CONDITION-BASED MAINTENANCE FOR GAS TURBINES PLANTS

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Abstract
Condition-Based Maintenance (CBM) is a maintenance approach for machinery and industrial equipment, where decisions are made based on the current condition of the asset, the operation of which is monitored. A CBM program consists of three parts: Data Acquisition, Data Processing and Decision Making, where the last one can further be divided into a Diagnostic part and a Prognostic part. This paper attempts an overview of the concept of CBM in the field of Gas Turbines. A review of certain key methods and techniques is provided, along with some existing commercial tools. Through this review, the benefits of incorporating CBM policies into Gas Turbine plants are revealed and the areas where future research should focus on are highlighted.

1 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. [1]: “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”.

In general, a CBM program consists of three main parts [1], [2]:

- The Data Acquisition part, where data are acquired from engines under monitoring;
- The Data Processing part, where the acquired data are validated and transformed properly according to the requirements of the decision-making techniques that follow;
- The Decision Making part, where a number of methods and techniques are applied to
the available data to obtain the current health condition of the engine and recommend maintenance plans.

The aim of the paper is to provide a comprehensive review of existing CBM tools, techniques and procedures. This review tries to reveal both the importance of incorporating CBM approaches into gas turbine plants and the fields where relevant future research should be focused on. Thus, the structure of the paper is as follows. A brief review of existing tools, methods and techniques related to CBM is given in Section 2. Methods developed by the research teams in the Laboratory of Thermal Turbomachines of National Technical University of Athens (LTT/NTUA) and the Department of Power and Propulsion of Cranfield University (CU) are also described in the same Section. Some existing commercial CBM programs are described in Section 3. Finally, a summary, discussions, conclusions and potential future research in the area are provided in Section 4.

2 BRIEF REVIEW ON CBM METHODS AND TECHNIQUES

This section provides a brief review of existing methods and practices covering all aspects of CBM, organized into sections representing the three parts of a CBM program. A more in-depth review can be found in [1], [2] and [3].

2.1 DATA ACQUISITION

The first part of a CBM program is related to Data acquisition, which is the process of collecting and storing useful information from engines for CBM purposes. There are two types of data that can be acquired; Event Data and Condition Monitoring Data. Event data include all historical data and records of the targeted gas turbine engines, such as history of faults, breakdowns, repairs, overhauls etc., while Condition Monitoring Data consist of all acquired measurement along the operating engines, indicative of its current operating and health condition.

Although the majority of available CBM methods and techniques rely only on Condition Monitoring Data, Event Data are equally important to efficient CBM, as stated by Jardine [1]. However, Event Data are not acquired usually in an automated way and therefore, manual data entry is required.

Condition Monitoring Data are normally collected by using available instrumentation on gas turbine engines: vibration measurements through accelerometers, velocity pick-ups and displacement sensors; pressure measurements at various gas path stations of the engines through pressure transducers; temperature measurements through thermocouples and/or resistance temperature detectors; shafts speed measurement; lube oil measurements (pressure, temperature, corrosion through corrosion probe); fuel system measurements through water capacitance probe, corrosion probe, and Btu detector; exhaust gas analysis; torque measurements; ambient conditions measurements, namely ambient pressure, temperature and relative humidity. A more detailed description on gas turbine condition monitoring measurements, sensors and sensing strategies are given in [1] and [4].

2.2 DATA PROCESSING

The second part of a CBM program is data processing, which can be divided into two main processes; Data Cleaning and Data Analysis.
2.2.1 Data Cleaning

Data cleaning is the first step of data processing. At this step the acquired measurements are filtered to reduce measurement noise and validated, through appropriate sensor validation techniques. Measurement noise can be significant and can alone lead to wrong assessment of engine health condition. Thus, data processing to reduce measurement noise, called noise filtering, should always be applied. A good summary of state-of-the-art noise filtering techniques and related signal processing processes is given in [2].

Existence of a sensor malfunction may mislead a CBM program. Thus, application of appropriate sensor validation techniques is common to CBM. These techniques aim at detecting and isolating any possible sensor fault, while more modern techniques allow also an estimation of the underlying sensor bias. Over the years, several types of Sensor Validation techniques have been proposed by many researchers, such as analytical redundancy methods [5], approaches related to Kalman filter [6] or Fuzzy Logic methods [7] and Artificial Neural Networks [8]-[12].

2.2.2 Data analysis

The second step of data processing is Data analysis. At this step acquired measurements are further processed in order to extract useful information that can be used at the Decision Making part of CBM for diagnostic and/or prognostic purposes. For this reason, this step can also be found in literature under the term ‘feature extraction’. The main principles of data analysis and signal processing techniques usually applied are described in [2].

Data analysis approaches strongly rely on the nature of available data. Condition monitoring data are versatile and can be grouped into two main categories [1]:

- **Value type**, where data of a condition monitoring variable is acquired in the form of single values. For example, temperatures and pressures along the engine gas path during operation are all value type data.
- **Waveform type**, where data of a condition monitoring variable is acquired in the form of time series, also called time waveform. For example, vibration data and acoustic emissions data are waveform type data.

**Value Type data**

Feature extraction on Value Type data depends mainly on the problem in concern. A typical approach applied on aerothermal data –which is the majority of Value Type data of Gas Turbines condition monitoring variables –is the estimation of the percentage deviation of a measurement from its nominal value, the co-called Delta of a measurement [13]. For an acquired measurement $Y$ of a condition monitoring aerothermal variable, where its nominal value during a fault-free operation of the Gas Turbine at the same operating conditions is $Y_0$, the Delta ($\Delta Y$) is defined as follows:

$$\Delta Y = \frac{Y - Y_0}{Y_0} \cdot 100\%$$

The use of Deltas has advantages over the use of raw measurements for two reasons. Firstly, the dependence of Deltas on the operating point is very weak when neighboring operating conditions are considered. Secondly, specific Gas Turbines fault conditions result in distinct measurements Deltas and therefore Deltas can act as patterns of specific engine health conditions.
Another issue related to Value Type data, is the Data Reduction. Value type data, although sound simpler than Waveform Type data, usually involve large number of variables, each of them having different degree of correlation with the phenomena of interest. In these cases, Data Reduction Techniques, such as Principal Component Analysis (PCA) and its extension, Independent Component Analysis (ICA), can be applied. A review of Data Reduction techniques can be found in [14], while an example of application is given in [15].

Waveform Type data

There are three main categories of Waveform Type data analysis in the literature: Time-Domain analysis, Frequency-domain analysis and Time-frequency analysis.

In Time-Domain analysis features are extracted directly from the waveform time-series. More traditional approaches rely on the principles of statistical analysis and involve the estimation of parameters, such as: mean values, standard deviations, peak-to-peak intervals, skewness, kurtosis etc. [1]. More advanced approaches involve time-series models, such as Auto-Regressive (AR) models and Auto-Regressive Moving Average (ARMA) models [16].

In Frequency-Domain analysis features are extracted through signal processing in the frequency domain. The most popular analysis is the Spectrum Analysis by means of Fast Fourier Transform (FFT). The most commonly used technique for Spectrum Analysis is Power Spectrum, although other techniques have also been developed, such as Cepstrum, High-Order Spectrum, etc. [17], [18].

Time-Frequency analysis allows feature extraction from Waveform Type data in both the time and frequency domain. This is particularly useful for transient data analysis, which is very common during Gas Turbines operation at the presence of faults [1]. The most commonly used techniques, among others, are: Short-time Fourier Transform (STFT) and Spectrogram [19], which is the power of STFT, Wigner–Ville distribution [20] and Wavelet Analysis [20], [21].

2.3 DECISION MAKING

The third part of a CBM program is Decision Making. This is the part of CBM where the assessment of the health condition of gas turbine plant takes place and also maintenance plans are proposed. This part of CBM covers two areas: Diagnosis and Prognosis. A brief review of available methods and techniques on both areas is given in this paragraph, along with a review on approaches related to Information Fusion. Fusion technique is highly associated with both Diagnosis and Prognosis. In the last few years it has attracted a lot of interests of researchers in CBM practices and therefore it is mentioned separately.

2.3.1 Diagnosis

Diagnosis can be described as a procedure of reasoning to interpret the health condition of machinery equipment using data acquired during its operation. As stated in [2], there is no consensus on the terminology related to Diagnostics. However the following definitions have been adopted by the military and other sectors of industry:

Fault diagnosis is defined as the procedure of detecting, isolating and identifying an impending or incipient failure condition, during which the affected component is still operational even though at a degraded mode.

Failure diagnosis is defined as the procedure of detecting, isolating and identifying a component that has ceased to operate.
Fault (failure) detection, isolation and identification can further be given the following meaning:
- **Fault (failure) detection**: An abnormal operating condition is detected and reported.
- **Fault (failure) isolation**: Determining which component is failing or has failed.
- **Fault (failure) identification**: Estimating the nature and extent of the fault (failure).

There is an extent bibliography on gas turbine diagnostics, containing a large number of methods that have been proposed by many researchers over the years. Existing diagnostic methods can be grouped into three main categories and are reviewed in the following:

**Model-based approaches**

This category includes diagnostic methods where the core tool for diagnostic reasoning is based on engine thermodynamic models, where the relationship among the involved parameters is determined through explicit mathematical and thermodynamic equations. In the field of gas turbines gas path diagnostics, model-based diagnostic approaches rely on engine thermodynamic performance models. Different model-based gas path diagnostic methods have been developed since GPA was first introduced by Urban [22] around 1967. For example, GPA and many of its derivatives were introduced by Urban et al. [23], Voponi [24], Doel [25] and [26], Stamatis et al. [27], Escher and Singh [28], Aretakis et al. [29], Li [30], etc.

**Statistical approaches**

In this category all methods in which diagnostic conclusions are derived mainly through the use of the principles of statistics. These methods are suitable in cases where a large amount of historical records are available or where various health conditions of the engines can be reproduced (e.g. through an engine performance model). In all these cases useful diagnostic information can be extracted through appropriate application of statistics. Moreover, statistical approaches are also able to handle the inherent stochastic nature of the diagnostic problem.

The simplest statistical approaches can deal with fault detection through a classic Hypothesis Test, with null hypothesis $H_0$: ‘Fault $A$ is present’, where the alternative hypothesis is $H_1$: ‘Fault $A$ is not present’. In actual diagnostic problems, however, more advanced statistical approaches are required. The most popular approach is Statistical Pattern Recognition methods, where the acquired set of measurements from an operating engine is compared with measurements sets that result from known engine faults. This is a classification method where an examined case is classified into one of a number of predefined known health conditions of the engine. A typical Pattern Recognition method is described in [29]. Another popular approach that fall into this category is Kalman Filters, where engine health condition is estimated through a recursive statistical processing of measurements time series. A good example of Kalman Filter-based diagnostic methods is described in [31]. Other statistical approaches used for gas turbine diagnostics are Hidden Markov Models (HMM) [32], which is a method based on the Markov Process of probability theory and Support Vector Machines (SVM) [33], which is a classification method.

**Artificial Intelligence (AI) approaches**

AI methods for gas turbine diagnosis have become very popular since more than a decade ago due to many reasons. For example, many AI methods are capable of reasoning and revealing the cause-effect relationship among observable measurement and non-
observable health parameters when the functional relationship between them is unknown or incomplete. Another reason is their ability to deal efficiently with large systems where lots of parameters may be involved and vast amount of calculations may be required, but the whole calculations may be divided into smaller actions taking place in parallel. Additionally, some AI methods offer higher efficiency in handling stochastic phenomena like those encountered in diagnostic problems.

There are many AI methods that have been developed for gas turbine diagnosis. The most traditional approach is the Expert Systems (ES) where an inference engine consisting of a set of IF-THEN type of rules [34] is used. One of the most popular AI methods is the Artificial Neural Networks (ANN). Different architectures and algorithms of ANNs have been introduced for gas turbine gas path diagnostics, for example, diagnostics using Feed Forward Back-Propagation (FFBP) ANN [35], Auto-Associative Neural Networks (AANN) [36], Radial Basis Function (RBF) networks [37], Probabilistic Neural Network (PNN) [12] and Self-Organizing Maps (SOM) which are unsupervised ANN [38]. A nested neural network approach was introduced by Ogaji and Singh [39]. In addition, Genetic Algorithms (GA) that mimics natural evolution processes is also a popular AI method [40]. Stochastic AI methods widely used are Bayesian Belief Networks (BNN) [41], which are a combination of probability Theory with Graph theory and Fuzzy-Logic that measure the degrees of truth of the involved parameters value [42].

2.3.2 Prognosis

Prognosis can be considered as the procedure of estimating the future health condition of an engine based on past and present information acquired from the engine and/or assessment of its current health condition. Prognosis is practically expressed through the estimation of the Remaining Useful Life (RUL), which is the remaining safe operating time before failure. RUL estimation requires estimation of the fault propagation process and knowledge of the failure mechanism. The fault propagation process is usually estimated through forecasting models and techniques given available historical measurements and health conditions of the engine. The failure mechanism, on the other hand, can be expressed in many ways varying from a simple set of hard limits of selected engine parameters to more sophisticated models (e.g. mathematical model of crack growth).

Compared to Diagnosis, the literature of Prognosis is much more limited. Nevertheless, existing prognostic methods are grouped into three categories, i.e. Model-based approaches [43], Statistical approaches [44], [45] and AI approaches [46].

The ultimate goal of any Prognostic approaches is to suggest maintenance actions and optimize maintenance plans. Maintenance plan optimization is practically a problem of optimizing some key factors, such as safety, risk, cost, reliability, availability etc. The concept of incorporating prognostics into maintenance plans is discussed in [1] while some early work in this area is described in [47] and [48].

2.3.3 Lifing Analysis

Life assessment has always been a major concern to the gas turbine users for both safety and economy considerations. Overestimating the engine’s life could lead to catastrophic incidents and economic losses while underestimating the engine’s life will cause the premature removal of the engine. The large safety margin imposed by Original Equipment Manufacturers (OEM) to ensure safety operations makes the engine’s life estimation too
conservative, which leads to a waste of engine life during engine life span. Moreover, as the life limits provided by the OEMs are normally calculated on the basis of a design envelope of expected base load, calculated mechanical and thermal stresses as a function of the operating condition and the capability of the materials within those conditions, the guidelines do not always address the specific operating environment and requirements of each operator.

Therefore, having the knowledge of how engine life responds to changes in the ambient, operating and health conditions becomes very important as these changes will affect the engine performance parameters and hence alter the engine life. If the changes can be quantified, it will help the users to make informed maintenance decisions, maximise operation effectiveness and thus cut down operating costs.

Many studies have been conducted in order to understand how these changes affect the creep life. While most of them focus on investigating creep life from the ‘material’ point of view, less information is available in the open literatures that discuss the creep life from the ‘performance’, ‘operation’ or ‘change of engine health’ points of view.

Some research focusing on engine creep life consumption due to varying engine operation and health conditions has been published. For example, Tinga et al. [49] examined the degradation effect on the high pressure (HP) turbine blades’ creep life of a turbofan F100-PW-220 engine using an integrated lifing model. Naeem et al. [50] used a lifing model to investigate the degradation effect on the HP turbine blades’ creep life of a turbofan F404-GE-400 engine. Abdul Ghafir et al. have introduced a “Creep Factor” to estimate the creep life consumption of HP turbine of a helicopter engine using a model based approach [51] and an artificial neural network approach [52].

2.3.4 Information Fusion

In the last few years more and more researchers recognize the need of combining multiple sources of information for the CBM needs as relying on a single source of information may lead to inaccurate conclusions (e.g. inaccurate diagnostic conclusions made from a specific diagnostic method) or unreliable condition monitoring (e.g. measurement acquired from a single sensor that may fail or malfunction). Additionally, combining many sources of information may expand the capability of a CBM program (e.g. combining many diagnostic methods, each perform better than the others on diagnosing specific fault conditions).

This combination of information sources is described by the term Information Fusion. Fusion is not a specific part of a CBM program, but a methodology that can be applied to all parts of it. Since it gains a lot of interest lately by the research community, it is described as follows.

Techniques allow Information Fusion can be grouped into three categories depending on the part of CBM they are applied. These are Data-Level Fusion, Feature-Level Fusion and Decision-Level Fusion. Data-Level Fusion refers to techniques allowing fusion of the readings of multiple sensors and resulting in a single value of the measured quantity. A description of the techniques on Data-Level Fusion is given in [2]. Feature-Level Fusion refers to techniques that combine different signal processing approaches and result in a feature extraction incorporating valuable information for the Decision making part of CBM. An example of a Feature-Level Fusion technique is presented in [53]. Decision-Level Fusion, on the other hand, refers to techniques that combine diagnostic/prognostic methods aiming at a more accurate and/or more reliable diagnostic/prognostic conclusions. At the Decision-Level Fusion, there are techniques that combine the results of independently acting methods
(see, for example, [54]) and techniques where one method feeds another, as in [55] for example. Another example of a Decision-Level Fusion approach applied to both diagnosis and prognosis is [56] where an information fusion system for engine diagnostics and health management developed for the P&W F117 engine is described [57].

Information fusion techniques are based on methods like Dempster-Schafer theory [54], Artificial Neural Networks [58], Fuzzy Logic [59] and so on.

2.4 CBM performance metrics

One question that the CBM community should answer is how the performance and effectiveness of CBM systems can be assessed. This question is important since neither commercial nor military standards exist to support a systematic and consistent approach to assessing the performance and effectiveness of CBM technologies and this is recognized as one of the main barriers between the research community and engine users, who are discouraged in investing and incorporating CBM systems into their plants [2].

Performance metrics involve well established, generally accepted and independently acting procedures that are able to assess both the technical and economic feasibility of CBM systems. Such procedures should not only allow validation and evaluation of incorporated methods and techniques at all parts of a CBM program (ranging from data acquisition and processing, to fault diagnosis, prognosis, lifting and maintenance planning), but also be able to measure the combined impact of the CBM program, including evaluating both costs and performance of the whole CBM system.

So far, efforts are limited in a number of few benchmark cases proposed by several researchers to allow the evaluation of available diagnostic methods [60], [35], [61]. Evaluation of diagnostic methods has been studied in a more systematic way during the OBIDICOTE project conducted by the European Research Community, where a set of benchmark fault cases have been considered and used by many researchers for diagnostic methods evaluation [62], [40], [55]. This idea has been further supported by the Engine Health Management Industry Review (EHMIR). The EHMIR provided references or theme problems to aid technology development and evaluation. A gas path diagnostic theme and associated metrics for benchmarking the performance of diagnostic solutions resulted from the EHMIR effort is described in [63].

A more detailed discussion on the concept of CBM performance metrics is attempted in [2] where the lack of standards is mentioned and also a number of approaches that can be used as starting points in filling the gap are described. These approaches involve:

- Feature-evaluation metrics
- Fault diagnosis performance metrics
- Prognosis performance metrics
- Effectiveness metrics (diagnosis, prognosis)
- Cost/benefit analysis of CBM

2.5 Contribution of the LTT/NTUA research group

The research group of the Laboratory of Thermal Turbomachines of the National Technical University of Athens (LTT/NTUA) is active for nearly 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 they have resulted in the development of a large number of methods and techniques, as well as complete monitoring and diagnostic systems that are on use.

Suggestively, LTT/NTUA has developed a number of methods allowing sensor validation and sensor fault diagnosis. Among them, there are Pattern Recognition Methods [29], Model-based methods through appropriate optimization techniques [64] and Probabilistic Neural Network based methods [12] that allow the detection, isolation and identification of sensor faults, even at the simultaneous presence of engine component faults. Additionally, LTT/NTUA has developed a number of model-based diagnostic methods, varying from Adaptive Performance Modeling methods [65], [66], Deterioration Tracking methods [13] allowing the estimation of engine performance parameters during gradual deterioration of its components performance, a combinatorial approach [67] and an optimization technique [60], [68] that both handle efficiently the problem of estimating engine performance parameters from a limited set of measurements, along with a performance model ‘zooming’ for in-depth component fault diagnosis [69]. A number of developed diagnostic methods have been applied in cases where Waveform Type data were available, including Pattern recognition Methods [70], Wavelet analysis [21] and Stochastic approaches [71].

A wide range of developed methods falls into the category of AI approaches, like methods based on Bayesian Belief Networks [40], Probabilistic Neural Networks [72], Fuzzy Logic [73] and Neural networks based methods for diagnosis through engine emissions [74]. In recent years fusion approaches have also been developed incorporating principles of the Dempster-Schafer theory [54], [75], Probabilistic Neural Networks [76] and Fuzzy logic [77]. In the area of prognostics incorporating maintenance policies, LTT/NTUA has recently proposed a procedure for compressor washing economic analysis and optimization [78].

The aforementioned methods have been applied successfully for the diagnosis of benchmark fault cases [41] and real implanted faults [79] and a number of CBM software have been developed by LTT/NTUA. Among them, is EGEFALOS software [80] that allows condition monitoring and fault diagnosis and so far is in operation on a FIAT TG-20 and an ABB-GT10 gas turbine. A condition monitoring software has also been developed for the Hellenic Air force, implemented in the J-79 jet-engines test cell. Currently, CBM software 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.

2.6 Contribution of the CU research group

Research in gas turbine gas path diagnostics at Cranfield University was initiated by Prof. Riti Singh and has been carried out around 30 years. It has been supported and funded by several industrial partners, including Rolls-Royce, Manx Electricity Authority (MEA) in the UK and China Aviation Powerplant Research Institute of AVIC in China. Different gas path diagnostic, prognostic and lifing techniques have been developed by the Cranfield team, a large number of technical papers have been published, several patents [81]-[83] have been filed and computer software has been developed. More details of the relevant technologies developed at Cranfield are described as follows.

One of the key technologies for gas turbine gas path diagnostics is the capability of accurate performance modeling of gas turbine engines. Rigorous gas turbine performance modeling techniques, including design and off-design performance modeling [84] with the
consideration of a variety of gas turbine configurations, varying ambient conditions, variable geometries, multiple fuels, water injection, degradation, etc. all implemented in computer program Turbomatch have been developed. More recently, design point performance adaptation [85] and off-design performance adaptation techniques [86], [87] have also been developed in order to adapt engine thermodynamic model to real engine performance due to the very high requirement of accurate performance models for gas path diagnostics.

In gas path diagnostics, different model based and non-model based techniques have been developed over the years, including linear and nonlinear GPA based on Influence Coefficient Matrix [88], [89], Genetic Algorithms based approach [90]-[93], diagnostics using nested Artificial Neural Networks [94], diagnostics using Fuzzy Logic [95], Adaptive GPA [30], diagnostics using non-linear weighted least squares approach [96], diagnostics using Rough Set theory [97], etc. Apart from the above gas path diagnostics where steady state gas path measurement data are used, gas path diagnostics using transient measurement data based on Genetic Algorithms [98] and Artificial Neural Networks [99] have also been developed.

Selection of gas path measurements for gas path diagnostics plays an important role in order to achieve satisfactory diagnostics results and obtain the best possible observability of engine health and performance conditions. The importance of the measurement selection was analyzed in [100] and a measurement selection approach to improve the quality of gas path diagnostics has been developed [101].

Gas path sensors provide essential performance information of gas turbine engines and therefore detection and recovery of failed sensors is one of the critical steps in gas path diagnostics. Different sensor diagnostic approaches have been developed, such as those using Genetic Algorithms [90], [102], Artificial Neural Networks [94], [103], [104], Influence Coefficient Matrix [89], etc.

Gas turbine lifting analysis is also an important part of engine condition monitoring. There are significant amount of research available on engine lifting analysis based on detailed m material information and using finite element approaches. However, those approaches are too complicated and very time consuming, which is not convenient for quick estimation of engine life consumption of gas turbine engines. Therefore, with a focus on creep life, a concept of Creep Factor [51] was introduced to assess the speed of creep lifting consumption and unique gas turbine creep life analysis approaches using a model based method [50], [51] and Artificial Neural Networks [52] with the consideration of varying ambient, environmental, operation and health condition have been developed.

Unique software for gas turbine thermodynamic performance simulation and gas path diagnostics, Turbomatch/Pythia [89], [84], has been developed at Cranfield. It is modular based so performance models for gas turbine engines with different configurations can be easily set up with excellent flexibility. Special versions of the software have been developed for industrial partners to meet their special needs in their performance and diagnostic analysis. Application of the developed gas path diagnostic system and the software to real gas turbine engines has been carried out and proved to be successful.

3 CBM ON GAS TURBINES APPLICATIONS

In this section a few existing commercial solutions that allow the use of CBM for gas turbine applications are described, along with some examples that demonstrate the benefits of incorporating a CBM approach.
3.1 EXISTING CBM COMMERCIAL TOOLS

In gas turbines industry there are a very limited number of commercial tools available for CBM applications. Two of them developed by engine manufacturers are briefly described here.

**GE Plant Maintenance Operations Software – Bently Nevada System1®** is a patented condition monitoring platform for real-time optimization of equipment and selected processes, condition monitoring, and event diagnostics of GE gas turbine plants. An extension of this platform is Bently PERFORMANCE™ that offers online thermodynamic performance monitoring of machinery. An additional capability of System 1® is the Predictive Emissions Monitoring System (PEMS) that is able to predict the level of stack emissions generated by gas turbines based on ambient conditions, fuel composition and machine operating conditions while taking into account real time degradations. More details about Bently Nevada System1® and associated solutions and services can be found in GE’s measurement and control official site: [http://www.ge-mcs.com/](http://www.ge-mcs.com/)

**Siemens Power Diagnostics® Services** is a group of products providing CBM related services for gas turbine plants. One of these products includes an automated expert system for power plant operational data analysis, monitoring, fault diagnosis and prognosis. Other products in the group provide the capability of Fiber Optic Vibration Monitor (FOVM), the Blade Vibration Monitoring System (BVM4), and the Radio Frequency Monitor (RFM). A more detailed description of Siemens Power Diagnostics® Services is given in [105].

3.2 BENEFITS FROM INCORPORATING CBM SOLUTIONS

The benefits from incorporating CBM policies into gas turbines plants are many and include increased safety, asset reliability and availability along with cost-efficient plant operation. As stated by Boyce in [4], gas turbines operating costs amount to 70–80% of the life cycle costs of the facility. Operating a plant as close as possible to its design conditions will guarantee that its operating costs will be reduced. For example, the fuel cost for modern fossil fuel gas turbine power plants ranging from 600–2800 MW can be between $72 million and $168 million per annum. Savings of 1–3% of these costs, due to efficient condition monitoring and CBM, can result in an overall cost reduction of up to $1 million per annum.

In addition, application of CBM brings the following benefits to gas turbine users. From maintenance’s point of view, condition monitoring provided by CBM allows better maintenance planning due to being able to order spare parts and arrange personnel and necessary maintenance equipment in well advance, which would result in improved availability and reduced operating costs. From gas turbine users’ point of view, since a CBM program estimates the confidence level of plant operation, it allows also changing operating profile based on the actual health condition of the engines. If, for instance, a fault at an early stage has been detected and the development of this fault is accelerated later at specific operating conditions, it becomes possible to ensure safe operation of the gas turbine before the next scheduled maintenance by operating the engine at different operating points or at lower power level.

A few success stories of incorporating CBM policies and related diagnostic approaches into gas turbine plants are reported in [106] - [108].
4 CONCLUSIONS AND SUGGESTIONS FOR FUTURE RESEARCH

In this paper an overview of the concept, the technology and the importance of CBM in the operation of modern gas turbine plants have been reviewed. The details of CBM and related diagnostic, prognostic and lifing methods and techniques are also provided. In addition, research work in this area contributed by the Laboratory of Thermal Turbomachines of the National Technical University of Athens (LTT/NTUA) and the Department of Power and Propulsion of Cranfield University are described. Furthermore, some commercial applications of the CBM technology have also been presented.

This paper has revealed that the degree of penetration of CBM policies in the gas turbines market is disproportional to the potential importance and benefits of CBM. Future research should focus on bring advanced CBM technologies into gas turbine industry in order to benefit gas turbines users. With that in mind, the following research topics are suggested:

- Further development/integration of gas turbine diagnostic approaches. Although a large number of diagnostic methods have been proposed by researchers, each method is applicable on a limited range of underlying health conditions. Integration of methods into a diagnostic tool being capable of addressing the entire diagnostic problem is required.
- Development of efficient prognostic approaches. Gas turbine prognostic approaches should be further developed and evolve into tools covering all important aspects of remaining useful life of gas turbine assets (i.e. safety, reliability, availability, maintenance and operating cost).
- Development of gas turbine lifing approaches. Such approaches may include prediction of gas turbine engine life, including creep life and low cycle fatigue life, as a function of ambient, operating and health conditions of gas turbine engines. Such capability will enhance the effectiveness of condition based maintenance.
- Development of efficient CBM validation approaches. Without CBM performance metrics, qualitative and quantitative evaluation of any CBM policy or planning will be subjective and its effectiveness over existing maintenance practices cannot be justified.
5 REFERENCES


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