THE ROLE OF GAS PATH DIAGNOSTICS IN THE CHANGING GAS TURBINE AFTER-MARKET

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Abstract

Aero gas turbine maintenance strategies are likely to see profound changes in the future. The remarkable size of the aftermarket for both military and civil aero gas turbines has already changed the nature of the business case. The aftermarket is large, more lucrative and not subject to the cyclical downturns of the original equipment sales. The competition which this considerably profitable after market creates will spur advances in diagnostic techniques. Of particular importance is advanced gas path diagnostics where, in recent years, engineering science research has opened pathways using somewhat surprising technologies. The paper will present work covering linear and non-linear gas path analysis, genetic algorithms, neural networks, fuzzy logic and hybrid systems. Much of the costs associated with the gas turbine after market relates to the gas path and these techniques are seen to play an important role.

Introduction

The Aero-engine After-market

The civil aero-engine market has undergone numerous changes throughout the years. Even today, we are witnessing a change in the business paradigm that is forcing engine manufacturers to redefine the way they operate.

For the next 20 years, the total value of the Aero-engine market has been estimated to be approximately $750bn, of which 45% is judged to be the aftermarket. This is large by any measure [1]. Further, the importance of the aftermarket to the original equipment manufacturers (OEMs) is critical and twofold. Firstly, the margins are higher than in original equipment sales. Next, whilst new equipment sales can be deferred during economic downturns, the aftermarket may sustain the business until the next upturn. One of the challenges for the manufacturers is to make the aftermarket more profitable while reducing the burden from the airlines in order to make them more competitive.

The civil aero-transportation market is very much tied to global economy, and suffers the influences of downturns in the latter. The latest crises have forced the airline industry to thoroughly examine their costs in an effort to remain competitive. Reducing the engine operating costs has become the keyword. The high competition among airlines reflects in a severe competition among gas turbine manufacturers and this context is going to be played in the aftermarket sector: recently considerable interest has been devoted to operating costs gaining improvements in engine reliability and "life on wing". From one side, the airlines demand for fleet management and comprehensive engine aftercare service based on an agreed rate per engine flying hour. The engine is paid for when the aircraft is in the air producing revenue. From the other side, the improvements in gas turbine life, could led to a scenario in which engines will not require a major service for the duration of the aircraft’s life. The result could be the partial or complete loss of the engine manufacturers’ aftermarket business. A new business model seems therefore to provide a win-win situation for airlines and engine manufacturers. "TotalCare™", (trade mark held by Rolls-Royce) type of contracts, which includes the capital cost plus a blend of financing and maintenance are increasingly being demanded. In a similar manner General Electric’s "Maintenance Cost per Hour™" (MCPH™) contracts and Pratt and Whitney "Fleet Management Programme™" (FMP™) contracts offer long-term service agreements. These programs expand the scope of the service from traditional support such as spare parts’ supply, repair and overhaul, including additional capabilities such as engine health monitoring and predictive maintenance. The service is provided on a flat rate per engine flight hour basis, enabling airlines to accurately forecast operating costs, reduce cost of ownership and improve asset utilization [2].

As a result, more and more responsibility for maintaining cost-effectively the engines is placed on the OEMs. In these circumstances, a key competitive advantage for
the OEMs will be their advanced engine health monitoring capability. Besides, particular consideration is given to gas-path diagnostics and prognostics that play a primary role in an aero-thermal performance oriented business.

**Maintenance, Repair, and Overhaul: Strategies from the Early Years up to Now**

The early years of commercial aero gas turbine (GT) operation were characterized by short mean times between failures (MTBF). Engine manufacturers began offering spares and overhaul services to aircraft operators, and planned maintenance was carried out at fixed intervals recommended by the manufacturer.

Despite the high safety margins, much of the maintenance was unplanned, and not much was done to improve the situation, since research emphasis was placed on achieving better performance: variable geometry was introduced in 1956, and high-bypass turbofans came into service in 1964 [3]. The advent of blade cooling allowed better performance to be achieved, reaching higher turbine entry temperatures.

Nevertheless, the high operating costs resulting from unplanned maintenance were recognized, and unplanned breakdowns can compromise the stability of the operation. A ‘Maintenance Steering Group’ was formed in 1967 by a group of Boeing 747 operators to devise maintenance planning strategies for the entire aircraft [4].

In the 1970s and 1980s the economic crisis brought about by the steep rise in oil prices in the early seventies began to change the face of the aftermarket. Airlines, faced with lower profits and higher costs, demanded lower prices from OEMs. As a result, the purchase prices of engines were driven down [1] in a trend that has lasted to present day. Faced with minute margins on engine sales, engine manufacturers found a means of survival in the aftermarket: spares were sold to airlines and third party MRO (maintenance, repair, and overhaul) outfits at increasingly high prices, recouping the losses made by offering low purchase prices. As a senior aero gas turbine industrialist once famously stated, "the aero engine business was like the razor business: you can give away the engines because the money is made on the blades!". The high margins of profit available on the spare part sales used to sustain the business even during economic downturns.

Maintenance practices in the 1970s were consistent with the economic aspects described above: most operations strategies were based on overhaul interval setting. High safety margins meant that overhauls were carried out frequently. This practice has two drawbacks:

- By setting high safety margins, engines are retired from service far earlier than they should. As a consequence, an important part of their useful life is wasted.
- Overhauls re-introduce the possibility of assembly errors and defects in new components (i.e. infant mortality).

Engines were therefore affected by a considerable number of premature failures [3], until the end of the 70s when a significant effort was addressed to improve engine reliability. During this period, the concept of reliability-centred maintenance (RCM) was developed and modular engines were introduced.

The late 80s and 90s were characterized by increased reliability and longer engine lives [1,3]. Fig.1 illustrates the IFSD (in-flight shutdown) rate and removal rate trends over the years for some of the main RR engines. As can be seen, the removal rate for new engines is less than a fifth of what it used to be in the 70s.

The implications for airlines were serious. Until the 1980s, it was not common to outsource maintenance. Most major carriers had their own maintenance departments, and their relationship with OEMs consisted mainly in parts procurement and major overhauls. Realising that their expertise and control over spares could represent a great economic advantage, engine manufacturers began offering comprehensive MRO services. Not only the original equipment manufacturers, but also competitors, users and new specialist players are entering these markets.

**Potential Benefits from the Use of Gas Path Diagnostics**

Engine condition monitoring and engine diagnosis have been recognised, for some time, as important assets in making more informed decisions on the usage, maintenance, over-haul or replacement of the engine or one of its components. The importance of such techniques has been re-emphasised by the changes in market positioning discussed earlier. Additionally, improvements in instrumentation quality, information technology and web-based system have resulted in large quantities of data being routinely gathered from the operation of individual and fleets of engines. Industry has yet to obtain the full extent
of the added value that advances in gas turbine diagnostic systems offer, particularly when, in these changed circumstances, they are coupled to business objectives. Gas path diagnostics is an important element of such future ambitions. That gas turbines routinely deliver high availability and long life is now broadly accepted. The question that remains is whether the availability and life is achieved by using relatively large "safety margins", as these imply additional maintenance, shorter component lives and hence higher costs. Among the quantifiable benefits from the use of appropriate gas path diagnostics are:

- Life extension, based on individual engine/component condition and usage profile. Exchange of "life expired" engines to other uses to absorb residual creep or fatigue lives.
- Reduced need for spares holding.
- Availability management to limit the need for unplanned maintenance. Improved "departure" statistics. Reduced in-flight shutdown rates and maintenance away from base. Enhanced airline reputation.
- Definition of work packages based on actual diagnosed condition, instead of "average" engine.
- Clarity in defining cost-effective aftermarket agreement objectives. Scope and resource management.
- Performance management to include "thrust rating" and adaptive control.
- Instrumentation selection against usage objectives.

Gas Path Diagnostics: Fundamentals

Problem Definition

The performance of an aero-engine deteriorates over time as a consequence of its components’ degradation. The identification of the exact component(s) responsible for the performance loss facilitates the choice of the recovery action to be undertaken. An engine gas-path diagnostic process calculates changes in the magnitude of the component performance parameters (e.g. efficiency and flow capacity) given a set of measurements (e.g. temperatures, pressures, shaft speed and fuel flow) through the engine. However accurate assessment is complicated by (i) only having relatively few measurements available, and (ii) errors in the measurements (e.g. due to uncertainties, noise and biases). The relationship between measurements and performance parameters can be expressed analytically as follows:

$$Z = H(X, W) + \sigma + b$$  \hspace{1cm} (1)

where z is the measurement vector, x the performance parameters vector, w the vector of environment and power-setting parameters, \sigma the measurement noise vector, b the sensor bias and h() a vector valued non-linear function: h() is provided by the performance simulation program.

In a fundamental sense, performance monitoring and fault diagnostics involves the processing of engine measurements. In all cases, some performance parameters of the investigated engine are compared to the corresponding values of an engine considered to be "healthy". The parameters used and the way of deriving them characterise each different diagnostic method [6].

The solution of the problem requires the search for a best match between some simulated measured parameters (such as temperatures, pressures and speeds) and the corresponding values taken from the deteriorated engine. Fig.2 illustrates the nature of the gas path diagnostic problem described above. Distinct gas path diagnostics techniques may differ in:

- The number of measurements (level of instrumentation).
- The quality of the measurements (quality of instrumentation).
- The way of identifying the above-mentioned best match.
- The number of operating points at which the measurements are taken.
- The algorithm for searching for the solution.

Choice of the Most Suitable Measurement Sets

A thorough evaluation of the health of the various gas-path components requires a large number of performance parameters to be assessed and a large number of sensors to be installed. On the other hand, the number of sensors is seriously limited by weight, bulk and cost concerns. Besides, the reliability of the monitoring system may even be reduced if the number of sensors increases,
as the probability of a sensor fault increases. As a consequence, in-service monitoring is currently carried out with a limited number of sensors. In order to diagnose specific faults the instrumentation set should be properly chosen. In fact given a set of sensors some faults will be more observable than others. Nevertheless, diagnostics usually has to be performed using the available sensors, which may not be the most suitable, because often the choice of sensors is not dictated by gas-path diagnostics requirements.

Provost [7] presented a method developed in order to identify the correlations between the measured parameters and the correlations between the performance parameters. This method helps choose the most suitable measurement set by highlighting the presence of redundant sensors and/or the necessity of introducing additional measurements to facilitate more effective diagnoses. Marinai [9] and Bechini [8] further developed this method and developed a test capable of comparing a considerable number of combinations of measurement sets and identifying the most effective one.

The choice of number and type of sensors is a critical issue which can greatly affect the final results as well as the computational burden of the diagnostic technique. With reference to the diagnostics method based on the minimization of the Objective Function reported in Equation 3 using Genetic Algorithms that is described below, a high number of sensors invariably makes the Objective Function search space smoother and therefore reduces the computational burden. If genetic algorithms are used as the search technique, the population size and the number of generations can be kept to a reasonably low level. The importance of the choice of instruments is highlighted in 2 plots of the search space relative to the low-pressure compressor of an intercooled and recuperated gas turbine. Fig.3 shows the search space generated with 9 instruments. At a first glance this looks smooth and simple to solve, but the flatness of the plot around the minimum implies that the search technique will have difficulties in identifying the minimum. For the same engine and under similar conditions, however, the search space generated with 16 instruments (shown in Fig.4) shows a distinct convergence to a global minimum, which is easier to locate.

Overview of Research in Gas Path Diagnostics

The role of gas path diagnostics has been long recognised and notable research contributions have been made over the last three decades. A recent review of this subject has been completed by Li [10], while another focussing on advanced techniques is given by Singh et. al. [11]. The underpinning theory for Gas Path Analysis (GPA) was first proposed by Urban and this was followed by a number of important contributions by Urban and Volponi, as well as others [12-23]. Though a powerful tool for the modeling of gas turbines for purposes of performance analysis and diagnostics, GPA as it is known suffers from various drawbacks and in order to overcome these, a number of other techniques were developed. These techniques, including the use of Kalman filters and optimal estimation, were developed by Volponi, Provost and others [7,24-27]. Research by Provost formed the key element in the "COMPASS" monitoring system. Doel et al. favoured the weighted least squares algorithm [13,28], together with GPA. At the same time, as these techniques continued to be developed and improved, some researchers worked on other model-based methods and other techniques based on residuals. Over the last decade, research by Mathioudakis and others has been directed towards the use of artificial-intelligence-based techniques such as Artificial Neural Networks (ANN) [6,29-38], Fuzzy Logic [9, 39-41] and other expert system-based techniques [42-44]. These methods have shown promise and efforts are still under way to further improve them. A technique based on optimising an objective function using genetic algorithms has been proposed by Zedda et al. [45,46] and further developed by Gulati et al. [47,48] and Sampath et al. [49,50], all at Cranfield. Another useful recent publication [51] includes fundamentals and applications of most of the techniques referred to above.

Gas Path Analysis

Gas Path Analysis (GPA) constitutes the theoretical basis of all the developed gas path diagnostics techniques. Assuming that the changes in the independent parameters are relatively small, the new set of equations can be linearised by a Taylor series expansion. These equations can be expressed in matricial form by introducing a matrix, which is usually given the name of Influence Coefficient Matrix (ICM). The ICM is then inverted to provide the Fault Coefficient Matrix (FCM). By multiplying the measured changes in the dependent parameters by the FCM, the changes in the independent health parameters can be found. This allows the cause of the engine deterioration to be determined. If this method is used to identify multiple faults, the linear GPA becomes less reliable, because the rates of degradation are seldom known and are not likely to be linear [19-22]. A further limitation is that linear GPA
is, by definition, only suitable for small changes or degradations.

GPA is clearly an effective tool for assessing the health of a gas turbine. However, the available linear GPA models suffer from the limitation that, in many circumstances, the level of error introduced by the assumption of the linear model may be of the same order of magnitude as the fault being sought. It has therefore been recognised that there was, and there still is, a powerful case for improving the accuracy of GPA systems. This led to the development of the non-linear GPA concept, the basis of which is the successive application of a linear GPA, until an exact solution is obtained. The non-linear GPA technique developed at Cranfield [52] has been validated for several different gas turbine configurations and was found to be both robust and accurate.

Advanced Techniques

Fundamental limitations exist for each of the techniques described above, such as the inability to take into account the non-linearity, the requirement for many sensors to achieve an accurate diagnosis and the difficulty to cope with sensors inaccuracy and faults. These limitations have led to efforts being directed towards more sophisticated techniques using Artificial Neural Networks (ANN), Fuzzy Logic and Genetic Algorithms (GA). The following paragraphs describe some of the research investigations being undertaken in this direction.

Neural Networks

Artificial Neural Networks (ANN), one of the most extensively used artificial intelligence techniques, were introduced into gas turbine diagnostics in the late 1980s. An ANN is a parallel, distributed processor constituted by simple processing units. It simulates the functional relationship between dependent and independent variables by storing knowledge in the network (training phase) and making it available for use (application phase). An ANN is especially useful when there is no model at all to describe the physical phenomenon under analysis, or when the model itself is either too poor or too complex to be used. In gas turbine diagnostic applications, the input to the network are the deviations of the gas path performance parameters such as pressures and temperatures, while the output are the shifts of some gas turbine component characteristics, such as changes in flow capacities and efficiencies. The functional relationship is stored in the weights (or synapses), which are obtained by training the ANN with training samples.

The features which make ANN suitable for engine diagnostics tasks are:

- ANN can cope with the large amount of noise affecting gas turbine measurements.
- Even though some parameters have to be chosen at the design stage and at the beginning of training, ANN do not require the setting of critical parameters, such as the ones, required in Kalman filter-based techniques, fixing the standard deviation of each performance parameter.
- ANN could be trained online to monitor the engine health in real-time.
- ANN are capable of dealing with the large non-linearity that characterises the correlation between measurements and performance parameters in a gas turbine.
- ANN could be used to perform diagnostics using different data sources. Vibrations, aerothermodynamic results and gas-path debris data represent, amongst others, a comprehensive input to an ANN-based system.

For complicated gas turbine diagnostic problems, a single neural network may not be enough to get robust and accurate results. The diagnostic task can be better done if it is divided and shared with a nested neural network approach. Such a technique has been developed by Ogaji and Singh [53] and an example of such system is shown in Fig. 5.

Fuzzy Logic

Fuzzy logic was introduced because of its inherent capability of dealing with gas path diagnostics problems due to its rule-based nature and its fuzzy approach. The rule-based architecture is used to perform pattern recognition of measurement fault signatures, while the fuzzy approach is advantageous in order to deal with the uncertainties that typically affect the diagnoses, namely the measurement errors and the undetermined mathematical formulation. The fuzzy inference process is the process that performs pattern recognition and therefore diagnoses. It includes three main phases: fuzzification of the inputs,
evaluation of the rules, and defuzzification of the outputs to compute a numerical outcome.

A single IF-THEN fuzzy rule assumes the form ‘if \( z \) is in the fuzzy set A then \( x \) is in the fuzzy set B’. With reference to the Fig.6, an NM-dimensional input space (measurements) is mapped into a NP-dimensional output space (performance parameters) by means of \( m \) rules.

\[
f : Z \in \mathbb{R}^{NM} \rightarrow x \in \mathbb{R}^{NP}
\]  

(2)

In general, one rule by itself does not do much good. What is needed is a number of rules that can play off one another. Each input vector partially activates all the rules in parallel. The outcome of each rule is a fuzzy set partially activated for each output of the fuzzy system. The output fuzzy sets for each rule are then aggregated. Finally, the resulting sets are defuzzified and resolved to a single number for each output. Each rule can also be coupled with a pertinent rule-weight \( w_i \) that can be introduced in order to give more importance to the rules associated with more likely faults. It can be proved that an additive fuzzy system compute a conditional expectation \( E(X|Z) \) and therefore an optimal non-linear estimation.

In a fuzzy diagnostics system the rules are expressed as IF-THEN statements such as: “if the exhaust gas temperature is high and the compressor delivery pressure is high then the compressor efficiency is low”. Such rules can be stated using numerical data obtained via a performance simulation model. It is necessary to state a rule for each combination of variation of health parameters that identifies the search space. The main phases of the rule generation procedure for one rule are summarised in Fig. 7.

The brain of the fuzzy logic system is in the rules and these must be carefully formulated. Recent research by Marinai [9,41] shows further promise of this technique. The main advantages of fuzzy logic are as follows:

- Because of its fuzzy nature, fuzzy systems can cope with uncertainty and noise.
- It is a fast method, and can be used on-line. Unlike ANN, it does not require extensive training time. In fact, a set of rules can be generated automatically in a few minutes.
- Since it is based on a rule-driven inference engine, it is very flexible and does not have to be limited to gas path analysis. For example, information derived from vibration or oil analysis can be introduced in the rules enabling data-fusion capability.

However, there is a disadvantage: like many other artificial-intelligence-based methods, the size of a fuzzy diagnostic system increases dramatically with the number of simultaneous faults that are considered to affect the engine. Nevertheless, if the search space involves up to 2 simultaneously faulty components (4 health parameters deteriorated at a time), the amount of rules stated are comfortably managed with the current average computational capability. Besides, this problem could be addressed through hybridisation with other techniques.

Genetic Algorithms

GAs are effective optimisation tools. From a diagnostic perspective, GAs are used in order to identify the minimum of a pertinent objective function that is associated with the solution of the diagnostics problem.

Objective Function : If an objective function is used, this should be a representation of the problem, should be easy to compute and should take into account measurement noise and sensor bias. Zedda and Singh [45] have developed an objective function to be minimised for a single operating point case and for well instrumented engines. This is:

\[
J_{KL}(x,w) = \sum_{j=1}^{NM} \left| \frac{z_{odj}(w) \cdot \sigma_j}{z_j(h_j(x,w))} \right|
\]  

(3)

where:

- \( z_{odj} \) is the value of the j-th measurement in the off design undeteriorated condition.
- \( z \in \mathbb{R}^{NM} \) is the measurement vector and is the number of measurements.
- \( h \in \mathbb{R}^{NM} \) is the measurement vector from the engine performance model and NM is the number of measurements.
- \( x \in \mathbb{R}^{NP} \) is the performance parameter vector and NP is the number of parameters.
• $w \in \mathbb{R}^{NP}$ is the vector of the environment and power setting parameters (e.g. inlet condition parameters and fuel flow) and NP is the number of parameters.

$K$ and $L$ are the measurements that are biased and neglected in the calculation of the objective function (it is assumed that two measurements can be biased), $\sigma$ is the standard deviation used to account for measurement noise.

Figure 8 shows the high-pressure compressor search space associated with a particular engine model and obtained by varying the deterioration in mass flow from $-3.5\%$ to $+3.5\%$ and the deterioration in efficiency from 0 to $3.5\%$. The values obtained are then compared with data generated by introducing a $2.75\%$ efficiency deterioration in the high-pressure compressor. Each point on the surface plot is a potential solution and the best solution is the one having the lowest objective function.

If the number of measurements is higher than the number of performance parameters and power setting parameters to be determined, a technique using a single operating point can result in a high degree of accuracy. However, if the number of measurements is far less than the number of performance parameters, a more judicious choice of diagnostic technique is needed. One possibility is to use a Multiple Operating Point Analysis (MOPA) technique [18], which uses information obtained from different operating points.

GA’s functionality: The metaphor underlying the genetic algorithm is that of natural evolution. In evolution, the problem that each species faces is that of searching for beneficial adaptations to a complicated and changing environment. GAs follow the natural principle of survival of the fittest. The GA nomenclature is also borrowed from the vocabulary of natural genetics [54]. In the context of this technique, a string refers to a possible solution and a collection of possible solutions or strings is called a population. The fitness of the string is a function of the objective function and is inversely proportional to it. The best string would therefore have the highest fitness, which means that the value of objective function would be minimised.

A diagnostics algorithm based on a GA typically starts with a population that is created at random; subsequently the objective function is calculated for each of the strings in the population. The objective function is then mapped into a fitness function and the larger the fitness, the higher the probability of survival. This mapping can be linear or non-linear. The GA then works over a number of iterations or generations, each containing three fundamental operators: selection, crossover and mutation. The selection operator chooses the strings to be used in the next generation according to a "survival of the fittest" criterion. The crossover operator allows information exchange between strings, in an attempt to generate fitter strings. Crossover is carried out by swapping parts of two parameter vectors. Mutation is used to introduce new or prematurely-lost information in the form of random perturbations to the values of a parameter vector, without exceeding the fixed upper and lower thresholds. Fig.9 shows a schematic diagram of a typical generation.

The diagnostic techniques using GA have been tested on both commercial and military engines and have been applied on simple cycle engines as well as on advanced ones, such as the intercooled and recuperated turboshaft. The results have shown a high level of accuracy even in presence of measurement noise and sensor biases. Furthermore, such diagnostic systems are flexible: in case sensitive guesses on the maximum number of faulty sensors are available, the optimiser can be tailored accordingly.

GA using a Master-Slave configuration: The development of diagnostics techniques using GA has opened up new avenues for investigation. The traditional GA-based diagnostic systems require long run-times. Depending on the number of faulty components being investigated, the type of faults and other issues, the algorithm may run for several hours, making it unsuitable for online application. A solution to this problem may be the utilisation of an intelligent analysis system in which the progress of the algorithm is monitored by a master program.

A master-slave module has been developed, in which the master GA monitors a slave-GA process which is similar to the GA process shown in Fig.9. The master monitors the slave process based on certain predefined parameters, such as the population diversity factor (the solution variety available in a solution set), the improvement in mean fitness etc. Based on these parameters, the master decides whether to increase the population size or to selectively withdraw the under-performing individuals. The master also monitors the fitness improvement history to establish a termination condition. Such a technique ensures that all the fault classes are subjected to the same rigorous investigation.
Future Directions and Prospects

Whilst research in gas path diagnostics is directed towards several different topics, the main trend relate to (i) developing hybrid systems, (ii) the possible utilisation of transient performance, and (iii) the development of advanced prognostics capability.

Hybrid Systems

If we take a look at the entire host of techniques that are in use or being researched today, we can conclude that no single technique addresses all the issues. Some techniques are complementary and each has its own advantages and limitations. These considerations have led to the strategy of combining more than one technique to offset the limitations of one with the advantages of the other. Hybrid diagnostics systems research is gaining momentum and many possibilities are currently under investigations.

Neural Networks with Genetic Algorithms: ANN have been widely used for pattern recognition, data classification etc. The concept of using ANN for engine fault diagnosis has been explained earlier in this paper. The hybrid method developed at Cranfield University uses ANN along with GA. One of the main disadvantages of ANN is that it requires a lot of data, and time, for the training. However, once the networks are trained, the classification takes only a fraction of a second. While the quantification of a fault is quite difficult for an ANN, its classification is relatively easy, needs comparatively less data and is accurate. The hybrid method therefore makes use of the classification capability of the ANN by making a preliminary assessment, ruling out unwanted fault classes and thereby reducing the total run-time. This technique has been tested and has proven to be advantageous towards online diagnostics applications.

Expert Systems with Genetic Algorithms: One of the diagnostic techniques being investigated uses expert systems with GA. The basic GA technique was discussed earlier. In general it identifies and quantifies the fault through an optimisation process. The process continues till it meets a termination criteria. However, an "a priori" knowledge of the engine is likely to be useful in directing the search process more effectively. The expert system being explored at Cranfield is a rule-based system (IF-THEN) which interrogates a database containing the engine performance and fault data previously recorded. In addition, an expert system receives the output from the GA-based diagnostics system and advises the user on the limitations imposed by the fault and on possible remedial actions.

Diagnostics Using Transient Data

Transients lead to pressure and temperature gradients, which contain further information on the health of the engine. Most of research undertaken on engine diagnostics has been at steady-state, but it may not always be possible to get reliable steady-state data, especially for military engines which may operate for up to 70% of their mission time under non-steady-state conditions [55]. With the advent of modern control systems and Engine Monitoring Systems (EMS), the time-history of all important engine parameters are becoming available for post-flight analysis and therefore provide an opportunity for transient analysis.

Some of the engine component faults, such as those leading to reduced surge margins in the compression system, may not be apparent in a steady-state diagnostic analysis, but could seriously limit the handling capability of the engine.

Figure 12 shows the path of the low-pressure spool speed plotted against time [56]. The data was obtained during a slam acceleration between two steady-state points. It shows that the deteriorated engine lags behind a clean engine and the difference is substantial when compared with steady-state conditions. For the purpose of optimisation, the difference between the areas projected by the two curves is converted into a Cumulative Deviation (CD). The search technique uses a GA and is similar to that used for steady-state conditions.

Gas Path Prognostics

Gas path diagnostics is aimed at assessing the health of the engine at the current time. On the other hand gas path prognostics studies the evolution of the deterioration over time (see Fig.13).

Prognostics is the capability of providing forecasts regarding the engine health and decision-making competences based on them. It has been recognised that any attempt to prognostics requires an associated business intention: different parameters may be required to be investigated with different confidence levels according to different business strategies.
Gas path prognostics is emerging as a novel research area of major interest for the gas turbine industry. Maintenance support, flight operations, fleet management reliability engineering and quality-assurance teams would benefit from the use of a gas-path prognostics process that provides forecasts, prognoses and advice based on the expected short and long term behaviours of the engine suffering from the diagnosed condition.

A general gas path prognostics framework was described in Marinai [9, 57]. It uses two different time-series analysis methods for short and long term investigations providing the capability of dealing with a considerable variety of gas path prognostic problems. These methods can forecast the performance deteriorations of civil aero-engines providing significant benefits in mission scheduling and maintenance planning. Differently from previous studies described in the literature which are mainly qualitative and lack of statistical rigour, prediction intervals are introduced to take into account errors in deterioration modelling as well as forecasting errors. Under some assumptions relative to the potential scenarios of application, the framework was used in the study of Rolls-Royce Trent 800 engine simulated and real data providing promising results.

Conclusions and Future of Gas Path Diagnostics

The changes in the role of the aftermarket, which are re-defining the business paradigm for the civil air transport business, also have a resonance in the defence sector. Concepts such as comprehensive engine aftercare service based on an agreed rate per engine operating hour, already introduced within the airline industry, are becoming a reality for marine propulsion as navies move towards lean manning of ships and reduced manpower in ship yards. Gas turbines also play a major role in the energy business and here too changes are becoming apparent in the aftermarket, where major users are setting up as competitors to the engine manufacturers, changing industry relationships and economics.

Some of the methods presented earlier are in regular use by the industry in managing engine maintenance and repair, often in conjunction with other diagnostics techniques (vibration, oil etc.). The combination of such information with detailed understanding of the design, operation and usage profiles and logistics, provide competitive advantage in the aftermarket. The next stage for gas path diagnostics will see the emergence of powerful hybrid techniques, combining the most appropriate features of several gas path diagnostic techniques and coupling these to other methods. The availability of large quantities of operational data from individual engines and fleets will provide statistical databases which, when taken together with advanced diagnostic methods, will allow important advances to prognostics, further increasing the market value of these technologies.

The improvements in the in-service operations of engines have had a fundamental impact on the industry [58]. Firstly, engines are getting more reliable. This is measured by ‘in-flight shutdown rates’. Another issue of more long-term consequence is the expected trend in engine ‘life on wing’. With the steadily improving life of aero engines, it could be that an engine will not require a major service for the duration of the aircraft’s twenty-five year life. This implies that, in fifty years time, the oldest engine in use will not have entered service until twenty-five years from now. The result could be the partial or complete loss of the engine manufacturers’ aftermarket business.

Companies would have to make compensating higher profits on the original equipment sale. More interestingly, the loss of the aftermarket revenues based on decades of Prime incumbency eliminates a major market entry barrier. Perhaps this is when a new wave of companies will gain entry into the business. Another scenario is that technology advances will drive to more appropriate business solutions. The optimisation of engine management systems may include internal flows (sealing and leakage), adaptive systems and cycles, embedded micro and nanosensors [59] and actuators coupling performance, cycle and environmental impact management. Future engines may have to be optimised for global warming [60]. Any future solution will have to offer a high level of diagnostic and prognostic capabilities, integrated to life cycle management, including perhaps both economics and global warming.

In the past, the civil air transport business has delivered strong long-term growth by reducing unit cost and hence allowing more people to participate in air travel. This reduction in unit cost has been achieved both because of market pull and technology push. A further contributory factor has been the technology advances made possible because of the large number of technologists this industry employs.

As the business emphasis shifts to the aftermarket, the changing paradigm will favour those business leaders who recognise that this new market cannot be dominated by
focus on logistics and management, or even advanced diagnostics. Advantage will flow to those who recognise the importance of the contribution that "intellectual adventure" can make in the aftermarket as it has, in the past, in other areas of gas turbine technology.

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Fig. 5 A nested neural network

Fig. 6 Additive fuzzy system architecture

Fig. 7 Fuzzy rule generation phases ($\Delta \eta_i$ and $\Delta \Gamma_i$ represent respectively efficiency and flow capacity % deviations respect to a clean condition of the 3 compressors and 3 turbines of a 3 shaft engine)

Fig. 8 Search space for high-pressure compressor (values are percentage deviations from clean conditions)

Fig. 9 Single generation of GA reproduction cycle
Fig. 10 GA using a master-slave configuration

Fig. 12 Low-pressure spool speed plotted against time for a clean and a deteriorated engine [56]

Fig. 13 Diagnostistics vs Prognostics