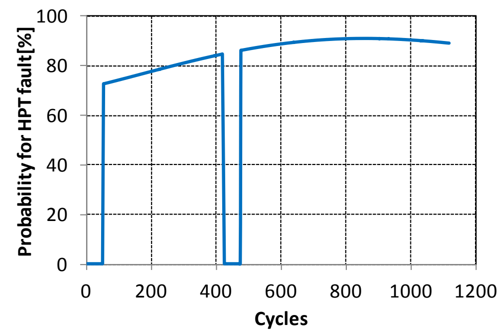

Figure 20. PNN results (Aretakis et al., 2014)

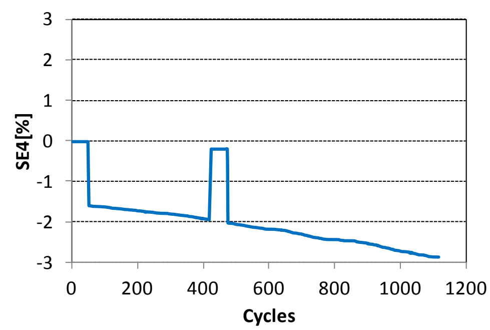

Figure 21. The Deterioration tracking method results (Aretakis et al., 2014)

From the above it can be concluded that the fault is probably connected to an HP turbine sub-system. The specific engine is equipped with Active Clearance Control (ACC) where air from the bypass is bled and circulated around the external casing of the HP turbine for cooling it, restricting its expansion and decreasing the tip clearance during steady state operation (not during take-off).

A failure of the bleed valve is expected to cause increased tip clearances, thus decreasing HP turbine efficiency, as detected by the deterioration tracking method.

Indeed, this was confirmed by the ACC valve position recordings, which are shown in Figure 22 in conjunction with ΔEGT evolution. It is observed that the ACC is closed everywhere except the regions of the step changes.

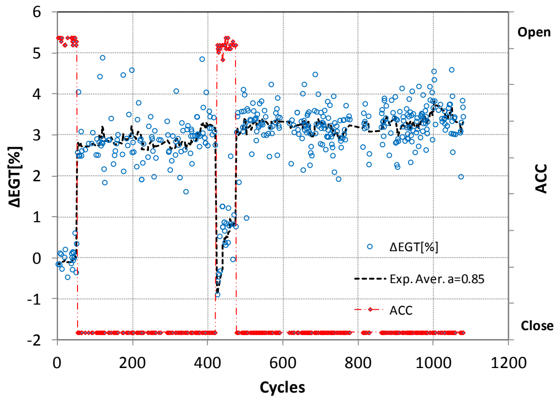

Figure 22. ACC valve position recordings (Aretakis et al., 2014)

SUMMARY–CONCLUSIONS

In this paper an overview of methods and tools developed by the research group of the Laboratory of Thermal Turbomachines at the National Technical University of Athens has been demonstrated, together with some real world applications of these methods.

The developed methods expand to the whole range of the CBM area and rely on aerothermodynamic measurements and waveform type data acquired from the engine. These methods and techniques support CBM software platforms that have been developed so far and are in service today.

Application of these tools and methods on a number of operating engines, stationary and aircraft, for the detection of compressor and turbine fouling, burner malfunctions, engine subsystem faults, demonstrate that advanced diagnostic methods can lead to efficient engine health assessment. Efficient health assessment is crucial for applying corrective actions such as compressor washing and further implementing prognostic methods.

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