Chapter 8

Engine Condition Monitoring and Diagnostics

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Additional information is available at the end of the chapter

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1. Introduction

Any engine exhibits the effects of wear and tear over time. Several mechanisms cause the degradation and potential failures of gas turbines such as dirt build-up, fouling, erosion, oxidation, corrosion, foreign object damage, worn bearings, worn seals, excessive blade tip clearances, burned or warped turbine vanes or blades, partially or wholly missing blades or vanes, plugged fuel nozzles, cracked and warped combustors, or a cracked rotor disc or blade.

Fouling is caused by liquid or solid particles accumulated to airfoils and annulus surfaces. Deposits consist of varying amounts of moisture, oil, soot, water-soluble constituents, insoluble dirt, and corrosion products of the compressor blades material whish are held together by moisture and oil. The result is a build-up of material that causes increased surface roughness and to some degree changes the shape of the airfoil. Hot corrosion is the loss or deterioration of material from flow path components caused by chemical reactions between the component and certain contaminants, such as salts (for example sodium and potassium), mineral acids or reactive gases (such as hydrogen sulfide or sulfur oxides). Corrosion is caused by noxious fumes or ash-forming substances present in the fuel such as aluminum, calcium, iron, nickel, potassium, sodium, silicon, magnesium. Corrosion increases surface roughness and causes pitting. Erosion is the abrasive removal of material from the flow path by hard or incompressible particles impinging on flow surfaces. Damage may also be caused by foreign objects striking the flow path components (Figure. 1a). Foreign Object Damage (FOD) is defined as material (nuts, bolts, ice, birds, etc.) ingested into the engine from outside the engine envelope. Domestic Object Damage (DOD) is defined as objects from any other part of the engine itself.

Different causes and mechanisms of performance deterioration of jet engines are reviewed in [1]. Degradation in both land and aero gas turbines is also reviewed by Kurz and Brun

[2], who pointed out differences in mechanisms for the two types. Industrial gas turbine deterioration has been discussed by Diakunchak [3].

(a) (b)

Figure 1. (a) FOD effects, (b) Turbine nozzles with deposits.

Three major effects determine the performance deterioration of the gas turbine compressor due to fouling: Increased tip clearances, changes in airfoil geometry, and changes in airfoil surface quality. In compressors, erosion increases tip clearance, shortens blade chords, increases pressure surface roughness, blunts the leading edge, and sharpens the trailing edge. Turbine blade oxidation, corrosion and erosion are normally longtime processes with material losses occurring slowly over a period of time. However, damage resulting from impact by a foreign object is usually sudden. Impact damage to the turbine blades and vanes will result in parameter changes similar to severe erosion or corrosion. Corrosion, erosion, oxidation or impact damage increases the area size of the turbine nozzle. When crude oil is burned in the GT the hot end is subjected to additional harmful deposits, including salt deposits originating in the inlet or from fuel additives. As hot combustion products pass through the first stage nozzle, they experience a drop in static temperature and some ashes may be deposited on the nozzle blades decreasing the nozzle area (Figure 1b). The combustion system is not likely to be the direct cause for performance deterioration. The combustion efficiency will usually not decrease, except for severe cases of combustor distress. However, plugged nozzles and/or combustor and transition piece failures will always result in distorted exhaust gas temperature patterns. This is a result of the swirl effect through the turbine from the combustor to the exhaust gas temperature-measuring plane. Distortion in the temperature pattern or temperature profile not only affects combustor performance but can have a far reaching impact as local temperature peaks can damage the turbine section.

All the above causes and effects may be considered as faults. Generally speaking, fault is a condition of a machine linked to a change of the form of its parts and of its way of operation, from what the machine was originally designed for and was achieved during its initial operation. In this respect a fault manifests itself by a change of geometrical characteristics or/and integrity of the material of parts of an engine. Change in geometry is inevitably linked to common experience faults, as for example when a part is broken, or deformed. Typical integrity fault is the occurrence of cracks inside the material, which are not associated to any geometrical change but can nevertheless result into catastrophic consequences. Some of the

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faults will become evident as vibration increases or by a change in lubrication oil temperature. However, some serious faults can be detected only through gas path analysis. The gas path, in its simplest form, consists of the compressors, combustor, and turbines.

Diagnosis of a mechanical condition is the ability to infer about the condition of parts of the engine, without dismantling the engine or getting direct access to these parts, but only from observations of information coming to the engine exterior. The field of engineering science covering the techniques for achieving a diagnosis is called diagnostics. The aim of diagnostics is to detect the presence and identify the kind of faults appearing in a engine. Diagnostics does not require that the engine is either stopped or disassembled. Information is gathered while the engine is in operation. This is vital for engines in the process industry or energy production, as they must run without interruption for long time intervals. Detection of an incipient failure in a jet engine leads to taking action necessary to prevent a catastrophic failure which might follow.

In order to establish the possibility of diagnosing engine condition a correspondence of this condition to the values of the measured quantities should be known. In general terms, this correspondence is intrinsically established through the physical laws governing the operation of the machine. The behavior of any relevant physical quantity is linked through these laws to the detailed geometry of the machine and the kind of phenomena taking place in it. If we consider a machine using a fluid as a working medium, the variation of the flow quantities at one particular location in the machine is determined, via the laws of fluid mechanics, from the geometry of the solid boundaries and the physical properties of the fluid. A change in geometry will then reflect on the values of the flow quantities and could be calculated by application of the relevant physical laws. If suitable quantities are measured, they reflect changes in geometry or material and can therefore be used to indicate the presence of a fault. It is obvious that according to the change occurring in an operating machine, different quantities will be influenced. For example, the operation of rotating components is always linked to the exertion of periodic forces, with a frequency which is usually a multiple of the frequency of rotation. In this respect, the quantities characterizing a vibration are suitable for diagnostic purposes. On the other hand, severe corrosion, as it changes turbine airfoil geometry, is detectable through gas path analysis.

Many techniques for inferring engine status or change in engine condition have been proposed and/or applied to various engine configurations with varying success. Some of them (e.g. Vibration monitoring, Trending Analysis) are parts of computer-controlled data-acquisition systems that permit the on-line acquisition and reduction of a very large amount of performance information. While fault detection or general deterioration could be based on immediate observation of reduced measurable quantities, such observation is not, generally, adequate. It should also be noted that a change in any measured parameter does not necessarily indicate a particular independent parameter fault. For example, a change in compressor discharge pressure (CDP) does not necessarily indicate a dirty compressor. The change could also be due to a combined compressor and turbine fault or to a turbine fault alone. In order to have access to the variables, which possess diagnostic information (such as component efficiencies) modeling of an engine is essential. Thermodynamic (Gas Path) analysis methods employ engine models to process measurement data, in order to diagnose changes in component performance which may be linked to degradation, aging, or incipient failure.

2. Gas path analysis

An engine may be viewed as a system, whose operating point is defined by means of a set of variables, denoted as $\mathbf{u}$. The operation of each component follows predictable thermodynamic laws. Therefore, each component will behave in a predictable manner when operating under a given set of conditions. The health condition of its components is assumed to be represented through the values of a set of appropriate ''health'' parameters such as efficiencies and flow capacities, contained in a vector $\mathbf{f}$. The system is observed through measured variables, such as speeds, pressures, temperatures, contained in a vector $\mathbf{y}$. When the engine operates at a certain operating point measured quantities are produced for given values of health parameters. The operating engine establishes a relationship between these parameters, which can be expressed though a functional relation:

$$\mathbf{y} = \mathbf{F}(\mathbf{u}, \mathbf{f}) \tag{1}$$

A computer model materializing this relation can reproduce the values of any thermodynamic quantity measured along the engine gas path. It is interesting to note that by assigning appropriate values to the components of vector $\mathbf{f}$, the effect of engine component faults or deterioration on measured quantities can be reproduced.

The problem of diagnostics (Figure 2) is to seek a solution to the inverse problem, namely to determine the values of the estimated health parameters $\hat{f}$ from a given set of measurements using a diagnostic method (*DM*). Particular faults can then be detected if deviations of health parameters from the reference state are observed.

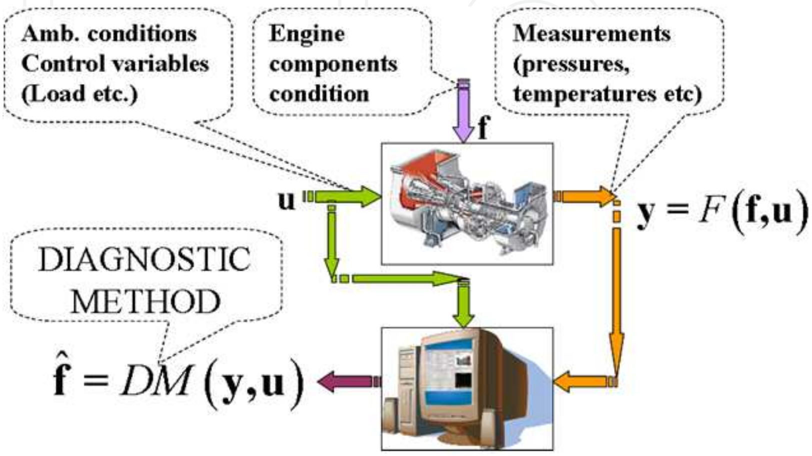

Figure 2. Gas Path Analysis diagnostics formulation.

Many variants of Gas Path Analysis based diagnosis with different features and complexity have been developed and reported in the open literature. Extensive reviews of existing methods provided by Li [4], and Marinai et al. [5].

Generally speaking any GPA method at least consists of the following elements:

- Measured data
- A data processing model relating measured data with health parameters
- A diagnostic decision making procedure.

The data used can be taken in steady state or transient operation. The model could be a physical one representing the aerothermodynamic processes taking place in the engine components and the mechanical coupling between them or a black box mathematical model relating data with health parameters. The diagnostic decision making procedure may be a conventional pattern recognition technique applied to health parameter space or an artificial intelligence based expert system.

Accordingly the proposed methods are classified on the basis of the kind of the comprising elements as: Steady state or Transient, Physical or Mathematical, Conventional or Artificial intelligence method.

3. Physical models based GPA

3.1. Linear methods

In linear gas path analysis, the health parameters are represented as the unknown ''deltas'' of component performance parameters (typically efficiency and mass flow capacity). They are related to known measurement ''deltas'' through relations produced by linearization of the general nonlinear thermodynamic relations, assuming small deviations. [6].The classical linear approach is formulated as follows: For a given operating point u the measurement values depend only on the health condition of engine components. After linearization and taking into account measurement uncertainty (by adding a noise vector **v** with zero mean and known covariance R), the typical GPA equations take the form:

$$\mathbf{\Delta y} = \mathbf{C} \cdot \mathbf{\Delta f} + \mathbf{v} \tag{2}$$

where Δ is called delta and represents percentage deviation from a reference value(when the engine is in intact condition) and C the well-known influence coefficient matrix. Estimation of health parameters is obtained from the relations

$$\mathbf{\Delta\hat{f}} = \mathbf{S}^{-1} \cdot \mathbf{C}^{T} \cdot \mathbf{R}^{-1} \cdot \mathbf{\Delta y} \tag{3}$$

$$\mathbf{S} = \mathbf{M}^{-1} + \mathbf{C}^{T} \cdot \mathbf{R}^{-1} \cdot \mathbf{C} \tag{4}$$

where M represents known statistics for the deviation of health parameters.

Although the formulation for classical GPA has proven to be successful for practical purposes and existing commercial systems ([7, 8]) are based on it, identifiability problems exist due to limited instrumentation. Sufficient engine health assessment requires at least the estimation of the parameters associated with the main engine components. Considering an existing engine, a typical situation is characterized by the fact that the number of available sensors is smaller than the number of parameters to be calculated. Accordingly, all the initially implemented methods were compelled to adopt various assumptions. Most of the methods use a priori information about the statistics of the calculated parameters introducing thus bias in the estimation. In that case, inversion of matrix S is only possible when it is dominated by M. The main drawback is the effect discussed by Doel [9]. The algorithm tends to ''smear'' the fault over many components.

3.1.1. Multi operating point GPA

GPA Multi Operating Point Analysis (MOPA) methods have been developed trying to exploit information provided by the existing sensors when different operating points are considered. The origin for the multi operating point analysis (MOPA) methods was the Discrete Operating point GPA, introduced in [10].The method, based on information given by existing sensors when different operating points are considered, improved significantly the diagnostic effectiveness. The implementation of the method was an extension of the classical linear gas path analysis. MOPA methods though do not use a priori statistics for the parameters rely on the questionable assumption of non-varying health parameters. Other research groups applied the same principle for the nonlinear case, [11-13].

The linear implementation for the MOPA approach using NOP operating points is given by Eqs. (5)-(9).

$$\Delta\mathbf{y}_k = \mathbf{C}_k \cdot \Delta\mathbf{f} \qquad k = 1, \mathrm{NOP} \tag{5}$$

$$\mathbf{C}_k = \left[c_{ij,k} \right] \tag{6}$$

$$c_{ij,k} = \left(\partial \Delta y_i \,/\, \partial \Delta f_j \right)_k \tag{7}$$

$$\Delta\hat{\mathbf{f}} = \mathbf{P}^{-1} \cdot \sum_{k=1}^{\mathrm{NOP}} \left(\mathbf{C}_k^{T} \cdot \mathbf{R}_k^{-1} \cdot \Delta\mathbf{y}_k \right) \tag{8}$$

$$\mathbf{P} = \sum_{k=1}^{\text{NOP}} \left(\mathbf{C}_k^T \cdot \mathbf{R}_k^{-1} \cdot \mathbf{C}_k \right) \tag{9}$$

The so called information matrix P is crucial in the sense that its condition determines the diagnostic effectiveness. The condition of the matrix is represented by its condition number. Investigations concerning effects of both the number of operating points used and the 'distance' of the operating points on information matrices have been reported ([14]-[15]). Additional details on assessing identifiability in multipoint gas turbine estimation problems are given in [15]. Although all the works implementing the multipoint approach agree that the idea more or less improves the diagnostic effectiveness, there are also results (see [16]), indicating that the theoretically attainable multi-point improvements are difficult to realize in practical engine applications.

In order to understand the reasons for potential problems concerning diagnosis using a multipoint approach it is necessary to examine the underlying assumptions of the method. The main assumption of the method is that the 'deltas' concerning the health parameters remain constant with regard to change in operating conditions. This assumption is obviously true for some parameters (for example the parameter expressing the effective turbine area or the area of non-variable nozzle jet engine), but there are indications that for other parameters this is a week assumption. Several works ([3], [17]), have provided evidence that when deterioration is present, the deviations of parameters such as flow compressor capacity and efficiency change with the operating point. In fact different working-point means different aerodynamic conditions and, in this sense, efficiencies and flow capacities deltas can significantly vary with the operating condition. The resulting diagnosis risk is not only to imprecisely calculate the engine new state after some deterioration but even more to indicate as responsible for the fault the wrong component(s).

Recently a new variant of GPA method named Artificial Multi Operating Point Analysis (AMOPA) has been proposed [18]. The new method uses existing sensor information produced when artificial operating points are used close to an initial operating point by using different parameters for each operating point definition. Therefore the assumption that the 'deltas' of the health parameters remain constant is reasonable. The method proved to be capable of both isolating and identifying the fault in individual components.

3.2. Nonlinear methods

In nonlinear methods, the full thermodynamic equations are treated directly without simplification. An example of such a method, the method of adaptive modeling introduced by Stamatis et al. [19], uses component maps ''modification factors'' as health parameters and solves for them through an optimization procedure applied to a function based on differences of the predicted and measured values. Variants of the nonlinear GPA have been proposed (see [20-22]), the main differences being the objective function formulation as well as the method used for the optimization. The more general objective function (OF) to be minimized was proposed in ref. [23]:

$$\mathrm{OF} = \sum_{i=1}^{m}\left[\frac{y_i^{calc}(\mathbf{f}) - y_i}{y_i\,\sigma_{Y_i}}\right]^2 + C_A\cdot\sum_{j=1}^{n}\left|\frac{f_j\ \text{-}\ f_j^r}{f_j^r\sigma_{f_j}}\right| + C_S\cdot\sum_{j=1}^{n}\left[\frac{f_j\ \text{-}\ f_j^r}{f_j^r\sigma_{f_j}}\right]^2 \qquad (10)$$

where n and m the dimensionalities of **f** and **y** correspondingly. The first term express the fact that the health parameters under estimation **f** must be such that the values of measured quantities **y** are reproduced as accurately as possible. The second and third terms ensure that the values of health parameters cannot be significant different from their reference, a fact resulting from experience. It is the addition of these terms that allows the derivation of a solution for **f**, even when a smaller number of measurements is available. All *deltas* are weighted by the inverse of the standard deviation of the corresponding quantity. Weight factors C_A, C_S are also included, for the possibility to change the relative importance of the two groups of terms. The reference values $\mathbf{f}^r$ of the health parameters can be chosen to represent a 'best' guess of the values to be determined. From studies in estimation theory, it has been found that it is useful to include in the objective function a term of sum of absolute values, since this term may improve the numerical behavior of the estimation procedure by increasing its robustness (see [24]).

The way of determining the vector **f** for minimization of this function can take advantage of the physical characteristics of the problem to be solved. For example the fact that deviation of component efficiencies should not be positive could be formulated as a constraint in the optimization. In the case of slow deterioration tracking, the reference values can be chosen to vary slowly with time while a filtering procedure can be applied, taking advantage of the regular variation of component deviations, as described in [25]. For the case of individual component faults the fault usually affects one or two neighboring components.

All these features should be taken into account when formulating the diagnostic algorithm. The solution is obtained with the interaction of a non-linear engine performance model and an optimisation algorithm, as shown in figure 3.

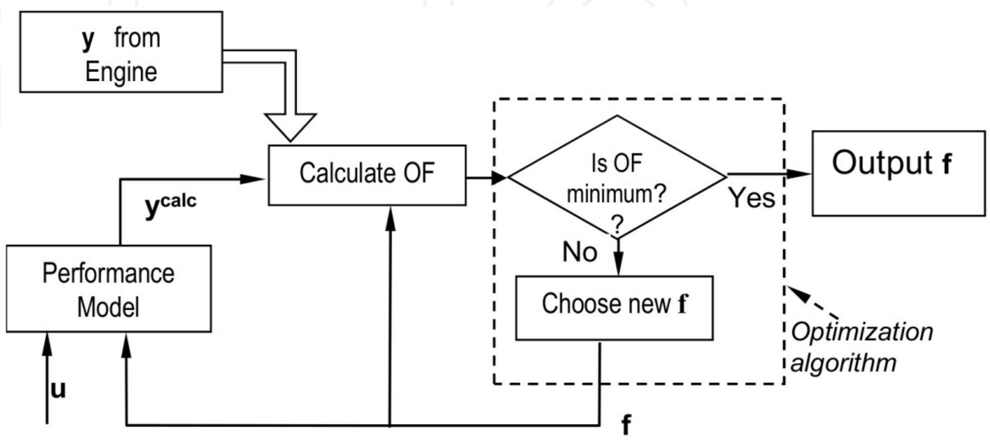

Figure 3. Schematic representation of nonlinear diagnostic procedure

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The methodology for diagnosing single component faults using the above procedure is based on the following reasoning. Since measurement data are noisy, the estimations based on a single data set differ from the actual values due to noise propagation. They can be improved when more than one measurement data sets are available. In such a case a solution is obtained for each individual data set. A series of values for each health parameter f_j becomes thus available. The mean value and standard deviation of the percentage change from reference Δf_j are then calculated. A criterion then is proposed for isolating the parameters of the components that are faulty, with the aid of a parameter, which we call diagnostic index. We define as diagnostic index the ratio of the absolute mean value to the standard deviation for each estimated health parameter.

$$DI_j = \frac{\left|\overline{\Delta f_j}\right|}{\sigma_{f_j}} \tag{11}$$

Health parameters exhibiting small deviations from reference state or parameters with large standard deviations (large uncertainty on derived estimations) will have small values for diagnostic index. On the other hand, health parameters with large mean value or small standard deviation (small uncertainty on derived estimations) will present large values for diagnostic index. It is thus expected that the health parameters, which deviate due to fault occurrence will be those with the largest value of the diagnostic index. Thus we identify as faulty the component containing the parameter with the largest diagnostic index. This stage is called fault localization.

After the detection of a faulty component, a more accurate estimation of fault magnitude can be performed. The optimization problem is solved again by keeping as unknowns only the health parameters of the component found faulty. C_A, C_S are zeroed, to avoid biases imposed by the corresponding terms. (Note that with much fewer unknowns a unique solution can be derived by minimizing differences only from measurements namely the first term of the objective function eq (10).) After performing a series of estimations with this formulation from the available data sets, the average values of the obtained parameters are kept as the estimations for the fault magnitude.

Nonlinear GPA methods have proved accurate and robust provided that appropriate measured variables and estimated health parameters have been selected. This is not a trivial problem as explained in the following.

3.3. Sensors and health parameters selection

When application of a GPA technique is envisaged on an engine, the existence of certain restrictions is recognized. Considering an existing engine, there is always a given set of available measurements. Addition of instrumentation can be difficult or even impossible. It is therefore important to have the possibility to adopt a convenient formulation of a method, so that an optimal use of the existing measurements is achieved. On the other hand, when a new engine is designed, or when an intervention to instrument an engine is performed, it is desirable to define an optimum combination of sensors to be installed.

The problems that may be faced in such a situation can be summarized as follows: When a given set of measured quantities is provided, what is the optimum set of health parameters? The particular problem is to define the best possible parameters for a given measurement possibility. This is a problem faced usually by the engine user, who has very few or no possibilities of intervening and adding measurements on the engine. When the decision for instrumenting an engine has to be taken, both the manufacturer and the user are faced with the inverse problem: (a) The user wants to know the optimum set of measuring instruments to be added in order to provide enough information for a required level of resolution. (b) The manufacturer wants to decide which instruments will accompany the engine, in order to ensure a good capability of in-service monitoring.

A systematic study for methods of choice of measurements and parameters in a way optimal as to diagnostic effectiveness was first presented by Stamatis et al. [26]. They introduced criteria for optimal measurement or health parameter selection. We present here the proposed method for measurement selection. Let $\mathbf{f}^{(r)}$ be the baseline diagnostic vector corresponding to a healthy engine (typically $\mathbf{f}^{(r)}= \mathbf{I}$), and $\mathbf{f}^{(j)}$ the diagnostic vector resulting when the jth element of / deviates from the baseline value (f(r)) by a percentage amount h_j.

$$\mathbf{f}^{(j)} = \mathbf{f}^{(r)} \cdot + h_j \cdot \mathbf{e}^{(j)} \quad j = 1,\dots,m \tag{12}$$

hj is a small constant (0.001 $< h_j <$ 0.01). Then, from Eq. (3) we have

$$\mathbf{Y}^{(r)} = \mathbf{F}\left(\mathbf{f}^{(r)}\right) \tag{13}$$

$$\mathbf{Y}^{(j)} = \mathbf{F}\left(\mathbf{f}^{(j)}\right) = \mathbf{F}\left(\mathbf{f}^{(r)} + h_j \cdot \mathbf{e}^{(j)}\right) \tag{14}$$

The sensitivity of each dependent parameter on each individual health index is evaluated as

$$\Delta Y_k^{(j)} = \left(Y_k^{(j)} - Y_k^{(r)}\right) / Y_k^{(r)} \qquad k = 1,\dots,n \tag{15}$$

We also define an overall sensitivity measure for each parameter with the norm

$$SY_k = \left[\frac{1}{m} \cdot \sum_{j=1}^{m} \left(\Delta Y_k^{(j)}\right)^2\right]^{1/2} \qquad k = 1,\dots,n \tag{16}$$

So, the problem of selecting the appropriate measurements is expressed mathematically as follows: For a given set of health condition parameters, we must select as measured parameters these parameters giving on the norm of Eq. (16) the m greater values.

In later years more works have appeared, approaching the problem from different points of view, [14, 27].

4. Artificial intelligence GPA methods

4.1. Neural networks

An Artificial Neural Network (ANN) is an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information. The key element of this paradigm is the novel structure of the information processing system. It is composed of a large number of highly interconnected processing elements (neurons) working together to solve specific problems. ANNs, like people, learn by example. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well. Two tasks which can be performed by neural nets, which are relevant to the procedure of monitoring and diagnostics of a gas turbine, are: modeling the performance of a gas turbine and detection and classification of faults.

A typical use of a model is to produce reference values for quantities which are monitored. It can be also used for other purposes such as generation of influence coefficient matrices, and sensitivity analyses. ANNs are known to be able to model non-linear systems and therefore can be used for gas turbine performance modeling. A first advantage offered by modeling engine performance through ANN is the much shorter computational time required, once the net is trained and verified, in comparison to any full scale aerothermodynamic model. The latter involves the solution of a set of non-linear equations, which is achieved through iterative schemes, resulting in a number of arithmetic operations significantly larger than those performed by an ANN. A further advantage is related to the possibility of adapting to a particular engine, if data is available. A well-known fact is that for a model to be accurately representing the operation of an engine, it has to be adapted to the particular engine (as discussed, for example, in [19]). A model using ANN provides inherently this possibility, through the way it is being set up. The existence of a learning phase, (called "training" in the ANN terminology) allows the adaptation to a particular engine, if enough data is available.

The second area of possible application, detection and identification of faults, comes from one of the most powerful capabilities of ANN, namely the capability of identifying and classifying patterns. Any method of fault detection and identification uses a set of changes in the values of some parameters, to detect and identify a component malfunction. The task of assigning such sets of changes to machine status is one very much suited to ANN. Neural networks, with their remarkable ability to derive meaning from complicated or imprecise data can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques.

There are various neural network models. Among all different neural networks, the back-propagation and the probabilistic neural nets are the architectures, which have mostly been investigated for gas turbine diagnostics. The majority of the researchers refer to performance diagnostics [28, 29], while fewer refer to sensor fault detection and isolation. Kanelopoulos et al. [30] studied the performance of back-propagation (BP) neural nets for both sensor and actual engine component faults for a single shaft industrial gas turbine. The BP neural networks, however, have two main limitations: (1) difficulty of determining the network structure and the number of nodes; (2) slow convergence of the training process.

Probabilistic Neural Networks (PNN), exhibit certain advantages that make them attractive, a significant one being that their particular structure does not require a training procedure, needed for other types of neural networks. The training information is produced during the network set-up and is then embedded in its structure. PNN `training' can thus be considered to be much faster than for other types of network, such as back-propagation. Additionally, PNNs perform a probabilistic rather than a deterministic diagnosis, something closer to physical reality.

4.1.1. Probabilistic Neural Networks (PNN)

The Probabilistic Neural Network (PNN) is a multi-layer feed forward network. The learning procedure of this network is a supervised learning procedure. During the learning procedure the PNN classifies the training patterns to classes (represented by the output nodes). When an unknown pattern is presented to the PNN, the network estimates the probability that this pattern belongs to each class. The procedure followed and the network itself is briefly described in the following:

Let us suppose that, for training the PNN, we use the group of the m, n-dimensional, training patterns:

$$\mathbf{x}_j = \left\{ a_{1j}, \quad a_{2j}, \quad .... \quad a_{nj} \right\}, \ \mathrm{j} = 1, \ldots \mathrm{m} \tag{17}$$

The graph of the resulting network is shown in figure 4. The PPN consists of three layers. The n nodes of the first layer represent the n-dimensional input. The m nodes of the second layer (hidden layer) represent the training patterns, while each one of the k nodes of the third (output) layer represents a class to which a pattern can be classified into.

Every node of the input layer of the PPN is linked to every node of the hidden layer. Each node of the hidden layer (representing a training pattern) is linked only to the node of the output layer that represents the class where the training pattern 'belongs'.

When a pattern $\mathbf{x} \in^{m}$ is given as an input to the network, the output is the probability density functions: $P(S_i \mid \mathbf{x})$, i=1,…,k.

If we assume that the probability density functions, $P(\mathbf{x} \mid S_i)$, are Gaussian, we have:

$$P(S_i \mid \mathbf{x}) = \frac{P(S_i)}{P(\mathbf{x}) \cdot (2\pi)^{m/2} \cdot \sigma_i^m \cdot |S_i|} \cdot \sum_{j=1}^{n_i} \exp\left[\frac{-(\mathbf{x} - \mathbf{x}_j^{(i)})^T (\mathbf{x} - \mathbf{x}_j^{(i)})}{2\sigma_i^2}\right] \tag{18}$$

where, $x_j^{(i)}$is the j-th pattern of the training set of patterns that 'belong' to class i, $|S_i|=n_i$ is the number of the training patterns that 'belong' to class i, σ_i is a smoothing parameter, $P(S_i)$ is the 'a priori' probability of class S_i, and $P(x)$ a normalization factor representing the 'a priori' probability of pattern x, which is constant assuming mutually exclusive classes, covering all possible situations.

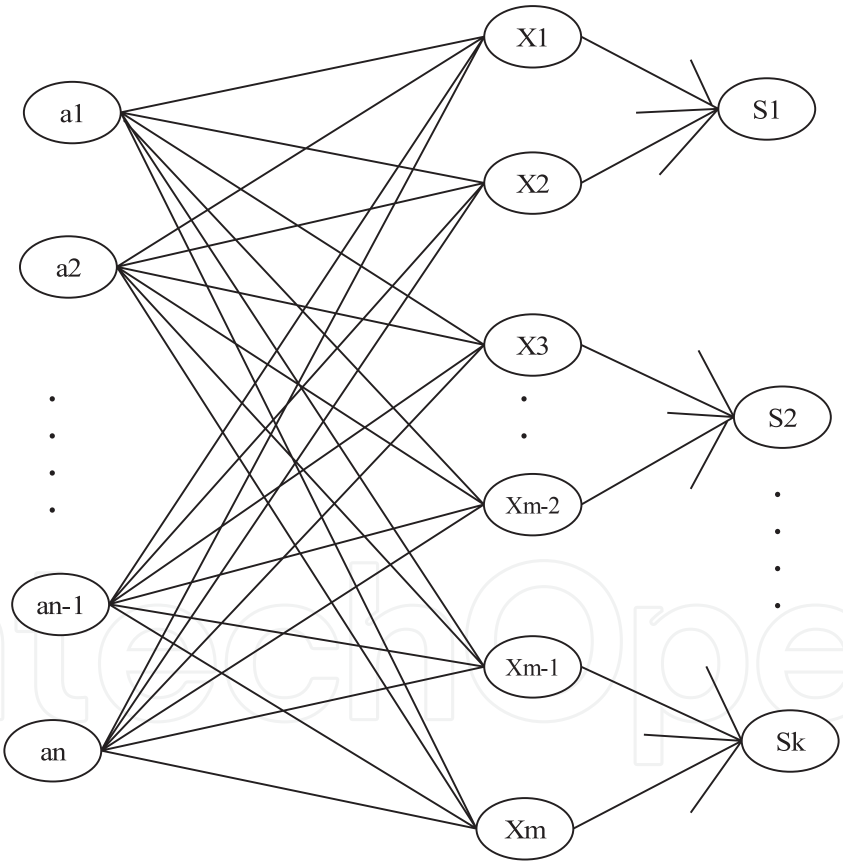


Figure 4. The general structure of the Probabilistic Neural Network.

For example if it is considered that the ‘a priori’ probability is equal for all classes,

$$P(S_i) = \frac{1}{k}, \text{ i} = 1, \ldots, \text{k} \tag{19}$$

During the training of the PNN, we provide the training patterns and the classes they belong to. From this information the number of nodes of each layer, as well as the links of the network with the related weights, are specified.

The weight of the link from node j1 of the input layer to node j2 of the hidden layer is:

$$w^{(1)}_{j1,j2} = a_{j1j2} \tag{20}$$

while, the weight of the link from node X_i of the hidden layer to node S_j of the hidden layer, is:

$$w^{(2)}_{X_i,S_j} = \frac{1}{2 \cdot \sigma_j^2} \tag{21}$$

where, $\sigma_j$is the smoothing parameter of class j, represented by node S_j of the output layer of the network. During the testing of the network, the probability density functions for each class are calculated, using equation (18).

Comparative and parametric investigations of the diagnostic ability of PNN on turbofan engines have been carried out in [31]. The work has also provided some general information about PNN diagnostic ability. The use of probabilistic neural networks for sensor fault detection and estimation of the sensor bias has been demonstrated in [32]. The technique proposed was shown to provide a powerful sensor validation tool, for cases where a rather limited number of measuring sensors is available, such as when data from an engine onboard an aircraft are available.

4.2. Expert systems

In contrast to neural networks, which learn knowledge by training on observed data with known inputs and outputs, Expert systems(ES) utilize domain expert knowledge in a computer program with an automated inference engine to perform reasoning for problem solving. Three main reasoning methods for ES used in the area of engine diagnostics are rule-based reasoning, case-based reasoning and model-based reasoning. In condition monitoring practice, knowledge from domain specific experts is usually inexact and reasoning on knowledge is often imprecise. Therefore, measures of the uncertainties in knowledge and reasoning are required for ES to provide more robust problem solving. Commonly used uncertainty measures are probability, fuzzy member functions in fuzzy logic theory and belief functions in belief networks theory. An expert system dealing with uncertainty and proved to be very efficient in fault diagnosis is described below.

4.2.1. Bayesian Belief Network (BBN)

BBN is a probabilistic expert system, graphically represented by a set of 'nodes' and a set of 'links' connecting them. The topological features of a BBN that must be fully specified in order the network to be complete are the following: Nodes express the parameters of the represented domain. In figure 5 an example of a belief network referred to a gas turbine is presented. This network has four nodes expressing the parameters of the engine taken into account. These are: the 'efficiency factor of the high pressure compressor' (n(HPC)), the 'efficiency factor of the high pressure turbine' (n(HPT)), the 'pressure ratio' (π_c) and the 'turbine inlet temperature' (TIT).

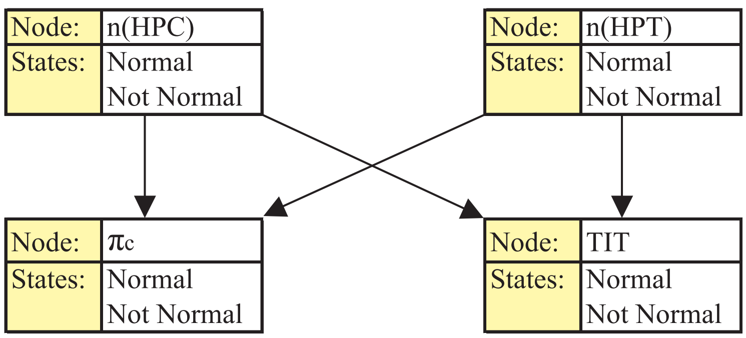


Figure 5. An example of a belief network of a gas turbine.

Each node has two or more discrete states, expressing all the different states of the parameter they refer to. For instance, in the network of figure 5, node TIT has two states: 'normal temperature' and 'not normal temperature'. In each case, the set of states of a node must be exhaustive and mutually exclusive. In other words, any possible condition of a parameter expressed by a node in a BBN is represented by one and only one state of this node. Links among the nodes express the 'rules' of interdependence that hold among them. For example, the link from node n(HPC), on the network of figure 5, to node πc expresses the fact that the condition (state) of node n(HPC) affects directly the condition of node πc. The absence of a link between two nodes doesn't mean that these two nodes are independent, but expresses the fact that the condition (state) of the one doesn't directly affect the condition of the other.

Each node has a Conditional Probability Table (CPT), expressing the probability each state of the node to occur, when the state of each other node, ending up directly to it (called 'parent node'), is known. In case that, a node has no other nodes ending up directly to it (called a 'root node'), the CPT of this node express the 'a priori' probability each state of this node to occur. In Table 1 an example of how the CPTs, of the nodes of the network of figure 5, could be, is shown.

Node:	n(HPC)	
States:	Normal	Not Normal
a priori probabilities	**0.90**	**0.10**

Node:	n(HPT)	
States:	Normal	Not Normal
a priori probabilities	**0.87**	**0.13**

Node	TC				Parent Nodes
States	Normal	Not Normal	n(HPC)	n(HPT)	
Conditional Probabilities	**0.97**	**0.03**	Normal	Normal	States of parents
	0.68	**0.32**	Normal	Not Normal	
	0.26	**0.74**	Not Normal	Normal	
	0.02	**0.98**	Not Normal	Not Normal	

Node	TIT				Parent Nodes
States	Normal	Not Normal	n(HPC)	n(HPT)	
Conditional Probabilities	**0.97**	**0.03**	Normal	Normal	States of parents
	0.16	**0.84**	Normal	Not Normal	
	0.38	**0.62**	Not Normal	Normal	
	0.08	**0.92**	Not Normal	Not Normal	

Table 1. An example of the CPTs of the nodes of the network of figure 5.

Once a BBN is constructed, inference can be realized any time evidence is available. Inference is the procedure where the probabilities of each state of each node of the network are updated each time that evidence is available. 'Evidence' is the knowledge of the state of one or more nodes of the network.

Bayesian Belief Networks have some features that make them very attractive in the field of diagnosis of faults in gas turbines. The most important of these features are: BBN allow probabilistic diagnosis; it is more realistic to make diagnosis expressing the belief (probability) of whether an event occurred or not, than expressing a deterministic answer. Mathematical relationships among the variables of a network are not required in order to form a BBN. Only the way that these variables affect each other is required. This is very helpful since such mathematical relationships may be unknown. Modern approximate algorithms for inference with BBN are able, nowadays, to answer queries, once 'evidence' is provided, within few seconds, even for complicated networks, performing with adequate accuracy. Each node of a BBN can be an 'evidence' as well as a 'query'. There is no restriction to the number of 'query' or 'evidence' nodes. Therefore, there is no limitation on how many or which are the 'evidence' nodes in order to estimate the probabilities of all the other nodes of a network. It allows also the inclusion of information of different nature and from different sources for diagnostics.

Such networks have been employed in the field of gas turbine diagnostics by few researchers. Breese et al. [33], presented a method for detecting specific faults on large gas turbines that combines a thermodynamic model of the engine under examination and a BBN, constructed by use of statistical data of the engine. Palmer [34], presented a statistically also constructed BBN for fault detection of the CF6 family of engines.

The first attempt to propose a general procedure of building a BBN for diagnostic purposes, has been presented by Romessis et al. [35]. The objective of the investigation was to reveal a possible way of setting up such a network with aid of an engine performance model. The way of building diagnostic BBNs, allowing implementation into any type of engine, and the disengagement of the BBN from hard to find statistical data, were two elements that made the work interesting and promising. The effectiveness of the proposed diagnostic method was examined on benchmark fault case scenarios, in a typical modern turbofan engine of civil aviation. The diagnosis was based on the observation of fewer measurements (7) than the considered fault parameters (11). Inference with BBN showed that such a network is very reliable, since in the 96% of the cases where a fault was detected, it was detected correctly. Only a 4% of the cases were attributed to a wrong fault.

A more efficient method even in fault cases with smaller health parameters' deviations was proposed in [36]. The improvement was due to the way the BBN is constructed: probabilistic relationships among variables are more accurately represented. The effectiveness of the proposed method has been demonstrated by its strong diagnostic ability with various fault scenarios and cases at several operating conditions, including coverage of an operational envelope of a typical flight.

5. Hybrid and fusion information techniques

Despite research in various methods for engine fault diagnostics, there is still no method which can effectively address all issues. One way to approach the problem is to try and offset the limitations of one technique with the strength of the other. Hybrid models have attempted to bridge this gap.

An integrated fault diagnostics model for identifying shifts in component performance and sensor faults using Genetic Algorithm and Artificial Neural Network was presented in [37]. The diagnostics model operates in two distinct stages. The first stage uses response surfaces for computing objective functions to increase the exploration potential of the search space while easing the computational burden. The second stage uses concept of a hybrid diagnostics model in which a nested neural network is used with genetic algorithm to form a hybrid diagnostics model. The nested neural network functions as a pre-processor or filter to reduce the number of fault classes to be explored by the genetic algorithm based diagnostics model. The hybrid model improves the accuracy, reliability and consistency of the results obtained. In addition significant improvements in the total run time have also been observed. Ecstase [38], presents an example of the use of fuzzy logic combined with influence coefficients applied to engine test-cell data to diagnose gas-path related performance faults. The diagnostic process to identify module level engine performance faults has been validated using eight examples from real-world test-cell data. Many combinations of faults were examined in an attempt to explain the performance degradation observed in the engine under- going repair. This aspect of the process enabled the status of 17 faults to be determined, despite only five engine parameters being used. The method correctly identified the faults for all except for one fault which had a very small degradation effect on the engine performance.

A diagnostic method consisting of a combination of Kalman filters and Bayesian Belief Network (BBN) is presented in [39]. A soft-constrained Kalman filter uses a priori information derived by a BBN at each time step, to derive estimations of the unknown health parameters. The resulting algorithm has improved identification capability in comparison to the stand-alone Kalman filter. Besides the improvements in accuracy and stability, this kind of method allows information or sensor fusion, which is a very important field of research for future works. The key advantage of combining methods is that it replaces the problem of comparing classification techniques to regression techniques by the problem of choosing which information they can share. Romessis et al. [40] proposed a statistical processing of the diagnostic conclusions provided by a least-square based gas path diagnostic method, in order to improve diagnosis. In a similar attempt (see [41]) a combinatorial approach (statistical evaluation of least squares estimations) combined with fuzzy logic rules to calculate fault probabilities. The possibility of creating a mixed fault classification that incorporates both model-based and data driven fault classes was investigated in [42]. Such a classification combines a common diagnosis with a higher diagnostic accuracy for the data-driven classes. The performed analysis has revealed no limitations for realizing a principle of the mixed classification in real monitoring systems.

Information Fusion is the integration of data or information from multiple sources, to achieve improved accuracy and more specific inferences than can be obtained from the use of a single sensor alone. It is generally believed that an ensemble of methods improves diagnostic accuracy when compared to individual methods. In [43] several fusion architectures and classifiers were evaluated. Fusing classifiers that are performing very well had little positive effect. However, it was shown that fusing marginal classifiers can increase the diagnostic performance substantially, while reducing their variability. Enhanced fault localization using probabilistic fusion with gas path analysis algorithms is referred in [44],while a fusion technique allowing the merge of conclusions provided by diagnostic methods that act independently for the detection of gas turbine faults is described in [45]. The proposed technique adopts the principles of Dempster-Schafer theory for the fusion of two diagnostic methods namely a Bayesian Belief Networks (BBN) and a Probabilistic Neural Networks (PNN). The technique has been applied for the detection of thermodynamic as well as mechanical faults on gas turbines. In all cases, the effectiveness of the proposed fusion technique demonstrated that the merge of diagnostic information from different sources leads to better and safer diagnosis.

A fusion method that utilizes performance data and vibration measurements for gas turbine component fault identification is presented in [46]. The proposed method operates during the diagnostic processing of available data (process level) and adopts the principles of certainty factors theory. Both performance and vibration measurements are analyzed separately, in a first step, and their results are transformed into a common form of probabilities. These forms are interwoven, in order to derive a set of possible faulty components prior to deriving a final diagnostic decision. Then, in the second step, a new diagnostic problem is formulated and a final set of faulty health parameters are defined with higher confidence. In the proposed method the non-linear gas path analysis is the core diagnostic method, while information provided by vibration measurements trends is used to narrow the domain of unknown health parameters and lead to a well-defined solution. Finally a comprehensive presentation of different fusion possibilities offered is given in [47].

6. ECMD integrated systems

Although many diagnostic methods have been proposed and some of them have been tested in real engines only few are known to be incorporated in ECMD integrated systems. An industrial monitoring and diagnostic system must comply with several requirements. For such a system to be effective it should:

- Be as automated as possible and integrated namely performing all actions from data collection to derivation of diagnostic decisions.
- Be "robust", namely not very susceptible to noise or faulty input information.
- Have an as wide as possible coverage of detectable faults. Additionally, it should allow additions of other newly discovered faults, which have not been included in the initial repertory of the system.
- Have prognostic capabilities concerning future maintenance and repair actions. This helps in ensuring that long lead-time spares are available and that outages be minimized.
- Derive information with high confidence. In this respect, derivation of the same conclusion by different methods is a very useful feature.
- Employ as few instruments as possible. The instrumentation should be kept as simple as possible and include the minimum number of instruments.
- Be modular and flexible with open circuit architecture in order to be adapted to operator's needs.
- Be very user friendly, so that it can be used by non-specialized personnel, while its output is clear enough to need very little or no interpretation.

In order to materialize a monitoring system, which possesses these features, the procedures, which should be implemented, are as follows:

i. Measurement data acquisition.

ii. Data evaluation in order to discard unreliable readings and possibly detect sensor faults.

iii. Data processing using appropriate techniques in order to derive diagnostic information.

iv. Diagnostic inference in order to decide what is the nature, the location and the severity of a malfunction present, if any.

v. Data management in order to keep historical data records for long term monitoring, without storing too much unnecessary information.

Such an integrated system and experience gained from its implementation on an operating industrial gas turbine has been presented in [48]. The main functions of this system materializing the procedures mentioned above are as follows:

Data Acquisition and Management: Data are acquired from a number of different measuring instruments, for slowly or fast varying quantities. The obtained measurements are being on-line validated and then organized in a database. The system also gives the possibility to play back measurements database in order to recreate real time operation. Additional features of the developed data acquisition feature are its flexibility and its capability to easily meet the requirements of any particular implementation.

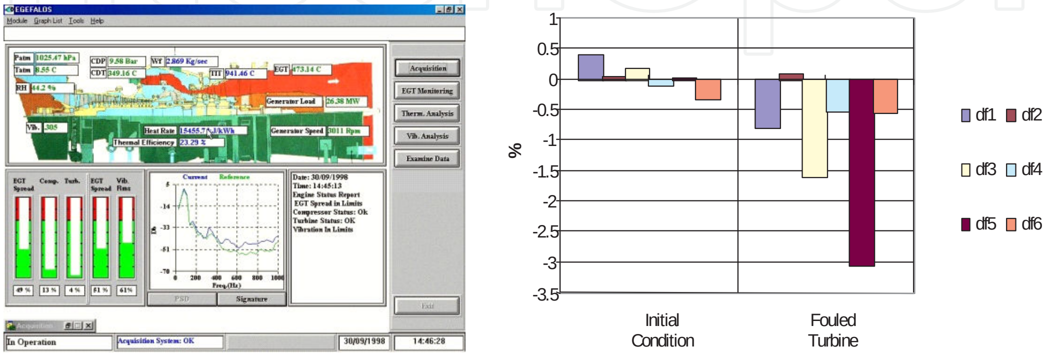
Performance Analysis: The acquired thermodynamic measurements are being on-line processed using the adaptive modeling method [19]). Thus, at any given operating conditions, the overall engine performances and individual components health indices are being evaluated. The method can also be used off-line for the analysis of previously recorded data.

EGT Monitoring: The hot section, being the most critical area of the engine, is receiving particular attention, through exhaust gas temperature profile monitoring ([49]. This monitoring provides indication of possible burner malfunctions or thermocouple faults. Off- line analysis of historic data stored in measurements database can also be performed.

Vibration Monitoring: The means of identifying mechanical faults are provided by this function of the system. For data from vibration sensors, the following diagnostic features are extracted and assessed: a) overall vibration level, b) power spectra (on-line frequency analysis), and c) spectral signatures [50]). Finally, as the other monitoring modules, it offers the possibility of off-line line analysis of historic data stored in measurements database.

These functions are performed by the system continuously, while the engine is in operation. Their implementation provides adequate diagnostic information about engine condition. This information is being further assessed using a rule based inference engine that provides an engine condition assessment. Thus, the user is being informed in real time about the engine's condition and performance. The main interface of the system implemented on a PC is shown in figure 6a. It comprises an axial cut-out of the monitored engine and gives the most critical information about the engine condition. The system offers the possibility to perform a more detailed analysis by activating the previously described functions through the buttons on the menu at the upper right hand corner.

An example of system effectiveness in diagnosing is the following. A twin-shaft industrial gas turbine with 21 MW nominal output, used for electricity production in a power station, is considered. The turbine suffered from the formation of deposits on gas generator and power turbine blades, very soon after it was put on operation (see figure 1a). A remedy action taken by the manufacturer was a small re-staggering (opening) of power turbine stationary blades. An easy and reliable way of identification of the malfunction of the turbine is provided by the method of adaptive modeling. The technique has been applied to test data from this turbine and it gave a clear picture of the problem. 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 6b. 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.



(a) (b)

Figure 6. (a) Display of a user friendly monitoring software for an industrial gas turbine. (b) Health Indices Percentage deviation, for a gas turbine, which has suffered severe turbine fouling, caused by fuel additives.

7. Conclusions

In this chapter, we have attempted to present basic principles of the engine condition monitoring and diagnostics (ECMD) subject. It would be impossible to cover in few pages all the aspects of ECMD. Thousands of papers have been published and a vast amount of knowledge has been accumulated. Even extensive reviews cannot mention all the proposed methods. In this respect we presented selective methods representative of three main steps of an ECMD approach, namely data acquisition, data processing and diagnostic decision-making, with emphasis on the last two steps. Few recently developed hybrid, data and method fusion techniques have also been briefly discussed. The structure of an integrated ECMD system incorporating different diagnostic technics and already in operation is also presented.

The following conclusions are the outcome of over twenty five years of experience in the area of ECMD.

- The main problems with respect to the industry adoption of advanced technics are the following: a) lack of data due to no data collection and/or data storage at all; b) lack of efficient communication between method developers and maintenance practitioners; c) lack of efficient validation approaches.

- Both physics based and data-driven models show benefits and drawbacks. From the decision making point of view both traditional and artificial intelligence techniques are used, although it seems that hybrid approaches are more promising.
- The value of vibration monitoring and other sources data in refining gas-path monitoring results has been recognized. The approach of combining different monitoring results, i.e., data fusion, is becoming an active area of research.
- Usage and life monitoring for fatigue critical or life-limited parts are increasingly important
- Collaboration of ECMD research groups is necessary in order to produce integrated platforms for enhancing an ECMD system since each research group has its own specialty and focus in the area.

The following research directions are required for the next generation of ECMD systems: Enhancement of ECMD systems to collect accurate information, especially fault event information. This information would be very useful for model building and model validation as well. Advanced models and methods for utilization of the transient data diagnostic information as well as detailed higher order models for deterioration mechanisms and faults reliable simulation should be developed. Accurate prognostic models development is also necessary. Finally, there is a need for establishment of efficient validation approaches through benchmark test cases to compare the merits and the drawbacks of different modeling and algorithmic approaches.

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