Proceedings of the Institution of Mechanical Engineers,
Part A: Journal of Power and Energy, Volume 216, Number 5 (September 1, 2002), pp. 363-377

Performance Analysis Based Gas Turbine Diagnostics: A Review

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Abstract

Gas turbine diagnostics has a history almost as long as gas turbine development itself. Early engine fault diagnosis was carried out based on manufacturer information supplied in a technical manual combined with maintenance experience. In the late 1960's when Urban introduced Gas Path Analysis, gas turbine diagnostics made a big breakthrough. Since then different methods have been developed and used in both aero and industrial applications. Until now a substantial number of papers have been published in this area. This paper intends to give a comprehensive review of performance analysis based methods available thus far for gas turbine fault diagnosis on open literature.

Keywords: gas turbine, engine, performance, diagnostics, fault detection, review

NOTATION

$\vec{e}$	Difference between $\vec{z}$ and $\hat{\vec{z}}$
F	Function
H	Influence coefficient matrix
$\vec{v}$	Measurement noise vector

$\bar{x}$	Engine independent (component) parameter vector
$\bar{z}$	Engine dependent parameter vector
ϕ	Function
Δ	Variation

Superscripts

-1	matrix inverse
$\wedge$	estimated

ABBREVIATIONS

AANN	Auto-Associative Neural Network
APNN	Adaptive Probabilistic Neural Network
ART	Adaptive Resonance Theory
BBN	Bayesian Belief Network
BPNN	Back Propagation Neural Network
CPN	Counter Propagation Network
DOCGPA	Discrete Operating Condition Gas Path Analysis
EHM	Engine Health Monitoring
EMD	Engine condition Monitoring and fault Diagnosis
FCM	Fault Coefficient Matrix
FIR	Finite Impulse Response filter
FPN	Fuzzy Petri Net
GA	Genetic Algorithm

GPA	Gas Path Analysis
ICM	Influence Coefficient Matrix
KB	Knowledge Base
LRF	Learning Rate Factor
LSE	Least Square Estimate
LVQ	Learning Vector Quantisation
MF	Modification Factor
MLE	Maximum Likelihood Estimate
PDF	Probability Density Function
PNN	Probabilistic Neural Network
RAN	Resource Allocating Network
RBF	Radial Basis Function neural network
RCC	Recurrent Cascade Correlation neural network
SOM	Self-Organizing Map
SVM	State Variable engine Model

1 INTRODUCTION

Gas turbine performance deteriorates during operation due to degradation of gas path components. The most common causes of the degradation are compressor fouling, blade tip clearance increase due to wearing and erosion, labyrinth seal damage, foreign and domestic object damage, hot end component damage, corrosion, etc. **[102].** These physical faults result in changes in gas turbine thermodynamic performance measured by efficiencies and flow capacities of components, which in turn produce changes in observable engine parameters such as temperature, pressure, rotational speeds and fuel flow rate. The degraded performance reflected from these measurements can be used to detect, isolate and accommodate component faults; such relationships were described by Urban **[134]** and shown in Figure 1. In order to keep high level of availability and reliability of gas turbines, effective maintenance are essential. With the development of gas turbine diagnostic technologies, gas turbine maintenance has been shifting from preventative type to reliability centred maintenance based engine health monitoring and fault diagnostics.

There are many approaches for gas turbine condition monitoring and fault diagnostics, such as performance analysis, oil analysis, visual inspection, borescope inspection, X-ray checks, eddy current checks, vibration monitoring, debris monitoring, noise monitoring, turbine exit spread monitoring, etc. **[146]**. Performance analysis based diagnostics is one of the most powerful tools among them, where the analysis of gas turbine gas path parameters provides the information of degradation severity of gas path components.

Gas path analysis (GPA), a linear model based method, was introduced for the first time in 1967 by Urban **[132]** and then followed by different derivatives such as optimal estimate based methods. In order to take into account the non-linearity of engine behavior, a non-linear model based method combined with conventional optimization was first introduced in 1990 by Stamatis et al. **[118]**. Unfortunately, conventional optimization may stop at a local minimum. This disadvantage of non-linear model based methods has been overcome by using genetic algorithms in recent years, firstly by Zedda and Singh **[146-147]**. Neural networks were first introduced to gas turbine diagnostic applications in 1965 by Denny **[17]** and have been widely used since 1989; they have the advantage that only engine experimental knowledge is required for the training of neural nets and the computation time for diagnosis is very short once the neural nets are trained. Application of expert systems to gas turbine diagnosis can be traced back to early 1980's. Expert systems are still one of the best types of methods for gas turbine diagnosis and are still under development. More recent advances of expert systems to gas turbine diagnostics is rule-based fuzzy expert systems, such as those introduced in 1997 by Fuster et al. **[37]** and Siu et al. **[115]**. Most diagnostic approaches are based on gas turbine steady state measurements. Some diagnostic information has been analyzed with engine transient measurements since late 1980's, but diagnostic approaches based on transient data have not been well developed.

Data uncertainty, the measurement noise causing data scattering around their true values, is another source of inaccurate fault diagnosis. Data averaging and filtering using different technologies are effective ways of reducing the impact of measurement noise and improving diagnostic accuracy.

In this paper, technologies relevant to gas turbine performance analysis-based diagnostics developed so far and published in the open literature are reviewed, including data validation and different approaches of gas turbine fault diagnostics. Major approaches for gas turbine diagnostic are included, i.e. linear model-based methods, non-linear model-based methods, artificial intelligence (neural networks, genetic algorithms and expert systems) based methods, fuzzy logic based methods, and fault diagnostics with transient measurement data.

2 DATA VALIDATION

Gas turbine fault diagnostics is based on the analysis of deviations of component parameters from their nominal conditions. Such information can only be obtained from measurement. The accuracy of all diagnostic systems is partially determined by the quality of the measurement. Unfortunately, measured data are usually contaminated by sensor noise, disturbances, instrument degradation and human errors. In order to improve the reliability of diagnostic results, it is very important to clean or rectify the measured data before they are input into diagnostic systems.

Usually, a measured parameter changes around its actual value and may be expressed statistically with a probability density function. The true value of a parameter can be approximated by its averaged measurement which is normally obtained with rolling average method where an average value is obtained with numerical average of certain preceding points. The disadvantage of rolling average is that it wastes the initial data points and is slow in responding to trend changes **[18]**. An exponential average equivalent of a ten point rolling average was introduced by DePold and Gass **[18]** to reduce the measurement noise, where with each new data point 15% of the remembered average is replaced by new data. It was proved that the noise reduction with an exponential average is significant and the exponential average is better than the rolling average in terms of response to data variation. More recently, different data filtering methods were explored by Ganguli **[39]** for removing noise from data while preserving sharp edges that may indicate a trend shift in gas turbine measurements. Compared with linear filtering, a non-linear filter, FIR median hybrid filter, was found to be far more superior in accurately reproducing the root signal from noisy data. A health residual, a scalar norm of the gas path measurement deltas, was used to partition the faulty engine from the health engine.

Auto-Associative Neural Network (AANN) can also be used to filter measurement noise to improve input data quality and was introduced by Roemer **[103]** and Mattern et al. **[79-80]**. A two-step neural network algorithm was developed for gas turbine sensor validation by Lu et al. **[73]**, where the first step is the construction of a noise-filtering and self-mapping Auto-Associative Neural Network based on the back-propagation algorithm, the second step uses an optimization procedure built on top of these noise-filtering and self-mapping nets to perform bias detection and correction. It is shown that AANN is an effective noise filter for raw data and is of paramount importance to improve the accuracy of diagnostic systems.

For those gas turbines that work in an environment with high absolute humidity, the impact of air humidity on component parameter deviation may be of magnitude similar to the magnitude of the deviations caused by faults, and the accuracy of diagnostics may be reduced. A correction method to reduce the impact of air humidity on measurement data was suggested by Mathioudakis and Tsalavoutas **[78]**.

3 LINEAR MODEL-BASED METHODS

The relationship between gas turbine dependent parameters (such as gas path pressures and temperatures, thrust, mass flow rate, etc.) and independent parameters (such as pressure ratio, flow capacity and efficiency at each component) is highly non-linear. To simplify the description of such a relationship, a linear approximation at certain operating point (such as maximum power or cruise) was introduced as follow:

$$\vec{z} = H \cdot \vec{x} \tag{1}$$

With this assumption, a first Gas Path Analysis (GPA) method was introduced by Urban in 1967 **[132]** and its application to gas turbine condition monitoring and multiple fault diagnosis was described in more details by Urban **[133-134]**. A review of Gas Path Analysis was given by Smetana **[116]**. This GPA method has been widely used in applications, such as those of Passalacque **[90]**, Staples and Saravanamuttoo **[122]**, Saravanamuttoo **[112]**, Danielsson **[16]**, Lazalier et al. **[71]**, Grewal **[45]**, Escher **[27, 28]**, Nieden and Fiedler **[88]** and Simani et al. **[113]**. In this method, the relationship between various engine measurable parameter deltas and unmeasurable component parameter deltas at certain engine operating condition is expressed with a linear influence coefficient matrix (ICM):

$$\Delta\vec{z} = H \cdot \Delta\vec{x} \tag{2}$$

The deviation of engine component parameters can be calculated with a fault coefficient matrix (FCM) (or diagnostic matrix) which is the inverse of the influence coefficient matrix:

$$\Delta\vec{x} = H^{-1} \cdot \Delta\vec{z} \tag{3}$$

The generation of the fault coefficients relies on the implantation of known degraded components. This method is idealistically simple and provides quick solutions to gas turbine diagnostics. It also has advantages of fault isolation, quantification and multiple fault diagnostics. Unfortunately, it requires several conditions that are difficult to satisfy: accurate influence coefficient matrix to describe the engine performance, fault and noise free sensors, the same number of uncorrelated measurements as that of engine component parameters and correct choice of measurement locations. In addition, "smearing" effect may reduce the accuracy of the diagnostic results.

Improvements were made to the estimate of $\Delta\vec{x}$ by using optimal estimation theory **[9, 41]** such as the minimum error (or maximum likelihood) estimation **[74, 135-136]**, weighted-least-squares **[22-24, 74, 140]**, maximum a-posteriori **[140]**, and Kalman Filter **[4, 76, 100, 137]**. A detailed analysis of optimal estimation for gas turbine applications was made by Grewal **[45]**. Measurement noises were taken into account in these methods. A comparison between Kalman Filter and Neural Network models for single fault diagnosis **[141]** shows that neural networks have very slight advantage to the Kalman Filter approach. Another problem of Kalman Filter approach is that the effects of genuine changes in a small number of component changes and/or sensor biases over the whole set of changes and biases being considered may be "smeared". An enhanced Kalman Filter (the so-called "Concentrator") was introduced by Provost **[101]** to overcome the problem. An analysis of measurement parameter selection for linear and non-linear GPA based on Kalman Filter estimate was given by Kong and Ki **[67]** with the conclusion that with an increase of number and kinds of measurement and proper selection of the measurement parameters the reliability of diagnostics can be improved.

In order to make all differential gas path analysis methods valid, the number of measured performance variables must be greater than or at least equal to the number of diagnostic parameters that have to be estimated. This requirement sometimes is difficult to meet due to the limited number of measurements available. To overcome this problem, a Discrete Operating Conditions Gas Path Analysis (DOCGPA) scheme was developed by Stamatis and Papailiou **[121]** and Stamatis et al. **[120]**.

The Kalman Filter algorithm has also been used in diagnostics of gas turbine with transient data. Details of the development in this area will be described in a following section.

4 NON-LINEAR MODEL-BASED METHODS

Linear model based methods assume that gas turbine engines behave linearly at the operation conditions where diagnosis is carried out, which is not true. In order to take into account the high linearity of engine behavior, non-linear model based diagnostic methods were introduced. This type of diagnostic methods is based on accurate modelling of non-linear steady state gas turbine performance developed during the past 50 years. Gas turbine modelling techniques have been reviewed by many researchers, such as Bird and Shwartz **[7]** and Sanghi et al. **[110]**. At steady state conditions, the dependent and independent parameters of gas turbines can be expressed with a non-linear relationship

$$\vec{z} = F(\vec{x}) + \vec{v} \tag{4}$$

The idea of the non-linear model-based methods is shown in Figure 1. The real engine component parameter vector $\vec{x}$ determines engine performance represented by the measurement vector $\vec{z}$. With an initial guessed parameter vector $\hat{\vec{x}}$, the engine model provides a predicted performance measurement vector $\hat{\vec{z}}$. An optimization approach is applied to minimize an objective function as follows:

$$\text{Objection Function} = \sum_i \phi\left(\left\|\vec{z}_i - \hat{\vec{z}}_i\right\|\right) \tag{5}$$

which is the function of the difference $\vec{e}$ between the real measurement vector $\vec{z}$ and the predicted measurement vector $\hat{\vec{z}}$. A minimisation of the objective function is carried out iteratively until the best predicted engine component parameter vector $\hat{\vec{x}}$ for real $\vec{x}$ is obtained.

An iterative non-linear GPA approach based on Urban's method **[132-134]** for non-linear fault diagnostics was explored by House **[57]** for a single shaft gas turbine for helicopters, Further development of the non-linear method was done by Escher **[27-28]** with a Newton-Raphson technique and a computer code, PYTHIA, was developed.

An adaptive model for accurate simulation of gas turbine performance with the possibility of adapting to engine particularities was developed and described for the first time by Stamatis et al. **[117]**. In this method, modification factors (MF) which are the ratio of parameter values of reference performance maps and the values of the actual maps were introduced. The modification factors for every component was obtained through a Non-linear Generalized Minimum Residual method **[117]**. Observation of the changes of modification factors between nominal and deteriorated engine can lead to detection of the location and the kind of fault of the engine **[118]**. Proper selection of modification factors with optimization can also be used for fault detection of gas turbine components and sensors. Lambiris et al. **[70]** introduced a weighted error function and used a polytope algorithm (downhill simplex method **[87]**) in their optimization. Stamatis et al. **[119]** introduced a sensitivity measure and a fast selection procedure based on the method of singular value decomposition for the optimization; a similar method was used by Tsalavoutas et al. **[131]** to produce diagnostic information and analyze faults of a two-shaft gas turbine engine. A direct adaptation of engine thermodynamic parameters, combined with a least square method, was described by Santa **[111]** for diagnostic purpose, where the changes of the parameters help to locate component damage.

A statistical (Bayesian) inference based on the Maximum Likelihood Estimate (MLE) method for monitoring the condition of gas turbine engines was presented by Consumi and d'Agostino **[14-15]**, where a Gaussian a priori PDF is initially assumed for the uncertain parameters. The deviation of engine component parameters was obtained which maximizes the likelihood of the observed data with respect to the corresponding engine nominal data by equivalently minimizing a cost function that is the sum of squared residuals. Different methods were used in the optimization, such as a Davidon-Fletcher-Power method **[99]** by Consumi and d'Agostino **[14-15]**, a second order algorithm of performance comparable to the Newton-Raphson method, and a Levenbery-Marquardt method **[99]** by Biagioni and Cinotti **[6]**. Sensor noise was proved to be sensitive to the accuracy of the diagnostics **[15]**.

Bettocchi and Spina **[5]** used the sum of the squared residuals between the computed and measured values of the same parameters as an objective function in their fault diagnosis. The deviations of engine component parameters were obtained by minimizing the objective function with the IMSL math library **[138]**. A weighted least squares estimation was used by Chen and Zhu **[11]** to identify single or multiple faults of jet engines with noisy measurements. An adjusting technique was introduced to minimizing the sum of squared weighted errors when the number of measurements is greater than the number of adjustable parameters. Another non-linear model-based method is the parameter identification/estimation approach developed by Grodent and Navez **[46]**. It includes two parts: the first part deals with the parameter estimation which allows to generate the residuals and then statistical tests are then built in the second part in order to distinguish between healthy and faulty parameters. The minimisation of an appropriate objective function with a Bayesian approach was used in the estimation process.

Non-linear model-based gas turbine diagnostics can also be performed by minimizing the cost (objective) function with Genetic Algorithm (GA). This will be described in more details in the next section.

5 ARTIFICIAL INTELLIGENCE BASED METHODS

5.1 Artificial Neural Networks

A neural network is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experimental knowledge and making it available for use **[53]**. Early applications of neural network to aircraft engine diagnostics were carried out by Denny **[17]** and Dietz et al.

[20], and to the Space Main Engine by Whitehead et al. **[142-143]**. Different neural networks have been used in gas turbine engine fault detection, diagnosis and accommodation since then.

The most popularly used artificial neural network in gas turbine diagnostics is the Feed-Forward Back-Propagation Networks where the configuration of a typical one of them is shown in Figure 3, a supervised network, where sensed information is propagated forward from input to output layers while calculated errors are propagated backward and used to adjust synaptic weights of neurons for better performance. Typically, such a network is made of an input layer where input values are received through input neurons, one or more hidden layers whereby functional relationship are expressed with a set of weights connecting succeeding neurons, and an output layer where output neurons receive output values. Training of the net is through a learning algorithm named back-propagation where the weights are modified based on the input-output patterns. Application of Feed-Forward Back-Propagation neural networks to gas turbine diagnosis have been performed by many researchers, such as Eustace **[29]**, Torella and Lombardo **[127-128]**, Kanelopoulos et al. **[61]**, Torella **[126]**, Roemer **[103]**, Tang et al. **[124]**, Cifaldi and Chokani **[12]**, Zedda and Singh **[147]**, Volponi et al. **[141]**, Sun et al. **[123]**, Lu et al. **[73]**, Kobayashi and Simon **[64]** and so on. Torella and Lombardo **[128]** described a calculation for learning rate factor (LRF), for improving the learning rate BPNN. Kanelopoulos et al. **[61]** presented a partial network architecture to perform sensor and component fault diagnosis step by step. Zedda and Singh **[145]** introduced a modular neural network system to tackle large-scale diagnostic problem and applied it to Garrett TFE 1042 engine, with the unfortunate drawbacks of a large number of nets and long training time. Comparison between the Feed-Forward Back-Propagation Neural Network and the model based Kalman Filter method for gas turbine engine single fault linear diagnostic problems **[141]** shows that such a network has slightly poorer performance than Kalman Filter approach in terms of accuracy. Volponi et al. **[141]** introduced a hybrid neural network where part of the network model was replaced by influence coefficients and the accuracy of such a network was favorable compared to back-propagation net and Kalman Filter approach. Sun et al. **[123]** employed a hybrid training rule to improve its convergence. Lu et al. **[73]** compared two feed-forward back-propagation neural networks with a similar configuration, one with four inputs and another with eight inputs, and found that both achieved high success rates. Kobayashi and Simon **[64]** applied a feed forward network in their hybrid diagnostic technique, where the neural networks were used to estimate engine health parameters, and a Genetic Algorithm was used for sensor bias detection and estimation.

Different unsupervised competitive learning neural networks are used in fault diagnostics. Common to them all is a layer that selects a single winner unit. The competitive learning consists of two phases, one for selecting the winner unit and the other for the updating of connection weights to the winner unit. The following is a description of the competitive neural networks used in engine diagnostics.

The first type is a Probabilistic Neural Network (PNN), a derivative of the Radial Basis Function neural network, used by Eustace and Merrington **[30]**, Patel et al. **[93]**, Sun et al. **[123]**, Eustace and Frith **[31]** and Romessis et at. **[108]** The training of the networks is a supervised learning procedure, where PNN classify the training patterns to classes. PNN is a network implementation of Bayesian statistics where the previous case studies are directly stored in the network as mathematical coefficients while no training is required. When an unknown pattern is input to the network, the Euclidean distances between the input pattern and stored case centres are calculated. The distances are then converted to probabilities via a density function; the smaller distance has the higher probability and vice verse. The fit for each case is compared and the case with highest probability indicates the most possibility. Application of the method to a fleet of engines **[30]** showed that it is capable of diagnosing faults even when the parameter changes due to fault are less than the no-fault engine-to-engine variation. An Adaptive Probabilistic Neural Network (APNN) was presented by Sun et al. **[123]** where the Maximum Likelihood Estimation Method was used to obtain the optimal Bayesian estimation and was more adaptive and fit better to quantitative diagnosis for multiple faults.

The second type is a Self-Organizing Map (SOM) (Figure 4) developed by Kohonen **[65]**, where the neurons are placed at the nodes of a lattice that is usually one- or two-dimensional. The neurons are selectively tuned to various patterns in the course of competition learning. The self-organizing map is characterized by the formation of a topographic map of the input patterns in which the spatial location of the neurons in the lattice are indicative of intrinsic statistical features contained in the input patterns **[53]**. A real-time engine health monitoring (EHM) and diagnostic system were described by Roemer **[103]**, where both self organizing neural network maps and trained network classifiers were utilized in diagnostic module. The self organizing neural network map (Kononen network **[66]**) was used for initial pattern clustering to identify similar patterns and a trained back-propagation network classified the coordinate location on the map into a specific diagnosis.

The third type is a Learning Vector Quantisation (LVQ) network designed by Kohonen **[66]** is a competitive neural network where the Voronoi cells are defined to partition the input space and a corresponding set of Voronoi vectors are defined to point to the cells. During the learning process, an input vector is picked at random from the input space. If the vector and a Voronoi vector agree, the Voronoi vector is moved toward the input vector; otherwise the Voronoi vector is moved away from the vector. Such a network was introduced by Eustace **[29]** and was applied to F404 turbofan engine. It has an input layer, one hidden layer and an output layer. The input layer receives the input pattern and each of the hidden layer is directly connected to an output neuron. Each of the hidden neurons, with weights connected to input neurons, represents one of the faults or no-fault condition. The network is trained with sample faults and no-fault patterns. When unknown data are input into the net, each of the hidden neurons compares the input engine parameters with the weights associated with the neuron. One of the neurons wins the comparison with a closest match and passes a value of unity to the corresponding output neuron as a diagnostic result, while other output neurons pass a value of zero. Comparison between the LVQ network and back-propagation network showed that both of them achieved high accuracy. The advantage of LVQ network is that of being quick to train, while the back-propagation network gives an indication of the confidence of its diagnosis.

A hybrid scheme combining supervised and unsupervised learning is a Counter Propagation Network (CPN), a competitive feed-forward network, developed by Hecht-Hielsen **[54]**. Its application to engine diagnostics was mentioned by Torella **[127-128]**. This type of neural network is based on a combination of input, clustering and output layers and they are particularly suitable for pattern recognition **[126]**. The training of such nets requires two steps. In the first step, an unsupervised competitive learning process, the presented patterns are clustered; only a neuron of clustering hidden layer wins and learns and is active for a given input. In the second step, a supervised learning process, the weights among cluster layer and output layer units are adjusted to obtain the desired output corresponding to the presented input pattern **[126]**. Torella **[126]** successfully applied the CPN to the fault diagnosis of a single spool turboprop engine and proved it to be robust.

Adaptive Resonance Theory networks (ART) introduced by Grossbery **[48]** are capable of stable categorization of an arbitrary sequence of unlabeled input patterns in real time. It was applied by Torella and Lombardo **[127]** and Torella **[126]** to gas turbine trouble shooting and diagnostics. Such architecture has the capability of stable categorization of an arbitrary sequence of unlabeled input patterns in real time. Three different groups of neurons usually form the networks and are arranged in two layers where the nodes on each layer are fully interconnected to the nodes of the other layer. The first layer manages the input information and the second layer clusters the information by grouping similar information. The networks are of the competitive type. A stable oscillation starts among the input layer and the winner cluster when a proper cluster has been chosen. There are two different types of ARTs: ART1, with binary (0-1) input by which trouble-shooting and trend analysis of gas turbines can be performed, and ART2 with information in the form of real numbers allowing engine diagnostics to be performed. ARTs have the capability of learning new patterns without repeating all of the training procedure, however they also have the limitation of being unable to store each pattern in each cluster, because similar patterns linked to different faults may be stored in the same units.

Opposite to fixed architecture neural networks are the Resource Allocating Networks (RAN) which have the capability to allocate new neurons, as needed, as more patterns are learned. One of RANs is a self-learning Radial Basis Function (RBF) network and was applied to gas turbine diagnostics by Patel et al. **[95]**, Patel et al. **[92, 94]**, Patel and Kadirkamanathan **[91]**, Patel et al. **[93]** and Arkov et al. **[3]**. The network can grow by itself by adding new hidden neurons and output neurons when new fault patterns are presented to it and also can improve its generalising qualities by adapting itself when presented with similar faults to those previously encountered. The novelty of a pattern is determined by comparison between the response of each hidden node and a pre-defined threshold.

Another Resource Allocating Network applied to gas turbine diagnostics is the Recurrent Cascade Correlation (RCC) Neural Network (Figure 5), a supervised neural network, developed by Fahlman and Lebiere **[33]**. It was introduced and compared with Back-Propagation Neural Network by Tang et al**. [124-125]** for jet engine fault diagnosis. The architecture and characteristics of RCC are different from BPNN and show many advantages compared to the BPNN. The non-neighbouring layers in the RCC are connected with each other and the RCC has only one neuron in each hidden layer. The RCC network does not have the non-convergence problem that may occur for the BP network. The initial values of the weights of the RCC network are determined automatically so that a different number of hidden layers will be produced for different training processes and therefore the convergence rate of the RCC is improved. In the RCC network, the weights of only one layer are permitted to change, while those of the others are kept constant, which provide higher learning rates and convergence rates than the BP networks. It was concluded that the

RCC network performs fault diagnosis as well as the BP network and does not become bogged down by slow learning. Therefore the RCC network can be substitute for the BP network in practical application of engine fault diagnosis and simultaneously satisfy the strict requirements of quick speed and high accuracy. However, the BP network is more robust than the RCC network.

5.2 Genetic Algorithms

Genetic Algorithm (GA) based diagnostics is a model based approach, which is theoretically similar to those of non-linear model-based methods described in a previous section. In other words, GA are applied as an effective optimization tool to obtain a set of engine component parameters that are used to produce a set of predicted engine dependent component parameters through a non-linear gas turbine model that best matches the measurement. The solution is obtained when an objective function (or cost function), which is a measure of difference between predicted and measured engine dependent parameters, achieves its minimum value.

Genetic Algorithms are a searching and optimization technique. Compared with typical calculus-based optimization methods, GA have several distinctive features **[146]**: no derivatives are needed so any non-smooth function can be optimized; constraints can be dealt with in a very different way, such as by means of penalty functions or design of specific operations; global search is used to avoid getting stuck in a local minimum; and probabilistic rather than deterministic transition rules are used to create the next generation of strings from the current one. Three operations are typically used in Genetic Algorithms; they are first a selection operation which chooses the strings for the next generation according to a "survival of the fittest" criterion, second a crossover operation which allows information exchange between strings in the form of swapping of parts of the parameter vector in an attempt to get fitter strings, and third a mutation operation which introduces new or prematurely lost information in the form of random changes applied to randomly chosen vector components.

A gas turbine engine and sensor fault diagnostic system in the presence of measurement noise and biases was presented by Zedda and Singh **[146-147]**. Estimation is performed through optimization of an objective function by means of a real coded Genetic Algorithm (GA) **[1]**. The only statistical assumption required by the technique concerns the measurement noise and the maximum allowed number of faulty sensors and engine components. The method is suitable for development engines where a relatively large number of measurements are available. It was applied to a three spool military turbofan engine RB199 **[146]** and two spool low bypass military turbofan engine EJ200 **[147]** and showed a high level of accuracy.

Gulati, Zedda and Singh **[50]** and Gulati, Taylor and Singh **[49]** combined a multiple point diagnostic approach **[120]** and Genetic Algorithm approach **[146-147]** and produced a GA, model-based multiple operation point analysis method for gas turbine fault diagnostics. This approach is suitable for diagnostic problems where limited instrumentation is available. It was applied to RB199 engine and showed good results. Similar method was also applied to a PW100 engine by Grönstedt **[47]**, where a gradient method was implemented to refine the estimate.

5.3 Expert Systems

An expert system is a computer program that represents and reasons with knowledge regarding some specialist subject with a view to solving problems or giving advice. It is usually built by assembling a knowledge base which is then interpreted by an inference engine. An empty knowledge base comes from program called a shell. The end user of the application interacts with the shell via the inference engine, which uses the knowledge put in the knowledge base to answer questions, solve problems, or offer advice **[59]**. The configuration of a typical expert system is shown in Figure 6. Different expert systems have been developed so far, such as rule-based, model-based and case-based systems. Reviews on expert systems applications in gas turbine diagnostics were given by Doel and LaPierre **[25]** and Doel **[21]**. Doel **[21]** concluded that the expert systems technologies were not going to make jet engine diagnostic and maintenance procedures "smart" but they could add a lot of new capability that will make them more effective and more convenient.

Earlier gas turbine fault diagnostics were carried out by gas turbine users by comparing the measurement parameter deviation patterns with fault signatures supplied by manufacturers. This is actually a pattern recognition/matching, one of the methods of expert systems. Further development and application of pattern recognition/matching methods were presented by Winston et al. **[144]**, Dundas et al. **[26]** and more recently by Lee and Singh **[72]** and Siu et al. **[115]**.

The most popular type of expert systems used in gas turbine fault diagnostics is knowledge and rule based expert systems. Typical examples of such type of expert systems are ENGDOC **[44]**, TEXMAS **[13]** for the Lycoming T53 engine, HELIX **[52, 114]** for a twin-engine gas turbine helicopter engines, XMAN **[60]** for TF-34 engine, TIGER **[129]**, IFDIS for the TF30 engine **[35-36]**, SHERLOCK for helicopter engines **[144]**, etc. More recently, this type of methods has been further developed and applied to gas turbine diagnostics by Vivian and Singh **[139]**, Torella **[126]**, Charchalis and Korczewski **[10]**, DePold and Gass **[18]**, Diao and Passino **[19]**, Forsyth and Delaney **[34]** and Pettigrew **[98]**. Hamilton **[52]** and Winston et al. **[144]** applied qualitative reasoning of de Kleer and Brown **[63]** in their expert systems. Meher-Homji et al. **[82]** described a hybrid expert system where both expert systems and algorithm approaches were utilized for gas turbine condition monitoring and diagnostics. The declaration of a fault by the inference engine is normally done by comparing engine component deviations with predefined thresholds. Pettigrew **[98]** introduced a six sigma method where the variation of observed engine data fits a normal probability function, a threshold of six sigma (sigma is standard deviation for the normal distribution) is applied for accepting the engine for operation and another six sigma is used as the criterion for declaring high risk.

Expert system can also deal with problems with uncertainty by using probability theory, fuzzy logic and belief functions. An expert system combining a Bayesian belief network **[96]** with model based thermodynamic analysis applied to two GE-Model MS7001 Industrial Gas Turbine engines was described by Breese et al. **[8]**. A Bayesian belief network knowledge base (KB) **[56, 96]** in a diagnostic system for the CF6 family of engines was described by Palmer **[89]**. This is a graphical representation of a probability distribution that represents the cause and effect relationship among predisposing factors, faults, and symptoms. The advantages and disadvantages of using the Bayesian belief network were presented. A Bayesian type statistical evidence approach was used by DePold and Gass **[18]** in their expert system to reflect the uncertainty of gas turbine parameters. Mast et al. **[77]** applied different Bayesian Belief Networks to different operating space of GE CFM56-7 engines in order to obtain the desired level of diagnostic accuracy. More detailed analysis of Bayesian Belief Network (BBN) for turbofan engine diagnostics was given by Romessis et al. **[107]**.

A static pattern analysis approach was proposed by Patel et al. **[93]** and Arkov et al. **[3]**, where the observation of gas turbine status was expressed by a probability density or histogram approach and any deviation of the engine from its normal condition can be indicated by a low likelihood of the observation. A probabilistic fault diagnostic approach was introduced by Ghiocel and Roemer **[43]** and Roemer and Ghiocel **[105]** and was further described by Ghiocel and Altmann **[42]** and used by Roemer et al. **[106]**. In the method, both the monitored and fault data uncertainties were considered and described with probability density functions. The detection of faults was carried out by comparing the random distance between the monitored data point location and the fault point location in a five dimensional parameter space with a predefined safety margin. When an anomaly is detected, the current measured parameter distribution is compared with each fault distribution to determine the degree of "overlap" between the measured data and fault distribution. Faults can be detected by comparing the fault probabilities of the measured data within a fault library. The safety degradation of gas turbine was measured with two reliability sensitivity indices: a cumulative and an evolutionary reliability sensitivity indices.

Another type of consideration for uncertainty in diagnostics is the application of fuzzy logic theory, where rule based fuzzy expert systems are used. This approach will be discussed in the following section.

6 FUZZY LOGIC BASED METHODS

Fuzzy logic is a method to formalize the human capability of imprecise reasoning. Such reasoning represents the human ability to reason approximately and judge under uncertainty **[109]**. It provides a system of non-linear mapping from input vector into a scalar output **[68]**. A typical fuzzy logic system (Figure 7) involves fuzzification, fuzzy inference and defuzzification by using a fuzzifier, an inference engine and a defuzzifier respectively. A fuzzifier maps crisp input numbers into fuzzy sets characterized by linguistic variables and membership functions. An inference engine maps fuzzy sets to fuzzy sets and determines the way in which the fuzzy sets are combined. A defuzzifier is sometimes used when crisp numbers are needed as an output of the fuzzy logic system. Combined with expert systems, neural networks, genetic algorithm or other techniques, fuzzy logic can be used for gas turbine diagnostics.

Combined with a knowledge based gas turbine model, AND/OR/NOT causal graphs which is an extension of abductive model **[97]** were introduced by Fuster et al. **[37]** to gas turbine fault diagnostics, where the uncertainty of component parameters was expressed by fuzzy logic likelihood value and the fault symptoms were described by *True* or *False*.

Tang et al. **[125]** presented a fuzzy logic reasoning together with a neural network for a jet Engine condition Monitoring and fault Diagnosis (EMD) system that classifies all possible faults into three categories: gas path components, instrument sensors, and rotor or oil subsystem. Three operations (AND, OR and NOT) were used in its inference engine.

A fuzzy Petri net (FPN) model to represent the fuzzy production rules of a rule-based system was proposed by Huang et al. **[58]**. An efficient algorithm of fault diagnostic reasoning for gas turbine fault diagnostics was described.

A fuzzy rule- and case-based expert system was presented by Siu et al. **[115]** and applied it to a number of real cases. A fuzzy logic based expert system for gas turbine engine fault isolation was described by Ganguli **[38]**. The system uses four basic engine measurements to detect single fault among five engine components with over 95% accuracy. Measurement noise was taken into account. Similar approach was used to automate the reasoning process of an experienced powerplant engineer **[40]**. Tests with simulated data show that prediction accuracy can reach over 90% with only four cockpit measurements. If additional pressure and temperature probes are considered, the fault isolation accuracy rises to as high as 98%. A rule based fuzzy expert system RSLExpert for gas turbine fault classification was provided by Applebaum **[2]**, where the fuzzy filter was used for residual evaluation to transform the quantitative knowledge of the residual vector of measurement deltas into the qualitative knowledge of faulty characteristics and faults.

7 DIAGNOSIS WITH TRANSIENT DATA

Most gas turbine diagnostics can be carried out with steady state measurement data. But in some cases good quality steady state data are difficult to obtain or even not available. For example, some combat aircraft can operate for up to 70% of the total mission time with their engines in non-steady-state conditions **[83]**. In addition, some gas turbine faults phenomena only appear during transient processes but could seriously degrade the operability of the engine especially at altitude, during aircraft maneuvers and following missile release, such as mis-scheduled nozzle and compressor blade movement due to control system faults **[83-84]**. Therefore, gas turbine fault diagnostics may be achieved using transient measurement data. An overview of transient diagnostics for gas turbine engines was given by Meher-Homji and Bhargava

[81]. A survey of the methods and applications of gas turbine steady and transient state modeling for fault diagnosis was provided by Bird and Schwartz **[7]**.

Luppold et al. **[76]** presented a piece-wise linear state variable engine model (SVM) for the simulation of engine performance in real-time and a Kalman filter algorithm was used to estimate both the cause and level of off-nominal engine performance. The method was suitable for diagnosing engine faults caused by hardware failure, foreign object damage, battle damage, etc. Further development of this method resulted in the second generation of Kalman Filter algorithm (an Observer Model) for the real time operation of detection and estimation of gas turbine damages caused by normal wear, mechanical failures, and ingestion of foreign objects **[62]**. Lunderstaedt and Junk **[75]** diagnosed engine high pressure turbine fault with non-stationary measurement of RB199 engine by applying linear GPA **[135]** to discrete points on a non-stationary process for non-linear parameter estimation and neural networks for the calculation of the non-stationary reference base lines.

Henry **[55]** analyzed the transient performance shift of F404 engine due to different reasons, such as throttle overshoot, effect of inlet screen, inlet temperature change and compressor damage. Fault signatures observed from the transient measurements, which were different from one to another due to different faults, were used to detect engine faults.

A parameter estimator using a matrix method **[84]** and a Least Square Estimate (LSE) **[83]** were described to simulate a gas turbine engine transient process from consistent non-linear idle/max or max/idle transient data and were used as an estimator for fault diagnosis, where two fault cases were discussed: one was a biased exhaust gas temperature sensor error and the other was a changed final nozzle schedule. In addition, the influence of the sampling rate and the measurement noise on the sensitivity of the technique was discussed. Further study on this method was done by Merrington et al. **[85]** and a model based method for gas turbine engine fault detection based on transient measurements (typically on take-off processes) and ordinary least square estimate was presented. The key feature of the method is that it accounts for the effects of measurement noise, model mismatch, and linearization errors. Eustace et al. **[32]** presented fault signatures for an F404 engine based on fault implant tests in a sea-level-static from take-off transient data. Their research showed that both transient and steady-state data contain the same essential fault information but the effect of a fault is more easily detected from transient data because the transient records are more sensitive to the implanted faults.

A knowledge and model based expert system, TIGER, for gas turbine fault detection and diagnosis based on dynamic system analysis was described by Trave-Massuyes **[129]**. Three diagnostic modules using a limit checking model, an explicit temporal model and an implicit model-based approach respectively were used in parallel and a fault manager coordinated the conclusions from the three modules and gave a higher level of conclusion. Diao and Passino **[19]** used Takagi-Sugeno fuzzy systems to model a turbine engine and a bank of multiple models for residual generation. An expert supervisory scheme was applied to determine the proper model bank and detect engine faults. A time delay for fault isolation was used to improve the robustness of the system.

Santa **[111]** used an adaptation method to model transient and steady operational modes of gas turbine engines and use the information of adapted thermodynamic parameters to determine the cause of engine component damage.

Some physical processes, such as the influence of bulk metal temperature, may bias the measured engine parameters and reduce the accuracy of fault diagnostics. A model-based technique **[83]** was applied by Merrington **[86]** to the problem of detecting degraded performance in a military turbofan engine from take-off acceleration-type transients by taking into account the impact of bulk metal temperature. A simple and convenient way of separating the influence of bulk temperature effect on the measured engine parameters from fast dynamic components was provided.

8 DISCUSSIONS

Difference diagnostic methods have their advantages and disadvantages and they are discussed as follows. Firstly, the linear and non-linear model based methods, such as the linear and non-linear GPA, the optimal estimates and the optimization based methods, have clear physical meanings while the non-model based methods, such as neural networks and rule-based expert systems, are generated with experimental knowledge. Secondly, the artificial intelligence based methods are more complicated than the model based methods. Thirdly, the linear and non-linear GPA, the neural networks (once trained) and the rule-based expert systems (once the rule library is created) are much faster in diagnostic processes than the non-linear model based methods with either conventional optimization or genetic algorithms. Fourthly, all the methods except the linear and non-linear GPA can dealt with measurement noises and biases. To have clear view of the advantages and disadvantages of different diagnostic methods, a comparison of major features of different diagnostic methods is illustrated in Table 1. More specifically, a comparison of models' complexity and computation speed required for diagnosis is shown in Figure 8.

9 CONCLUSIONS

A comprehensive review of gas turbine fault diagnostic technologies developed so far based on gas turbine performance analysis has been presented, from Urban's work at its beginning until the most recent state-of-the-art technologies. Such technologies include earlier linear model-based methods, nonlinear model-based methods, to more advanced artificial intelligence based methods, and fuzzy logic based approaches, for gas turbine component fault diagnostics on both steady state and transient measurement data.

Research in recent years shows that current research efforts on gas turbine diagnostics have focused on the improvement of reliability, accuracy, computational efficiency of the diagnostic systems, online application and inclusion of more practical considerations such as data preprocessing and validation, measurement noise reduction, multiple component faults, sensor faults, and data uncertainty, etc. Hybrid schemes would be better solutions for future gas turbine diagnostic systems.

AKNOWLEDGEMENT

The present research is supported by a Platform Grant of the Engineering and Physical Sciences Research Council (EPSRC), United Kingdom.

REFERENCES

1. **Antonisse, J.**, "A New Interpretation of Schema Notation That Overturns the Binary Encoding Constrain", Proceedings of the Third International Conference on Genetic Algorithms, 1989.
2. **Applebaum, E.**, "Fuzzy Classification for Fault Isolation in Gas Turbine Engines", Joint 9th IFSA World Congress and 20th NAFIPS International Conference, Vol.1, pp.292-297, 2001.
3. **Arkov, V. Y., Patel, V. C., Kulikov, G. G.** and **Breikin, T. V.**, "Aircraft Engine Condition Monitoring: Stochastic Identification and Neural Networks", 15th International Conference on Artificial Neural Networks, No.440, pp.295-299, 1997.
4. **Barwell, M. J.**, "Compass – Ground Based Engine Monitoring Program for General Application", SAE Technical Paper Series, 871734, Aerospace Technology Conference and Exposition, Long Beach, California, October 1987.
5. **Bettocchi, R.** and **Spina, P. R.**, "Diagnosis of Gas Turbine Operations by Means of the Inverse Cycle Calculation", ASME Paper 99-GT-185, 1999.
6. **Biagioni, L.** and **Cinotti, R.**, "Turboshaft Engine Condition Monitoring by Bayesian Identification", ISABE 2001-1034, 15th ISABE, 2001.

7. **Bird, J. W.** and **Schwartz, H. M.**, "Diagnosis of Turbine Engine Transient Performance with Model-Based Parameter Estimation Techniques", ASME 94-GT-317, 1994.

8. **Breese, J. S., Gay, R.** and **Quentin, G. H.**, "Automated Decision-Analytic Diagnosis of Thermal Performance in Gas Turbines", ASME 92-GT-399, 1992.

9. **Bryson, A. E.** and **Ho, Y.-C.**, "Applied Optimal Control-Optimization, Estimation, and Control", Hemisphere Publishing Corporation, 1975.

10. **Charchalis, A** and **Korczewski, Z.**, "Naval Gas Turbine Diagnostics", The 2nd International Conference on Marine Technology, ODRA'97, Szczecin, Poland, Sept. 1997.

11. **Chen, D.-G.** and **Zhu, Z.-L.**, "Model Identification-Based Fault Analysis Method Applied to Jet Engines", ISABE-2001-1111, 15th ISABE, Bangalore, India, Sept. 2001.

12. **Cifaldi, M. L.** and **Chokani, N.**, "Engine Monitoring Using Neural Networks", AIAA-98-3548, 1998.

13. **Collinge, K.** and **Schoff, K.**, "TEXMAS – An Expert System for Gas Turbine Engine Diagnosis and More", Aircraft Gas Turbine Engine Monitoring: An Update, SAE 871737, pp.121-127, 1988.

14. **Consumi, M.** and **d'Agostino, L.**, "Monitoring and Fault Diagnosis of a Turbojet by Bayesian Inference", ISABE 97-7148, 13th ISABE, Chattanooga, Tennessee, USA, Sept. 1997.

15. **Consumi, M.** and **d'Agostino, L.**, "A Statistical Inference Approach to Gas Path Analysis of a Turbofan", AIAA 98-3551, 1998.

16. **Danielsson, S.-G.,** "Gas Path Analysis to Pre and Post Overhaul Testing of JT9D Turbofan Engine", SAE Paper 770993, Aerospace Meeting, Los Angeles, Nov. 14-17, 1977.

17. **Denny, G.,** "F-16 Jet Engine Trending and Diagnostics with Neural Networks", *Applications of Neural Networks*, Vol.4, 1965.

18. **DePold, H. R.** and **Gass, F. D.**, "The Application of Expert Systems and Neural Networks to Gas Turbine Prognostics and Diagnostics", ASME Paper 98-GT-101, or *Journal of Engineering for Gas Turbines and Power*, Vol.121, Oct. 1999.

19. **Diao, Y.** and **Passino, K. M.**, "Fault Diagnosis for a Turbine Engine", 2000 American Control Conference, Vol.4, pp.2393-2397, Chicago, IL, USA, 28-30 June 2000.

20. **Dietz, W. E., Kiech, E. L.** and **Ali, M.**, "Jet and Rocket Engine Fault Diagnosis in Real Time", *Journal of Neural Network Computing*, Vol.1, No.1, pp.5-18, 1989.

21. **Doel, D. L.**, "The Role for Expert Systems in Commercial Gas Turbine Engine Monitoring", ASME Paper 90-GT-374, The Gas Turbine and Aeroengine Congress and Exposition, Brussels, Belgium, June 1990.

22. **Deol, D. L.**, "Gas Path Analysis – Problems and Solutions", Symposium of Aircraft Integrated Monitoring Systems, Bonn, Germany, 21-23 Sept. 1993.

23. **Doel, D. L.**, "TEMPER – A Gas-Path Analysis Tool for Commercial Jet Engines", *Journal of Engineering for Gas Turbines and Power*, Vol.116, pp.82-89, January 1994.

24. **Doel, D. L.**, "An Assessment of Weighted-Least-Squares-Based Gas Path Analysis", *Journal of Engineering for Gas Turbine and Power*, Vol.116, pp.365-373, April 1994.

25. **Doel, D. L.** and **LaPierre, L. R.**, "Diagnostic Expert Systems for Gas Turbine Engines – Status & Prospects", AIAA-89-2585, 1989.

26. **Dundas, R. E., Sullivan, D. A.** and **Abegg, F.**, "Performance Monitoring of Gas Turbines for Failure Prevention", ASME 92-GT-267, 1992.

27. **Escher, P. C.**, "Pythia: An Objective-Oriented Gas Turbine Path Analysis Computer Program for General Applications", Ph.D. Thesis, Cranfield University, UK, 1995.

28. **Escher, P. C.** and **Singh, R.,** "An Object- Oriented Diagnostics Computer Programme Suitable for Industrial Gas Turbines", 21st (CIMAC) International Congress of Combustion Engines, Switzerland, 15-18 May 1995.

29. **Eustace, R.,** "Neural Network Fault Diagnosis of a Turbofan Engine", XI ISABE 93-7091, Tokyo, Japan, Sept. 1993.

30. **Eustace, R.** and **Merrington, G.,** "Fault Diagnosis of Fleet Engines Using Neural Networks", XII ISABE 95-7085, 1995.

31. **Eustace, R.** and **Frith, P. C. W.,** "Utilising Repair and Overhaul Experience in a Probabilistic Neural Network for Diagnosing Gas-Path Faults", ISABE-2001-1050, 15th ISABE, Bangalore, India, Sept. 2001.

32. **Eustace, R. W., Woodyatt, B. A., Merrington, G. L.** and **Runacres, A.,** "Fault Signatures Obtained from Fault Implant Tests on an F404 Engine", *Journal of Engineering for Gas Turbines and Power*, Vol.116, pp.178-183, January 1994.

33. **Fahlman, S. E.** and **Lebiere, C.,** "The Cascade Correlation Learning Architecture", *Neural Information Processing System*, Vol.3, pp.524-532, 1990.

34. **Forsyth, G.** and **Delaney, J.,** "Designing Diagnostic Expert Systems for Long-Term Supportability", ASME 2000-GT-0031, ASME TURBO EXPO 2000, Munich, Germany, May 2000.

35. **Forsyth, G.** and **Larkin, M.,** "Concept Demonstration of the Use of Interactive Fault Diagnosis and Isolation for the TF30 Engine", Proceedings of the Second International Conference on Industrial & Engineering Applications of Artificial Intelligence & Expert Systems, IEA/AIE 89, University of Tennessee Space Institute, June 1989.

36. **Frith, D. A.,** "Engine Diagnostics – An Application for Expert System Concepts", 9th ISABE, Vol.2, pp.1235-1243, Athens, Greece, 1989.

37. **Fuster, P., Ligeza, A.** and **Aguilar Martin, J.,** "Abductive Diagnostic Procedure Based on an AND/OR/NOT Graph for Expected Behaviour: Application to a Gas Turbine", 10th International Congress and Exhibition on Condition Monitoring and Diagnostic Engineering Management, Espoo, Finland, COMADEM'97, Vol.171, pp.511-520, June 1997.

38. **Ganguli, R.,** "Application of Fuzzy Logic for Fault Isolation of Jet Engines", ASME 2001-GT-0013, ASME TURBO EXPO 2001, New Orleans, Louisiana, June 2001.

39. **Ganguli, R.,** "Data Rectification and Detection of Trend Shifts in Jet Engine Gas Path Measurements Using Median Filters and Fuzzy Logic", ASME 2001-GT-0014, ASME TURBO EXPO 2001, New Orleans, Louisiana, June 2001.

40. **Ganguli, R.,** "A Fuzzy Logic Intelligent System for Gas Turbine Module and System Fault Isolation", ISABE-2001-1112, 15th ISABE, Bangalore, India, Sept. 2001.

41. **Gelb, A.,** "Applied Optimal Estimate", The MIT Press, 1974.

42. **Ghiocel, D. M.** and **Altmann, J.,** "Critical Modeling Issues for Prediction of Turbine Performance Degradation: Use of A Stochastic-Neural-Fuzzy Inference System", AIAA-2001-1452, 42nd AIAA/ASME/ASCE/AHS/ASC Structures, Structure Dynamics, and Materials Conference and Exhibit, Seatle, WA, 16-19 April 2001.

43. **Ghiocel, D. M.** and **Roemer, M. J.,** "A New Probabilistic Risk-Based Fault Diagnosis Procedure for Gas Turbine Engine Performance", AIAA-99-1572, AIAA/ASME/ASCE/AHS/ASC Structure, Structure Dynamics, and Materials Conference and Exhibit, St. Louis, MO, 12-15 April, 1999.

44. **Gibbs, S. I.,** "An Expert System for Gas Turbine Fault Diagnosis", MSc thesis, Cranfield Institute of Technology, England, 1984.

45. **Grewal, M. S.,** "Gas Turbine Engine Performance Deterioration Modelling and Analysis", PhD thesis, Cranfield University, England, 1988.

46. **Grodent, M.** and **Navez, A.**, "Engine Physical Diagnosis Using a Robust Parameter Estimation Method", AIAA-2001-3768, 2001.

47. **Grönstedt, T. U. J.**, "A Multi-Point Gas Path Analysis Tool for Gas Turbine Engines with a Moderate Level of Instrumentation", ISABE-2001-1051, 15th ISABE, Bangalore, India, Sept. 2001.

48. **Grossbery, S.**, "Adaptive Pattern Classification and Universal Recoding", Biological Cybernetics, 1976.

49. **Gulati, A.**, **Taylor, D.** and **Singh, R.**, "Multiple Operating Point Analysis Using Genetic Algorithm Optimisation for Gas Turbine Diagnostics", ISABE-2001-1139, 15th ISABE, Bangalore, India, Sept. 2001.

50. **Gulati, A.**, **Zedda, M.** and **Singh, R.**, "Gas Turbine Engine and Sensor Multiple Operating Point Analysis Using Optimization Techniques", AIAA-2000-3716, 2000.

51. **Guo, T.-H.**, **Saus, J.**, **Lin, C.-F.** and **Ge, J.-H.**, "Sensor Validation for Turbofan Engines Using an Autoassociation Neural Network", AIAA-96-3926, 1996.

52. **Hamilton, T. P.**, "HELIX: A Helicopter Diagnostic System Based on Qualitative Physics", *Artificial Intelligence in Engineering*, Vol.3, No.3, pp.141-150, 1988.

53. **Haykin, S.**, "Neural Networks", Second Edition, Prentice Hall, 1999.

54. **Hecht-Hielsen, R.**, "Nearest Matched Filter Classification of Spatiotemporal Patterns", *Applied Optics*, Vol.26, pp.1892-1899, 1987.

55. **Henry, J. R.**, "CF-18/F404 Transient Performance Trending", AGARD-CP-448, Engine Condition Monitoring – Technology and Experience, Oct. 1988.

56. **Horowitz, E. J.**, **Breese, J. S.** and **Henrion, M.**, "Decision Theory in Expert Systems and Artificial Intelligence", *International Journal of Approximate Reasoning Special Issue on Uncertainty and Artificial Intelligence*, Vol.2, pp.247-302, 1988.

57. **House, P.**, "Gas Path Analysis Techniques Applied to Turboshaft Engines", MSc thesis, Cranfield University, England, 1992.

58. **Huang, X, Gao, M., Wang, Y.** and **Weng, S.**, "Application of Fuzzy Petri Net in Fault Diagnosis of Gas Turbine", *Journal of Aerospace Power*, Vol.15, No.3, pp.311-313, July 2000.

59. **Jackson, P.**, "Introduction to Expert Systems", Third Edition, Addison-Wesley, 1999.

60. **Jellison, T. G., Frenster, J. A., Pratt, N. S.** and **De Hoff, R. L.**, "XMAN – A Tool for Automated Jet Engine Diagnostics", AIAA-87-1931, 1987.

61. **Kanelopoulos, K., Stamatis, A.** and **Mathioudakis, K.**, "Incorporating Neural Networks into Gas Turbine Performance Diagnostics", ASME 97-GT-35, International Gas Turbine & Aeroengine Congress & Exhibition, Orlando, Florida, US, June 1997.

62. **Kerr, L. J., Nemec, T. S.** and **Gallops, G. W.**, "Real-Time Estimation of Gas Turbine Engine Damage Using a Control-Based Kalman Filter Algorithm", *Journal of Engineering for Gas Turbines and Power*, Vol.114, pp.187-195, April 1992.

63. **De Kleer, J.** and **Brown, J. S.**, "A Qualitative Physics Based on Confluences", *Artificial Intelligence*, Vol.24, Dec. 1984.

64. **Kobayashi, T.** and **Simon, D. L.**, "A Hybrid Neural Network-Genetic Algorithm Technique for Aircraft Engine Performance Diagnostics", AIAA-2001-3763, 2001.

65. **Kohonen, T.**, "Self-Organizing Formation of Topotogically Correct Feature Maps", *Biological Cybernetics*, Vol.43, pp.59-69, 1982.

66. **Kohonen, T.**, "Self Organizing and Associative Memory", New York, Springer-Verlag, 1987.

67. **Kong, C. and Ki, J.**, "Optimal Measurement Parameter Selection of Turboprop Engine for Basic Trainer Using GPA Approach", ISABE 2001-1036, 15th ISABE, 2001.

68. **Kosko, B.**, "Fuzzy Engineering", Prentice Hall, 1997.

69. **Kramer, M. A.**, "Non-Linear Principal Component Analysis Using Autoassociative Networks", *AIChE Journal*, Vol.37, No.2, pp.233-243, 1991.

70. **Lambiris, B., Mathioudakis, K., Stamatis, A.** and **Papailiou, K.**, "Adaptive Modeling of Jet Engine Performance with Application to Condition Monitoring", ISABE 91-7058, 1991.

71. **Lazalier, G. R., Renolds, E. C.** and **Jocox, J. O.**, "A Gas Path Performance Diagnostic System to Reduce J75-P-17 Engine Overhaul Costs", *Journal of Engineering for Power*, Vol.100, pp.691-697, October 1978.

72. **Lee, Y. H.** and **Singh, R.**, "Health Monitoring of Turbine Engine Gas Path Components and Measurement Instruments", ASME Paper 96-GT-242, 1996.

73. **Lu P.-J., Zhang M.-C., Hsu T.-C.** and **Zhang J.**, "An Evaluation of Engine Faults Diagnostics Using Artificial Neural Networks", ASME 2000-GT-0029 or *Journal of Engineering for Gas Turbines and Power*, Vol.123, April 2001.

74. **Lunderstadt, R.** and **Fiedler, K.**, "Gas Path Modelling, Diagnosis and Sensor Fault Detection", AGARD-CP-448, Engine Condition Monitoring – Technology and Experience, Oct. 1988.

75. **Lunderstaedt, R. A.** and **Junk, R. H.**, "Application of the Gas-Path Analysis (GPA) for the Non-Stationary Operation of a Jet Engine", ISABE-97-7062, 13th ISABE, Chattanooga, Tennessee, USA, Sept. 1997.

76. **Luppold, R. H., Roman, J. R., Gallops, G. W.** and **Kerr, L. J.**, "Estimating In-Flight Engine Performance Variations Using Kalman Filter Concepts", AIAA-89-2584, 1989.

77. **Mast, T. A., Reed, A. T., Yurkovich, S., Ashby, M.** and **Adibhatla, S.**, "Bayesian Belief Networks for Fault Identification in Aircraft Gas Turbine Engines", Proceedings of the IEEE International Conference on Control Applications, Kohala Coast-Island of Hawai'i, Hawai'i, USA, August 22-27, 1999.

78. **Mathioudakis, K** and **Tsalavoutas, A.**, "Uncertainty Reduction in Gas Turbine Performance Diagnostics by Accounting for Humidity Effects", ASME 2001-GT-0010, ASME TURBO EXPO 2001, New Orleans, Louisiana, June 2001.

79. **Mattern, D. L., Jaw, L. C., Guo, T. H., Graham, R.** and **McCoy, W.**, "Simulation of an Engine Sensor Validation Scheme Using an Autoassociation Neural Network", AIAA-97-2902, 1997.

80. **Mattern, D. L., Jaw, L. C., Guo, T.-H., Graham, R.** and **McCoy, W.**, "Using Neural Network for Sensor Validation", AIAA-98-3547, 1998.

81. **Meher-Homji, C. B.** and **Bhargava, R.**, "Condition Monitoring and Diagnostic Aspects of Gas Turbine Transient Response", ASME Paper 92-GT-100, International Gas Turbine and Aeroengine Congress and Exhibition, Germany, June 1992.

82. **Meher-Homji, C. B., Boyce, M. P., Lakshminarasimha, A. N., Whitten, J.,** and **Meher-Homji, F. J.,** "Condition Monitoring and Diagnostic Approaches for Advanced Gas Turbines", IGTI Vol.8, pp.347-354, ASME COGEN-TURBO, Sept. 1993.

83. **Merrington, G. L.**, "Fault Diagnosis of Gas Turbine Engines From Transient Data", *Journal of Engineering for Gas Turbines and Power*, Vol.111, pp.237-243, April 1989.

84. **Merrington, G. L.**, "Identification of Dynamic Characteristics for Fault Isolation Purpose in a Gas Turbine Using Closed-Loop Measurements", AGARD-CP-448, Engine Condition Monitoring – Technology and Experience, Oct. 1988.

85. **Merrington, G., Kwon, O.-K., Goodwin, G.** and **Carlsson, B.**, "Fault Detection and Diagnosis in Gas Turbines", *Journal of Engineering for Gas Turbines and Power*, Vol.113, pp.276-282, April 1991.

86. **Merrington, G. L.**, "Fault Diagnosis in Gas Turbines Using a Model-Based Technique", *Journal of Engineering for Gas Turbines and Power*, Vol.116, pp.374-380, April 1994.

87. **Nelder, J. A.** and **Mead, R.,** *Computer Journal*, Vol.7, p.308, 1965.

88. **Nieden, H. Z.** and **Fiedler, K.,** "The Influence of Serial Performance Deviation of Military Jet Engines on the Diagnostic Quality of the Gas Path Analysis", ISABE 99-7075, 13th ISABE, 1999.

89. **Palmer, C. A.,** "Combining Bayesian Belief Networks with Gas Path Analysis for Test Cell Diagnostics and Overhaul", ASME 98-GT-168, 1998.

90. **Passalacque, J.,** "Description of Automatic Gas Turbine Engine Trends Diagnostic System", First Symposium on Gas Turbine Operation and Maintenance, National Research Council of Canada, 1974.

91. **Patel, V. C.** and **Kadirkamanathan, V.,** "Adaptive Self-Learning Fault Detection System for Gas Turbine Engines", 9th International Conference: Condition Monitoring and Diagnostic Engineering Management, Sheffield, UK, July 1996.

92. **Patel, V. C., Kadirkamanathan, V.** and **Thompson, H. A.,** "A Novel Self-Learning Fault Detection System for Gas Turbine Engines", UKACC International Conference on CONTROL '96, Conference Publication No.427 @ IEE 1996, pp.867-872, 2-5 September 1996.

93. **Patel, V. C., Kadirkamanathan, V., Kulikov, G. G., Arkov, V. Y.** and **Breikin, T. V.,** "Gas Turbine Engine Condition Monitoring Using Statistical and Neural Network Methods", Colloquium – IEE, Leicester, September 1996.

94. **Patel, V. C., Kadirkamanathan, V.** and **Thompson, H.,** "An Intelligent Fault Diagnosis System for Gas Turbine Engines", I.Mech.E. Seminar: Aircraft Health and Usage Monitoring System, 1996.

95. **Patel, V. C., Kadirkamanathan, V., Thompson, H. A.** and **Fleming, P. J.,** "Utilising a SIMULINK Gas Turbine Engine Model for Fault Diagnosis", 2nd IFAC Symposium on Control of Power Plants and Power Systems, December 1995.

96. **Pear, J.,** "Probabilistic Reasoning in Intelligence Systems", Morgan Kaufman, San Mateo, CA, 1988.

97. **Peng, Y.** and **Reggia, J. A.**, "Abductive Inference Models for Diagnostic Problem-Solving", Springer-Verlag, 1990.

98. **Pittigrew, J. L.**, "Effective Turbine Engine Diagnostics", AUTOTESTCON Proceedings, 2001 IEEE System Readiness Technology Conference, Valley Forge, PA, USA, 20-23 Aug. 2001.

99. **Press W. H., et al.**, "Numerical Recipes: The Art of Scientific Computing", Cambridge University Press, Cambridge, MA, USA, 1985.

100. **Provost, M. J.**, "COMPASS: A Generalized Ground-Based Monitoring System", AGARD-CP-449, Engine Condition Monitoring Technology and Experience, Oct. 1988.

101. **Provost, M. J.**, "The Use of Optimal Estimation Techniques in the Analysis of Gas Turbines", PhD thesis, Cranfield University, England,1995.

102. **Razak, A. M. Y.** and **Carlyle, J. S.**, "An Advanced Model Based Health Monitoring System to Reduce Gas Turbine Ownership Cost", ASME Paper 2000-GT-627, 2000.

103. **Roemer, M. J.**, "Testing of a Real-Time Health Monitoring and Diagnostic System for Gas Turbine Engines", AIAA-98-3603, 1998.

104. **Roemer, M. J.** and **Atkinson, B.**, "Real-Time Health Monitoring and Diagnostics for Gas Turbine Engines", ASME 97-GT-30, 1997.

105. **Roemer, M. J.** and **Ghiocel, D. M.**, "A Probabilistic Approach to the Diagnosis of Gas Turbine Engine Faults", 53rd Machinery Prevention Technologies (MFPT) Conference, Virginia Beach, VA, April 1999.

106. **Roemer, M. J.**, **Howe, R.** and **Friend, S. R.**, "Advanced Test Cell Diagnostics for Gas Turbine Engines", IEEE Proceedings of Aerospace Conference, Vol.6, pp.2915-2926, 2001.

107. **Romessis, C.**, **Stamatis, A.** and **Mathioudakis, K.**, "Setting Up a Belief Network for Turbofan Diagnosis with the Aid of an Engine Performance Model", ISABE 2001-1032, 15th ISABE, 2001.

108. **Romessis, A., Stamatis, A.** and **Mathioudakis, K.,** "A Parametric Investigation of the Diagnostic Ability of Probabilistic Neural Networks on Turbofan Engines", ASME 2001-GT-0011, ASME TURBO EXPO 2001, New Orleans, Louisiana, June 2001.

109. **Ross, T. J.,** "Fuzzy Logic with Engineering Application", McGraw-Hill, Inc., 1995.

110. **Sanghi, V., Lakshmanan, B. K.** and **Sundararajan, V.,** "Survey of Advancements in Jet-Engine Thermodynamic Simulation", *Journal of Propulsion and Power*, Vol.16, No.5, 2000.

111. **Santa, I.,** "Diagnostics of Gas Turbine Engines Based on Thermodynamic Parameters", 6th Mini Conference on Vehicle System Dynamics, Identification and Anomalies, Budapest, 9-11 November 1998.

112. **Saravanamuttoo, H. I. H.,** "Gas Path Analysis for Pipeline Gas Turbines", 1st Canadian Symposium on Gas Turbine Operation and Maintenance, National Research Council of Canada, 1974.

113. **Simani, S, Patton, R. J., Daley, S.** and **Pike, A.,** "Identification and Fault Diagnosis of an Industrial Gas Turbine Prototype Model", Proceedings of the 39th IEEE Conference on Decision and Control, Sydney, Australia, December 2000.

114. **Simmons, D. W., Hamilton, T. P.** and **Carlson, R. G.,** "HELIX, A Causal Model-Based Diagnostic Expert System", *Journal of the American Helicopter Society*, Vol.32, No.1, pp.19-25, January 1987.

115. **Siu C., Shen Q. and Milne R.**, "TMDOCTOR: A Fuzzy Rule- and Case-Based Expert System for Turbomachinery Diagnosis", Proceedings of IFAC Fault Detection, Supervision and Safety for Technical Processes, Vol.2, Kingston Upon Hull, UK, August 1997.

116. **Smetana, F. O.,** "Turbojet Engine Gas Path Analysis – A Review", AGARD-CP-165, Diagnostics and Engine Condition Monitoring, Jun. 1975.

117. **Stamatis, A., Mathioudakis, K.** and **Papailiou, K. D.,** "Adaptive Simulation of Gas Turbine Performance", ASME Paper 90-GT-205, and also *Journal of Engineering for Gas Turbines and Power*, Vol.112, April 1990.

118. **Stamatis, A., Mathioudakis, K., Smith, M.** and **Papailiou, K.,** "Gas Turbine Component Fault Identification by Means of Adaptive Performance Modeling", ASME Paper 90-GT-376, 1990.

119. **Stamatis, A., Mathioudakis, K.** and **Papailiou, K.,** "Optimal Measurement and Health Index Selection for Gas Turbine Performance Status and Fault Diagnosis", *Journal of Engineering for Gas Turbine and Power*, Vol.114, pp.209-216, April 1992.

120. **Stamatis, A., Mathioudakis, K., Berios, G.** and **Papailiou, K.,** "Jet Engine Fault Detection with Discrete Operating Points Gas Path Analysis", ISABE 89-7133, or *Journal of Propulsion*, Vol.7, No.6, Nov.-Dec. 1991.

121. **Stamatis, A.** and **Papailiou, K. D.,** "Discrete Operating Condition Gas Path Analysis", AGARD-CP-448, Engine Condition Monitoring – Technology and Experience, Oct. 1988.

122. **Staples, L. J.** and **Saravanamuttoo, H. I. H.,** "An Engine Analyzer Program for Helicopter Turboshaft Powerplants", NATO/AGARD Specialists Meeting in Diagnostics and Engine Condition Monitoring, Liege, Belgium, April 1974.

123. **Sun, B., Zhang, J.** and **Zhang, S.,** "An Investigation of Artificial Neural Network (ANN) in Quantitative Fault Diagnosis for Turbofan Engine", ASME 2000-GT-32, ASME TURBO EXPO 2000, Munich, Germany, May, 2000.

124. **Tang, G., Yates, C. L.** and **Chen, D.,** "Comparative Study of Two Neural Networks Applied to Jet Engine Fault Diagnosis", AIAA-98-3549, 1998.

125. **Tang, G., Yates, C. L., Zhang, J.** and **Chen, D.,** "A Practical Intelligent System for Condition Monitoring and Fault Diagnosis of Jet Engines", AIAA 99-2533, 1999.

126. **Torella, G.,** "Expert Systems and Neural Networks for Fault Isolation in Gas Turbines", ISABE 97-7148, 13th ISABE, Chattanooga, Tennessee, USA, Sept. 1997.

127. **Torella, G.** and **Lombardo, G.,** "Utilization of Neural Networks for Gas Turbine Engines", ISABE 95-7032, XII ISABE, 1995.

128. **Torella G.** and **Lombardo G.,** "Neural Networks for the Diagnostics of Gas Turbine Engines", ASME 96-TA-39, the ASME Turbo Asia Conference, 1996.

129. **Trave-Massuyes, L.** and **Milne, R.,** "Diagnosis of Dynamic Systems Based on Explicit and Implicit Behavioral Models: An Application to Gas Turbine in Esprit Project TIGER", *Applied Artificial Intelligence*, Vol.10, No.3, pp.257-277, 1996.

130. **Trella, G.** and **Lombardo, G.,** "Neural Networks for the Diagnostics of Gas Turbine Engines", ASME Paper 96-GT-39, 1996.

131. **Tsalavoutas, A., Pothos, S., Mathioudakis, K.** and **Stamatis, A.,** "Monitoring the Performance of a Twin-Spool Ship Propulsion Turbine By Means of Adaptive Modeling", the RTO AVT Symposium on "Gas Turbine Operation and Technology for Land, Sea and Air Propulsion and Power Systems", RTO MP-34, Ottawa, Canada, 18-21 October 1999.

132. **Urban, L. A.,** "Gas Turbine Engine Parameter Interrelationships", HSD UTC, Windsor Locks, Ct., 1st edition, 1967, 2nd edition, 1969.

133. **Urban, L. A.,** "Gas Path Analysis Applied to Turbine Engine Condition Monitoring", AIAA-72-1082, 1972.

134. **Urban, L. A.,** "Parameter Selection for Multiple Fault Diagnostics of Gas Turbine Engines", AGARD-CP-165, also ASME Paper 74-GT-62, *Journal of Engineering for Power*, 1974.

135. **Urban, L. A.,** "Gas Path Analysis – A Tool for Engine Condition Monitoring", 33rd Annual International Air Safety Seminar, Flight Safety Foundation Inc., Christchurch, New Zealand, 1980.

136. **Urban, L. A.,** "Gas Path Analysis of Commercial Aircraft Engines", 11th Symposium Aircraft Integrated Data Systems", September 1981.

137. **Urban, L. A.** and **Volponi, A. J.,** "Mathematical Methods of Relative Engine Performance Diagnostics", SAE 1992 Transactions Journal of Aerospace, Section 1, Vol. 101, SAE Technical Paper No. 922048, 1992.

138. **Visual Nemerics, Inc.,** "IMSL MATH/LIBRARY: FORTRAN Subroutines for Mathematical Application", Houston, Texas, USA, 1994.

139. **Vivian, B.** and **Singh, R.,** "Application of Expert System Technology to Gas Path Analysis of a Single Shaft Turboprop Engine", 5th European Propulsion Forum, Pisa, Italy, 5-7 April 1995.

140. **Volponi, A. J.,** "Gas Path Analysis: An Approach to Engine Diagnostics", 35th Symposium Mechanical Failures Prevention Group, Gaithersbury, MD, April 1982.

141. **Volponi, A. J., DePold, H., Ganguli, R.** and **Chen, D.,** "The Use of Kalman Filter and Neural Network Methodologies in Gas Turbine Performance Diagnostics: A Comparative Study", ASME 2000-GT-547, ASME TURBO EXPO 2000, Munich, Germany, May 2000.

142. **Whitehead, B., Ferber, H.** and **Ali, M.,** "Neural Network Approach to Space Shuttle Main Engine Health Monitoring", AIAA-90-2259, 1990a.

143. **Whitehead, B., Kiech, E.** and **Ali, M.,** "Rocket Engine Diagnostics Using Neural Networks", AIAA-90-1892, AIAA/SAE/ASME/ASEE 26th Joint Propulsion Conference, July 1990b.

144. **Winston, H., Sirag D., Hamilton, T., Smith, H., Simmons, D.** and **Ma, P.,** "Integrating Numeric and Symbolic Processing for Gas Path Maintenance", AIAA-91-0501, 1991.

145. **Zedda, M.** and **Singh, R.,** "Fault Diagnosis of a Turbofan Engine Using Neural Networks: a Quantitative Approach", AIAA-98-3602, 1998.

146. **Zedda, M.** and **Singh, R.,** "Gas Turbine Engine and Sensor Fault Diagnosis Using Optimisation Techniques", AIAA-99-2530, 1999.

147. **Zedda, M.** and **Singh, R.,** "Gas Turbine Engine and Sensor Diagnostics", ISABE 99-7238, 13th ISABE, 1999.

Diagnostic Methods		Earliest year of use	Model based	Model complexity	Computation speed	Coping with noise	Coping with bias
Linear model-based methods	**Linear GPA**	1967	Yes	Low	High	No	No
	Optimal estimates	1980	Yes	Fairly low	High	Yes	Yes
Non-linear model-based methods	**Non-linear GPA**	1992	Yes	Low	Fairly high	No	No
	Conventional optimization	1990	Yes	Medium	Low	Yes	Yes
Neural networks		1965	No	Fairly high	High	Yes	Yes
Genetic algorithms		1999	Yes	Fairly high	Low	Yes	Yes
Rule-based expert systems		Early 1980's	No	High	High	Yes	Yes
Rule-based fuzzy expert systems		1997	No	High	Fairly high	Yes	Yes

Table 1. Comparison of diagnostic methods

List of captions:

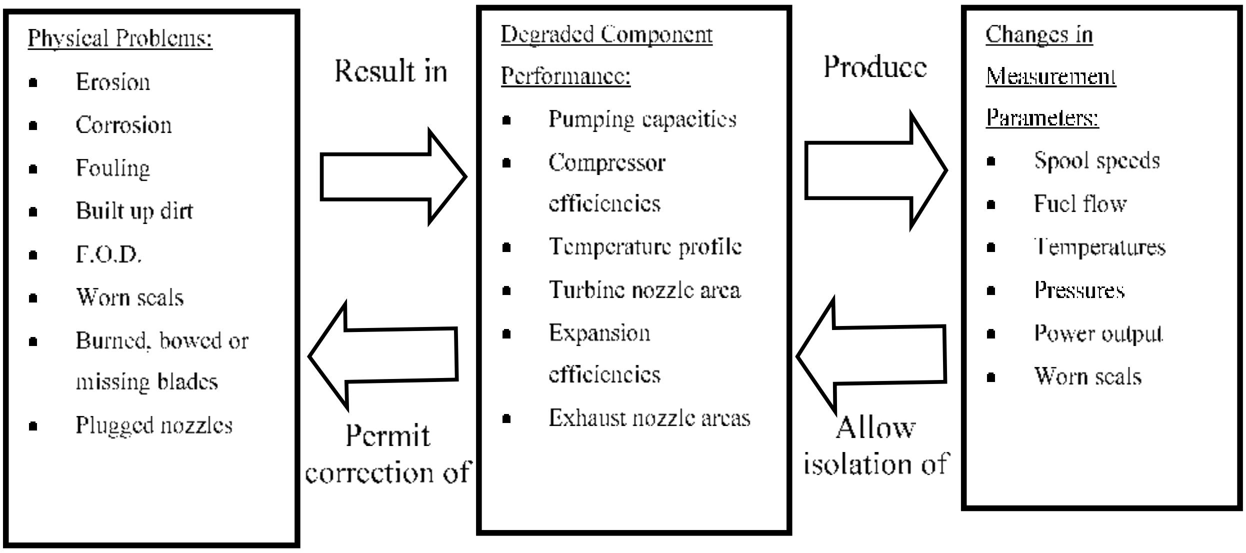

Figure 1: Gas turbine fault diagnostics approach **[134]**

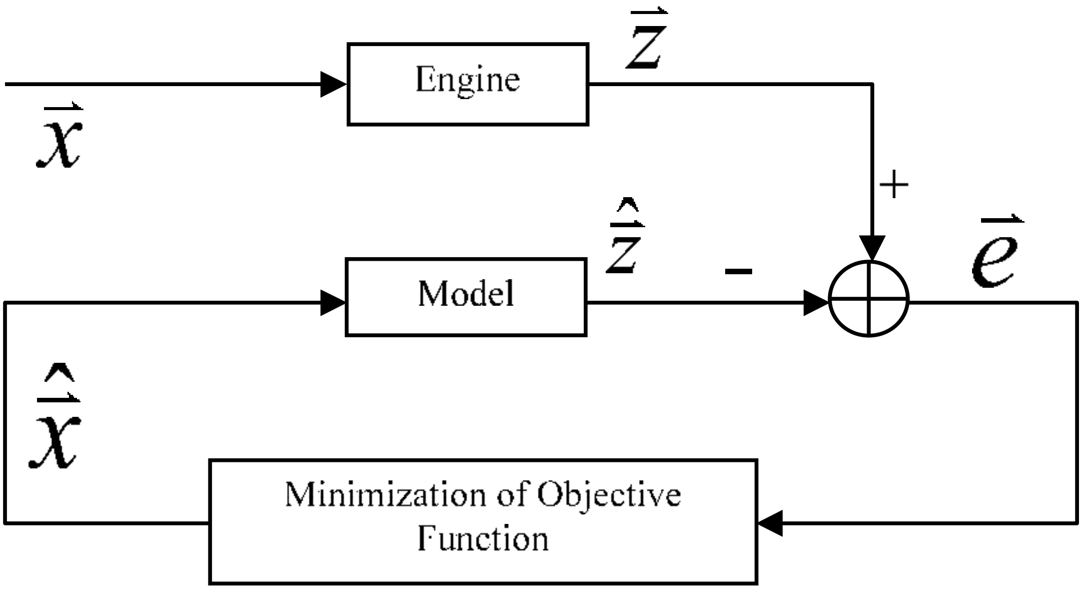

Figure 2: Non-linear diagnostic model

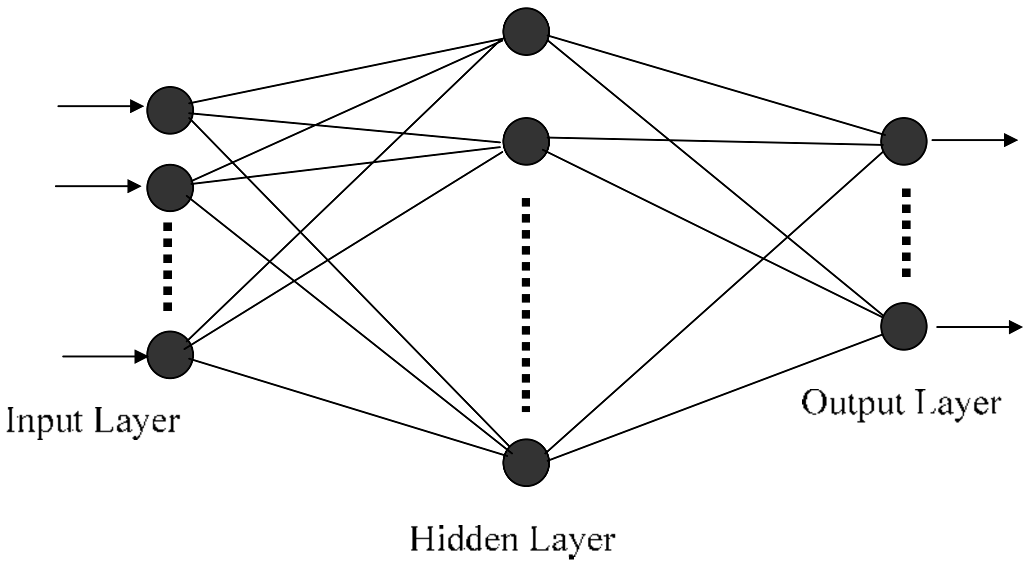

Figure 3: Configuration of a Feed-Forward Back-Propagation Network

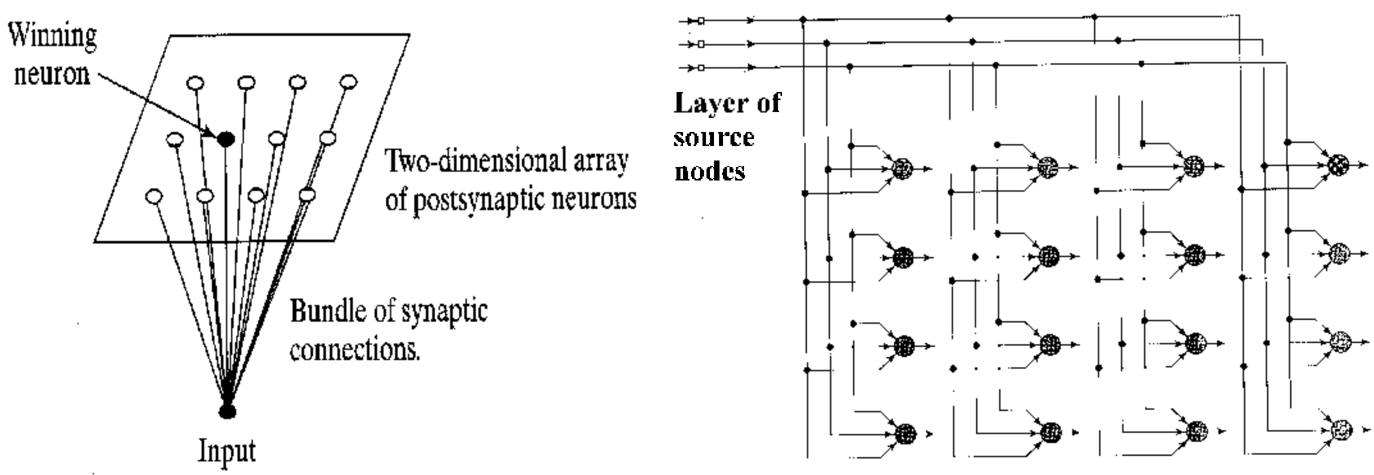

Figure 4: Configuration of Self-Organizing Map **[53]**

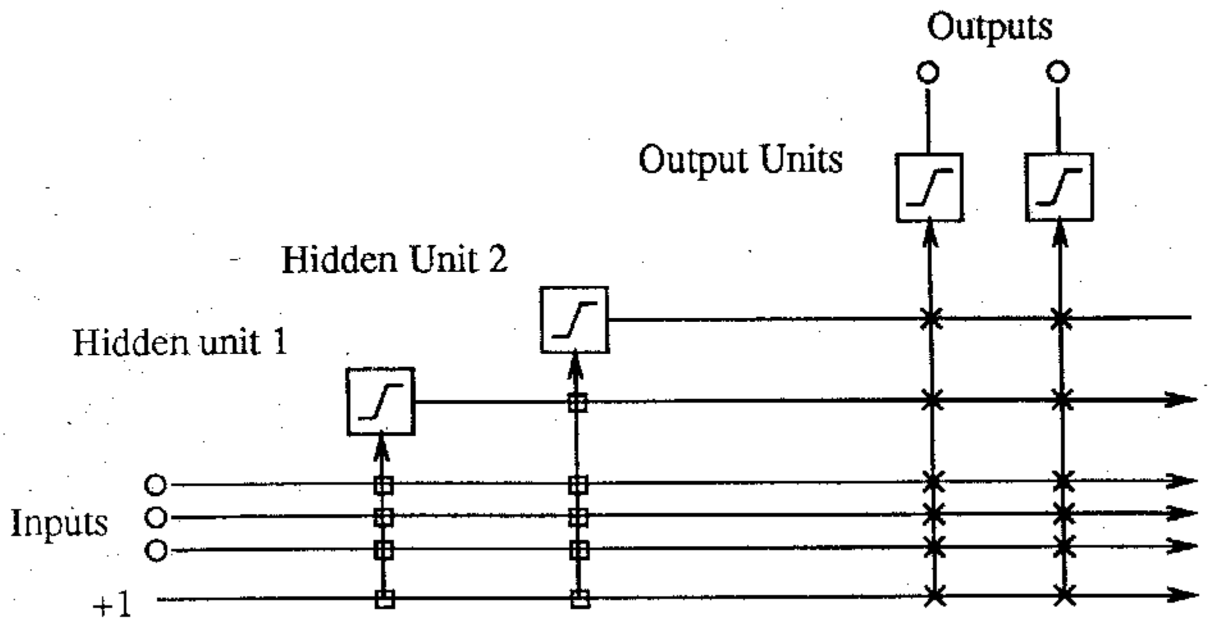

Figure 5: The cascade architecture [33], after two hidden units have been added. The vertical lines sum all incoming activation. Boxed connections are frozen, X connections are trained repeatedly.

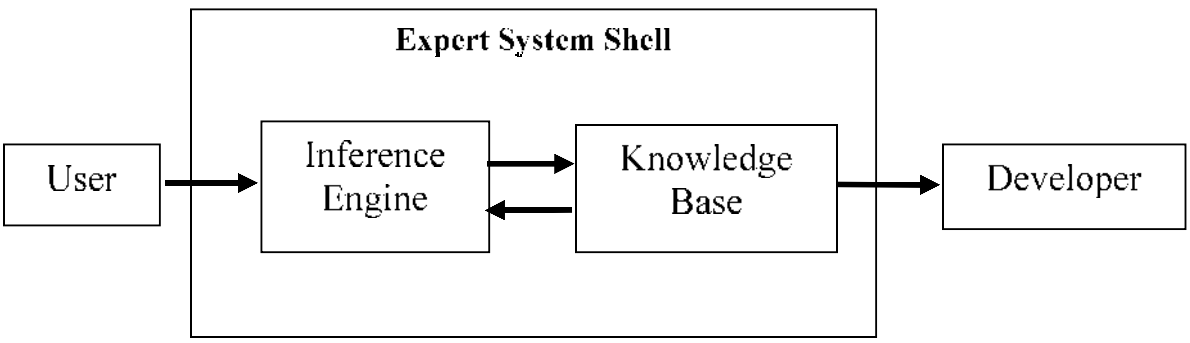

Figure 6: Configuration of an expert system

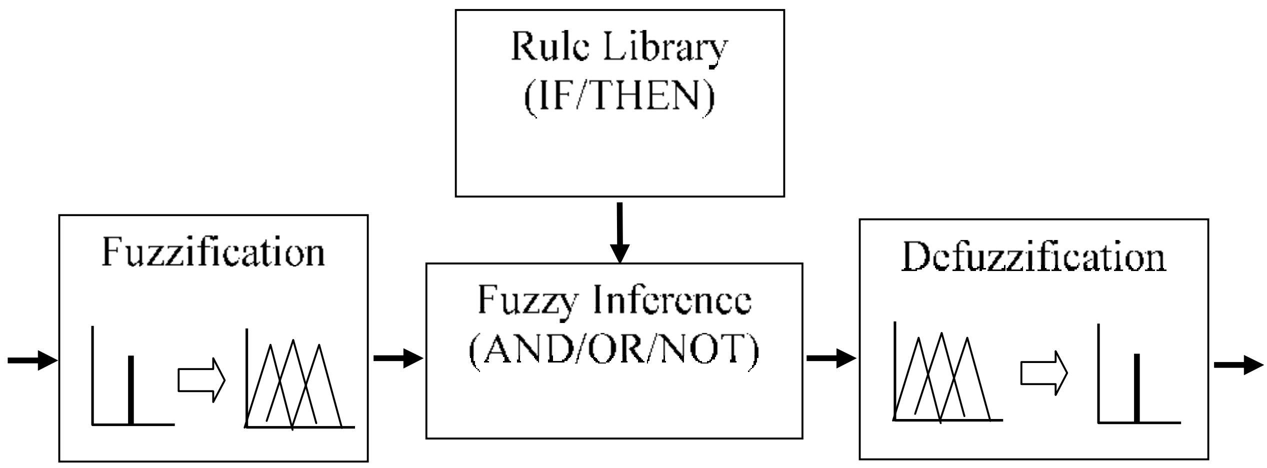

Figure 7: Configuration of a rule-based fuzzy logic expert system

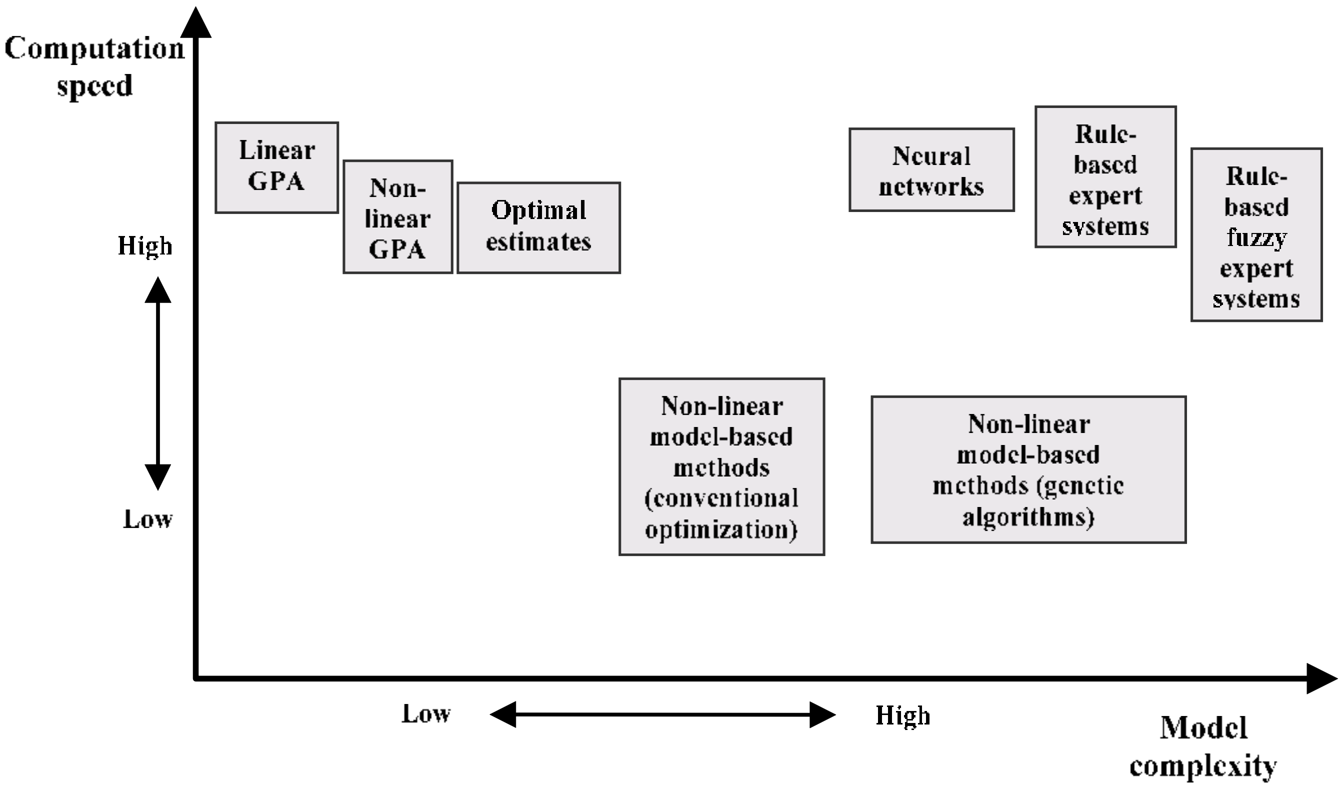

Figure 8. Comparison of diagnostic methods in terms of computation speed and model complexity