Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review

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Performance-based health monitoring, diagnostics and prognostics for condition-based maintenance of gas turbines: A review

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Abstract - With the privatization and intense competition that characterize the volatile energy sector, the gas turbine industry currently faces new challenges of increasing operational flexibility, reducing operating costs, improving reliability and availability while mitigating the environmental impact. In this complex, changing sector, the gas turbine community could address a set of these challenges by further development of high fidelity, more accurate and computationally efficient engine health assessment, diagnostic and prognostic systems. Recent studies have shown that engine gas-path performance monitoring still remains the cornerstone for making informed decisions in operation and maintenance of gas turbines. This paper offers a systematic review of recently developed engine performance monitoring, diagnostic and prognostic techniques. The inception of performance monitoring and its evolution over time, techniques used to establish a high-quality dataset using engine model performance adaptation, and effects of computationally intelligent techniques on promoting the implementation of engine fault diagnosis are reviewed. Moreover, recent developments in prognostics techniques designed to enhance the maintenance decision-making scheme and main causes of gas turbine performance deterioration are discussed to facilitate the fault identification module. The article aims to organize, evaluate and identify patterns and trends in the literature as well as recognize research gaps and recommend new research areas in the field of gas turbine performance-based monitoring. The presented insightful concepts provide experts, students or novice researchers and decision-makers working in the area of gas turbine engines with the state of the art for performance-based condition monitoring.

Keywords: Gas turbine, gas-path faults, monitoring, health assessment, diagnostics, prognostics.

Contents:

1. Introduction

The gas turbine is one of the main sources of power for many applications such as civil and military aircraft, naval and commercial ships, electricity production, gas compression, and high-scale pumping services. The deep penetration of renewables into the energy mix has amplified the need for gas turbines to operate more efficiently and in partnership with renewable energy sources such that energy is produced in an environmentally friendly manner. In addition, for many of the world's largest manufacturers, aftermarket service and parts operations are essential to their business. For example, Rolls-Royce has more than 14,000 aerospace engines in service, operated by more than 500 airlines and powering more than 5.5 million commercial flights per year and the company's service and part business revenue is about 55% of the approximately US$11 billion total revenues [1]. Within this context, several technical challenges with respect to the operation and lifecycle cost of gas turbines must be addressed to efficiently implement this technology in a volatile energy market. It is well known that the development and implementation of a robust, efficient and flexible maintenance strategy significantly improves the reliability and availability of gas turbine assets and, as a result, decreases the number of unpredicted breakdowns, operating costs, and downtime. The main factors affecting gas turbine maintenance planning are shown in **Figure 1**. It is clear from **Figure 1** that there are numerous trade-offs among environmental, technological, economic and operational factors that establish a successful maintenance and operational strategy of gas turbine assets [2].

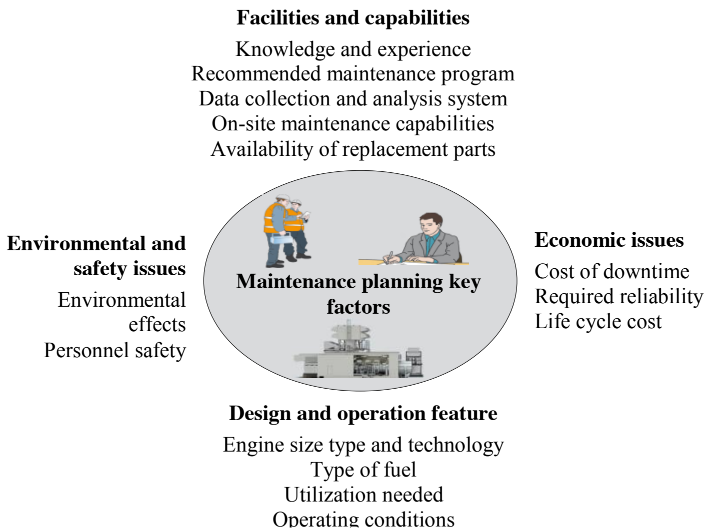

Figure 1. Principal factors that affect gas turbine maintenance planning [2].

In recent years, the gas turbine manufacturers have transformed into modern digital businesses by converging the industrial equipment, data and the internet into a platform that enables the optimization of asset monitoring and management [3]. Examples of such technologies are GE's Predix and Digital Twin where in the case of gas turbines numerous fleets of engines across the globe are simulated, monitored and analyzed as seen from **Figure 2**.

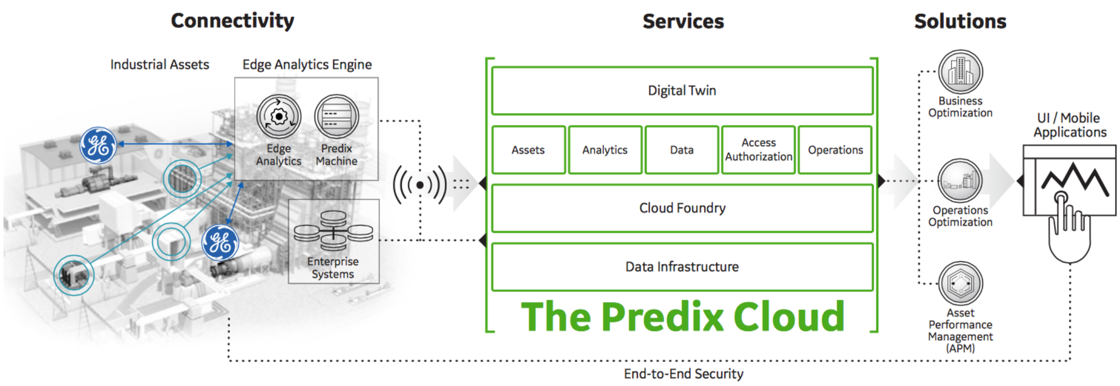

Figure 2. The principle of GE's Predix and Digital Twin [4].

The analytics methods, which are based on banks of data containing the operational and simulation history of the engines, are employed for improving the gas turbine operators understanding for these complex nonlinear machines. Therefore, the maintenance actions are based on informed judgments for the assets in order to maximize their profitability, life cycle costs, reliability and availability. It has been recently demonstrated that the implementation of such digital platform for analytics and optimization can have significant savings in the Oil & Gas and the Airline sectors to name a few. For instance, in the airline sector, both Southwest [4] and Quantas [5] airlines are in the process of saving millions of dollars in fuel cost by a data-crunching partnership with the engine manufacturers. On the other hand in the O&G sector [6], the savings attributed by implementing this digital platform is in the order of billions per year taking into account that an unscheduled downtime for an LNG facility and an offshore platform cost $25 million and $7 million per day, respectively. The opportunity for developing and adopting such a digital platform based on engine models, condition monitoring, diagnostics and prognostics solutions is spearheading the transformation of the conventional industrial environment into its digital era with huge prospects for the availability and reliability of equipment.

It is generally accepted [2, 7-9] that condition-based maintenance (CBM) is an effective method for enhancing the machinery maintenance strategy and shifting from classical ''fail and fix'' practices to a ''predict and prevent'' methodology. As summarized in **Table 1**, while reactive-based corrective maintenance performs just upon failure or error happening in the system, preventive maintenance employs the statistical machine information and operational experience to schedule successive overhauls in order to prevent unexpected failure in the system. However, to improve the reliability and availability of the system, in predictive maintenance, the operating conditions of the equipment are continuously monitored to detect the need for real-time maintenance. Consequently, the continuous development and implementation of condition monitoring, diagnostic and prognostics methods can significantly reduce both the economic losses caused by system breakdown and the costs attributed to unnecessary repair and replacement of components.

Table 1
Comparison of the most common maintenance strategies [9, 10].

Method	Theory/principle	Data required	Data analysis	Decision process
Corrective maintenance	• Fail and fix • Reactive-based • Unscheduled	-	-	-
Preventive maintenance	• Prevent strategy • Time-based • At regular intervals	Event/failure user/time-based data	Reliability theory based on bathtub curve assumptions	Determining the maintenance interval that optimizes the criteria of interest (cost, availability, reliability and so on).
Predictive maintenance	• Predict & prevent strategy • Condition-based • Just-in-time	Measurements that provides information about mechanical or performance condition of equipment	Monitoring the equipment degradation	Performing continuous condition monitoring for health assessment, prognostics, and diagnostics.

Generally, the informed judgment that supports any maintenance decision is the objective of the CBM, the success of which relies on two related processes described as follows:

A) Diagnostics is the process of determining the health status and the equipment deterioration using information delivered by the condition-monitoring system [11]. The main objectives of diagnostics are: (i) fault detection, which indicates that an undesirable event is imminent; (ii) fault isolation, which locates the faulty component; and (iii) fault identification, which aids in determining the root cause of the fault.

B) Prognostics is the ability to forecast the evolution of engine deterioration [12]. The two major objectives of prognostics are: (i) forecasting the impending failures and (ii) estimating the remaining useful life of the engine.

As discussed by Puggina et al. [13], the implementing implementation of proper diagnostic and prognostic approaches have has several merits mainly including tuning components costs and performing predictive maintenance actions, optimizing shop visits and providing spare parts for efficient maintenance management, and optimizing gas turbine operating condition. Brasco et al. [14] also explain that these models allow to make estimates on the relative lifetimes of engines under different conditions and subsequently the information can be used in financial considerations for producers and consumers.

A big family of research studies has been performed in the area of diagnostics and prognostics, which amplifies the importance of performance-based monitoring in gas turbine health management. Many advances and developments in the theory, application, and implementation of these tools have been recently presented in journals, technical reports, and conference proceedings. Moreover, the need of condition monitoring, diagnostic and prognostic tools is greater now, more than ever before, given that the gas turbines are operating under transient conditions which include fast start up and shut downs to compensate for the interminable nature of renewables. Under such operating conditions the gas turbines are consuming their useful life faster than a base load gas turbine. Within this context, a new group of research works dealing with the challenging aspect of performing diagnostic and prognostics under these conditions has emerged towards improved condition based maintenance. In contrary to the excellent existing reviews of gas turbine diagnostics by Li [15], Marinai et al. [16], and Volponi [17], this review aims to highlight the recent trend for performing diagnostics and prognostics with transient data. For transient engine operating conditions, the condition monitoring systems should capture the fast nonlinear dynamics of the engine at an increased frequency in order to establish a good quality data set for diagnostic and prognostic purposes. Under this scheme the most challenging aspect of gas turbine diagnostics is the fact that the engineers/data scientists have to extract, correct, filter and smooth the vast amount of gas path measurements from “data lakes’ in order to establish a high-quality data set for diagnostics and subsequently prognostics. The importance of performing diagnostics under transient conditions is amplified by the fact that prognostic methods are heavily relying on the engine operating and ambient conditions. The reduction of the downtime and improvement in the availability and reliability of dynamic operating gas turbines has transformed the field of diagnostic and prognostics into a challenging arena for scholars of diverse disciplines to propose numerous diagnostic and prognostic solutions. Given the plethora of papers in the field, this review article aims to provide insights about where the current research is heading and those issues that attract significant research and development in the short and long term. To achieve this goal, the state of the art of performance-based health monitoring technologies and applications for gas turbine power integration support are reviewed from different aspects. The frameworks used in a comprehensive gas turbine performance-based health management system, beginning with data collection and extending to advisory generation for decision support are presented. The article aims to organize, evaluate and identify patterns and trends in the literature as well as recognize research gaps and recommend new research areas in the field of gas turbine monitoring. This study brings together several concepts of gas turbine monitoring in an insightful way that has not been done before.

The remainder of this paper is organized as follows. Section 2 introduces the various types of gas turbine monitoring techniques. Section 3 describes the principles and the basic concept of gas turbine performance-based condition monitoring. Advances in engine performance simulation and adaptation are summarized in Section 4, followed by sections on recent research in gas turbine performance-based fault detection and isolation (Sections 5), fault identification (Section 6) and engine deterioration prognostics (Section 7). Finally, Section 8 offers concluding remarks together with research directions needed for the next generation of engine diagnostics and prognostics schemes.

2. Gas turbine condition monitoring

Typical maintenance contracts are progressively altered to reflect the bilateral interest among manufacturers and operators that demand the best deals in terms of operation and maintenance. Moreover, a significant trend has emerged in which the gas turbine operators demand from the manufacturers a guaranteed degradation rate and lifecycle cost depending on the use of the equipment. In gas turbine applications, a wide range of requirements set by the operators should be met by the manufacturers in global and long-term service contracts. The main objective is to reach effective responses to these requirements through the development of advanced tools for precise condition-based maintenance via condition monitoring. Generally, gas turbine condition monitoring can be implemented using different methods and technologies of different fidelity, each with its own advantages (**Figure 3**) [18].

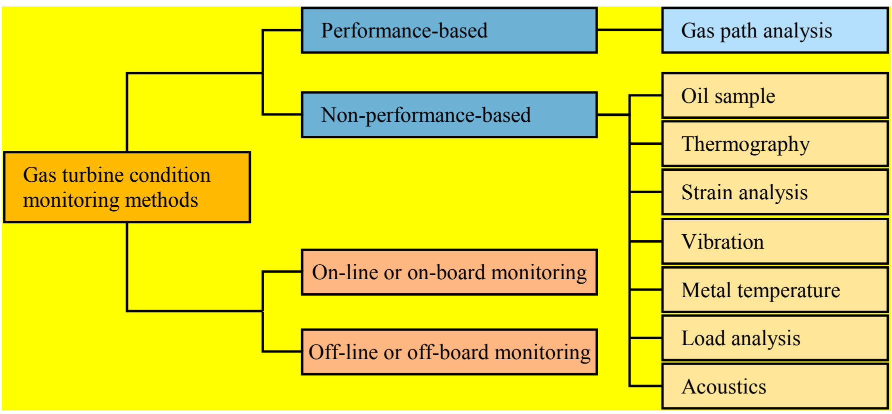

Figure 3. Gas turbine condition monitoring methods.

The causes of gas turbine deterioration fall into two categories. The first cause is of a mechanical nature where the phenomena are not aerodynamically coupled such as misalignment, unbalance, loose components, bearing defects, and lack of lubrication, etc. As shown in **Figure 3**, many techniques such as vibration, oil and wear debris analysis, acoustics, thermography, lubrication flow parameters, load analysis, and metal temperature (which are considered non-performance-based methods) can be used to assess this deterioration. The second cause is aerodynamic or performance related problems such as fouling and debris deposit in axial compressors, erosion, and corrosion of the blades, improper combustion, etc. In the case of this kind of deterioration, performance-based health monitoring, also known as gas path analysis (GPA), is a cost-efficient approach to delivering early warning information on ongoing or impending failures. It should be noted that as discussed by Mehr-Homhi et al. [19] several problems that manifest themselves as the mechanical error may, in fact, have underlying causes that are aerodynamic (or performance) related in nature and can be categorized as aeromechanical i.e. mechanically and aerodynamically coupled. Engine surge or corroded unbalance blades are examples of such a cases that are aerodynamic in nature but causes mechanical errors such as excessive vibration. The study by G. Barad et al. [20] emphasizes the need for implementation of performance-based health monitoring in gas turbine maintenance since it creates faster and more reliable information for gas turbine users who refine the maintenance strategy accordingly.

Table 2
The most important research efforts focused on non-performance monitoring.

Type of fault	Reference	Goal of research
Mechanical error	Wang and Zhang 2005 [21]	Engine prognosis based upon oil analysis
	Ogbonnaya 2009 [22]	Rotor shaft fault diagnosis and prognosis using misalignment, imbalance, crack and eccentricity
	Walker et al. 2012 [23]	Localizing unbalancy looking at stationary and rotating vibration phenomena
	Madhavan et al. 2014 [24]	Vibration-based damage detection of rotor blades
Faults in auxiliary subsystems	Pennacchi and Vania 2008 [25]	Diagnostics of a crack in load coupling
	Watson et al. 2010 [26]	Vibration diagnostics of accessories
Sensor uncertainties	Pourbabaee et al [27]	Sensor Fault Detection, Isolation, and Identification
	Fadlun et al. 2008 [28]	Demonstration of influence of instruments accuracy on condition-based maintenance
	Palmé et al. 2011 [29]	Fault detection and isolation of sensor

As shown in **Figure 3**, gas turbine monitoring system can be generally categorized as online and off-line monitoring. On line monitoring systems in industrial gas turbines is a common practice nowadays [30, 31] which offers the mean to continuously monitor the performance of the engine over its lifetime and can be used in engine fault diagnostics, prognostics and control purposes in real time. This philosophy has also started to be adopted in the case of aero engines. For example, Rolls Royce uses Engine Health Management (EHM) to track the health of the engine, using onboard sensors and live satellite feeds. Although many recent research efforts have driven great improvement in this area, the high costs and inaccuracy due to monitoring of data characterized by noise are the main limitations of these methods. However, in off-line or off-board monitoring, the essential data are acquired using an embedded device and are transmitted to the analysis server or ground station for further data analysis in the future. Off-line monitoring is not as costly as on-line methods and yields accurate results by implementing the appropriate data processing techniques. However, the increased risk of using off-line monitoring and consequently missing certain failure events that occur between successive data acquisitions should be noted.

3. Principles of gas turbine performance-based monitoring

The most popular performance-based concept for assessing the behavior of a gas turbine is gas path analysis (GPA), which is briefly described as follows.

Physical faults yield to deviations in one or more of the engine health variables or independent parameters, such as component flow capacity and efficiency. These factors in turn cause deviations in the measured variables or dependent parameters, such as pressure and temperature, fuel flow rate and rotational speeds [32]. Component health parameters are not directly measurable, such as mass flow functions and component efficiencies, but they are thermodynamically correlated with the measurable parameters. As a consequence, gas-path faults have observable effects on the measurements. With the availability of an essential measurement set and a model function that relates these data to the health parameters, it is possible to identify faulty components [33]. The theory underlying this concept is summarized in **Figure 4**.

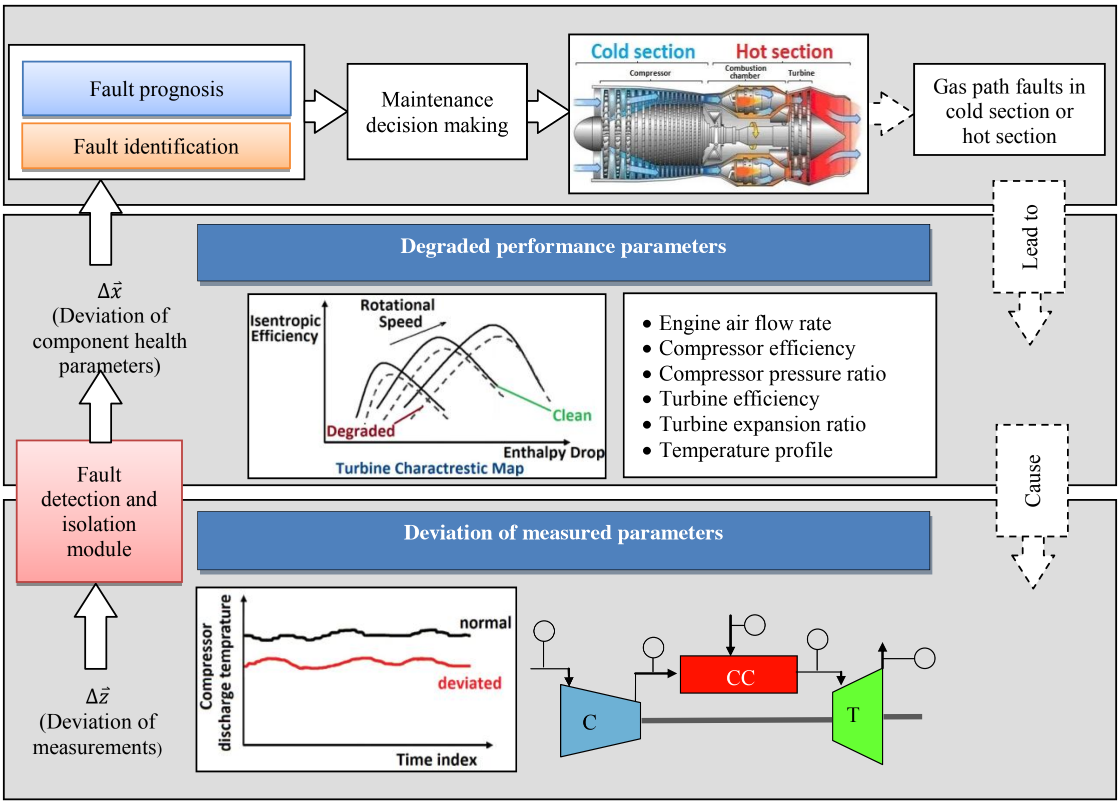

Figure 4. Concept of gas turbine performance-based condition monitoring, adopted from [34].

The most crucial component degradations are those that occur in compressors and turbines because these components are the most important and expensive components in gas turbine engines. Combustion chamber degradation is not likely to be the direct cause of performance deterioration and therefore cannot be detected by gas path analysis [35]. The degradation might be represented by the deviation of component health parameters, independent variable ($\Delta\vec{x}$), and measurements, dependent variable ($\Delta\vec{z}$).

Several limitations in the application of performance monitoring make the performance-based diagnostic and prognostic problem a challenging one. First, to perform a health assessment, diagnostics and prognostics in a comprehensive condition-based maintenance program, in-depth knowledge of the engine performance and a complete set of operating measurements are necessary. In addition, careful estimates are required to select the appropriate type and number of measurements and the corresponding sensor locations. Improper selection might lead to non-convergence of the solution process [36]. Measured data combined with sensor noise and bias is the third challenging issue. The sensor measurements are often distorted by noise and bias, thereby masking the true condition of the engine and leading to incorrect estimation result [37]. Finally, the combined effect of system non-linearity and sensor selection might result in multiple health degradation scenarios that produce similar measurement shifts. This is a difficult problem to deal with because of estimation techniques, in general, give only one set of estimated health parameters for a given set of measurements without the capability to indicate the level of confidence in the results.

4. Engine model performance adaptation

Before exploring the performance-based diagnostic and prognostic approaches, it is necessary to consider the possible sources of data and information that could potentially feed the process. As discussed in detail in subsequent sections, gas performance diagnostic approaches can be generally categorized into model-based and data-driven methods. In model-based methods, an analytical model of the engine must be developed and progressively updated to match the current status of the engine. Using this process, the health parameters can be continuously calculated, and their deviations from the normal condition can be implemented for performance-based monitoring. In data-driven methods, although the fault detection module can be developed only with data corresponding to the engine healthy condition, the fault isolation module must be developed for the healthy condition and all different faulty conditions. Therefore, the required data can be collected in three ways. First from the real engine over its lifetime, second from experimental tests, and third from an engine model. The first and second methods are costly and may require a high variety of sensors for computing accurately the mass flow and isentropic efficiency parameters of the engine components [38]. Reduction of the collected data or experimental measurements to a minimum and collection of the remaining quantities using a gas turbine model is an affordable way to address this problem. Although a 0-D model is adequate for performance diagnostic purposes, it is necessary to progressively tuned/adapt the model for improving the accuracy of the diagnostic analysis. Therefore, in the model-based methods, and even in data-driven methods for design and testing the accuracy of monitoring systems, access to an accurate engine model is beneficial. Although the knowledge of modeling gas turbines at the design point and in off-design conditions can be found in many references such as [39, 40], as indicated by many studies (e.g., ref. [41, 42]), the major drawback in development of these models is the lack of component maps. These data are usually proprietary to the gas turbine manufacturers, and only a limited portion of the performance data, in the form of characteristics charts derived from experimental tests or from an engine performance prediction program referred as the "engine deck", might be available to the final users. In this condition, the required engine model can be refined and matched for the engine under investigation using performance adaptation through component characteristic tuning. The implementation of the adaptive modeling diagnostic method allowed for accurate condition assessment during base and part load operation leading to the identification of engine components deterioration and the root cause of an engine performance shift [30]. As shown in **Figure 5**, performance adaptation uses an optimization algorithm to tune the non-measurable component parameters (x).

Toward this goal, for a specific controller set point (u), which is related to the required power and rotational speed, and in a specific ambient condition, the model will be optimized in such a manner that the model output measurements (z_m) match the collected measurements of the reference engine (z_r). Depending on the control architecture of the engine, the control parameter u which is also known as "handle" can be fuel flow, power output, turbine entry temperature, shaft rotational speed or any other quantity that governs the flow of the system's energy."

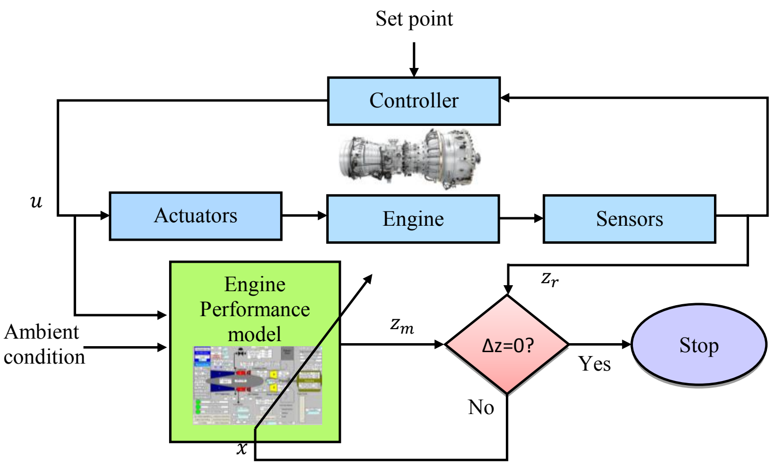

Figure 5. Flow chart of the performance adaptation process [43].

The overall objective of the component map modeling approaches is to obtain mathematical equations that can accurately exhibit the relationship between corrected rotational speed, corrected flow capacity, pressure ratio, and isentropic efficiency. To simplify the model using performance maps, it is common to normalize the corrected speed, corrected mass flow, pressure ratio and isentropic efficiencies using design point values. This work reviews a family of component map modeling methods aimed at improving the accuracy of gas turbine performance simulation for diagnosis and prognosis.

Scaling is one of the most common methodologies used in the process of component map representation [44-47]. In this method, all of the values of the original curve are multiplied by a specific factor to obtain the component characteristics of a similar engine. The conventional form of this method uses a constant scaling factor in such a manner that the design point of the targeted engine becomes the same as the design point of the reference engine. However, due to two major problems, use of this method in applications that require higher accuracy presents two main limitations. First, the selected reference gas turbine should be highly similar to the target engine. Second, the exact design points of both the reference and target gas turbines must be known. A modified version of the scaling method is presented by Kong, Ki et al. [45] et al. in which the experimentally collected performance data at certain off-design points are used in a performance adaptation model to promote the scaling factors with the aim of achieving better-scaled maps. Li et al. [46, 47] also applied genetic algorithms to search for an optimal set of linear and nonlinear scaling factor functions in a performance adaptation scheme.

Stage stacking is the procedure used to obtain the overall multistage compressor and turbine maps using generalized stage performance curves. This technique permits an in-depth stage-by-stage analysis of the flow through the compressor and turbine. This method is primarily used to tune the compressor map through stage-by-stage analysis. The general theory and the preliminary successful implementation of this method can be found in the works done by Muir et al. [48] and Howell and Bonham [49]. A recent development of this technique could be found in the work done by Spina [50]. In this study, the author introduced a technique during which the unknown parameters specifying the generalized stage performance are determined by combining a Cycle Program with the compressor and turbine performance maps obtained using the stage-stacking procedure. This is performed by seeking the values of the unknown parameters that better adapt to overall performance and thermodynamic measurements collected on a gas turbine. Muir et al. [48] applied this methodology for compressor map tuning and demonstrated that it is appropriate for predicting the performance of elements that incorporate variable stators. In another effort, Mirza-Baig and Saravanamuttoo [51] approximate the mass flow characteristics of multistage turbines by nozzle characteristics. Lee and Kim et al. [52] also employed the stage-stacking method for the compressor, and a stage-by-stage method considering blade cooling for the turbine to perform an off-design performance simulation. The result of this study showed that the component model obtained using this model are quite reliable for performance simulation.

In another group of component map representation methods known as Regression-based map fitting, an assumed mathematical model for the characteristic curves is tuned through performance adaptation and represents another effective technique. Kong and Ki [53] used this technique by applying three order polynomial equations to find the corrected compressor flow rates and efficiency curves as a function of pressure ratio and corrected speed. In this work, an error minimization genetic algorithm is used to find the regression coefficients in the process of performance adaptation. With the objective of higher prediction accuracy for engine performance, Tsoutsanis et al. [41, 42] established a new compressor map generation model using a novel regression technique, which assumes that at the constant corrected speed lines, the pressure ratio is an elliptic function of the corrected mass flow rate and the efficiency is a third-order polynomial curve of the corrected mass flow rate. Those researchers took advantage of genetic algorithms to determine the coefficients of the elliptical functions and polynomials. In another effort by Tsoutsanis et al. [54, 55], a set of polynomial equations for turbine pressure ratio versus flow capacity curves and a set of trigonometric functions were used to represent the isentropic efficiency versus corrected mass flow rate curves. These studies used Matlab's built-in nonlinear unconstrained optimization algorithm known as "fminsearch" in the performance adaptation process.

Table 3 presents the main features of these three techniques that are used to represent the gas turbine component characteristic maps.

Table 3
A comparison of map presentation methods for gas turbine components.

Method	Features
Scaling [38, 44, 56]	• Easier implementation in comparison to stage stacking methods since it only needs component design point and similar characteristic maps. • Includes either a constant, linear or quadratic regression model
Stage-stacking [50, 57]	• More general and enables a detailed stage-by-stage analysis of the flow through components • Suitable for variable stator geometry • Needs detail geometry of each stage
Regression [41, 42, 54, 55]	• Constructs relationships among key component parameters • More effective under transient conditions

All three introduced methods require an optimization process to finalize the component map tuning. In fact, in a particular model that simulates compressor and turbine characteristics, adaptation can aid in finding the optimal scaling factors, the rating parameters of the stage, and the regression model coefficients.

In addition to the above groups of component map modeling techniques that have been successfully integrated into engine models and tested for diagnostic purposes, it is worth mentioning a group of studies that examined the representation of the compressor map alone. In principle, the compressor map is the most challenging and crucial performance characteristic of an engine model, and this importance has led to the development of several methods for representing the compressor map characteristics. The majority of these studies used artificial neural networks [58-60] and fuzzy expert systems [61] to represent the shape and predict the operating points within the modeled curves of the compressor performance maps. Maps can also be determined by flow analysis schemes such as the stream line curvature (SLC) methodology [62] or high-fidelity computational fluid dynamics approaches (CFD) [63] if the geometry of the mechanical device is accessible.

A variety of models and software tools have been developed for both off-line and real-time performance adaptation of gas turbines with different levels of complexity, fidelity, accuracy and computer performance requirements. In the Aerospace Department of Delft Technical University, a software package known as GSP (a gas turbine simulation program) [64] was developed and is capable of simulating almost all types of gas turbines (turboshaft, turboprop, turbofan, single and multi-shafts, etc.). Another software product known as GASTURB, developed by Kurzke [65], is updated to version 12.0 and is extensively used as a gas turbine performance simulator. GASTURB is able to simulate most of the normal engine types, including mixed and unmixed turbofans with or without boosters, turboshafts with or without heat exchangers, and one-shaft or two-shaft turboprop engines. US engine manufacturers and research institutes, including NASA, have collaboratively developed NPSS [66, 67] (Numerical Propulsion System Simulation) which is a powerful gas turbine simulation tool with several advanced capabilities. In another effort, an interactive gas turbine simulation and modeling environment called “PROOSIS” [68] (PRopulsion Object Oriented SImulation Software) has been developed as part of the “VIVACE-ECP” (Value Improvement through a Virtual Aeronautical Collaborative Enterprise - European Cycle Programme) project to be used by European industries. Since the mid-1990s, SIMULINK and many other GUI (graphical user interface) programs have been developed using MATLAB [69-71].

5. Fault detection and isolation (FDI) approaches

Over the last two decades, significant research efforts have focused on the development of performance-based fault detection and isolation for gas turbines. In the fundamental sense, FDI involves continuous processing of engine performance measurements in regard to controller set point (u) and ambient condition to track the deviations of selected engine health parameters (z_r) from their corresponding values at the clean/healthy condition (z_m). The main procedure of this method is illustrated in **Figure 6**.

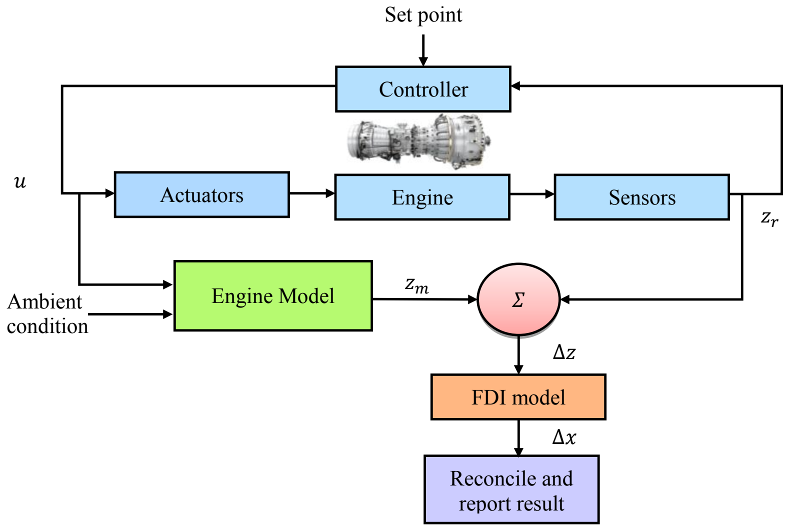

Figure 6. Schematic representation of an engine FDI system.

The chosen parameters and the analysis method characterize each different diagnostic method. Generally, three different categories of performance monitoring approaches are used in the condition-based maintenance of gas turbines. The first category includes model-based methods, which involve analytical modeling of gas turbine operation and are quite promising for real-time condition monitoring. Model-based approaches have proven their ability to detect both abrupt and more notably, gradual degradation in engine performance in real-time online implementations. However, as the modeling uncertainties and system complexity increase, the monitoring accuracy decreases [72]. The second group refers to data-based models such as neural networks systems that ‘learn’ from examination of real data containing nominal and known faulty conditions. Research results how shown that these methods offer a flexible tool for addressing the complex and non-linear characteristics of dynamic systems. The last group includes systems that embody ‘rules of thumb’ that have been developed and refined by human maintenance experts. Examples of these systems are rule-based expert systems and fuzzy logic approaches. Although these methods are capable of offering explanations and methods that reach a particular solution, it is highly complex to find a proper set of rules, functions, and tuning that can obtain a satisfactory solution as the system complexity increases. These two latter groups of approaches, which are also known as data-driven techniques, heavily rely on real-time or collected historical data from engine sensors and do not directly require a detailed mathematical model of the system.

Gas turbine performance diagnostic approaches can be generally categorized as linear or non-linear methods. Kamboukos and Mathioudakis [73] compared these two methods theoretically and presented an overall assessment of their merits and weaknesses with the conclusion that the use of linear methods might lead to substantial inaccuracies in estimation of degradation. The inadequacy of the linearity assumption has led to the development of non-linear alternatives. Although all data-driven approaches are non-linear, model-based methods involve both linear and non-linear methods. With the plethora of techniques available to monitor the health of equipment, the question always arises as to the optimal technique for interpreting the condition of the engine. The following subsections offer a summary of key approaches applied for this purpose.

5.1. Model-based methods

Using the engine performance model, a nonlinear relationship between gas path measurements ($\vec{z}$), and engine component health parameter ($\vec{x}$) at a given operating point and at certain time during operation can be simplified to a linear approximation.

$$\vec{z} = H.\vec{x} \qquad (1)$$

where H is known as the influence coefficient matrix (ICM). With this assumption, the first gas path analysis method was introduced by Urban [74], which is now referred to as linear GPA using influence coefficient matrix (ICM) inversion. The original concept of this diagnostic technique relies on using the inverted ICM, H^{-1}in Equation (2), known as the fault coefficient matrix (FCM). FCM assists in obtaining deviations in the engine component health parameter ($\Delta\vec{x}$) by examining the deviations in the gas path measurements ($\Delta\vec{z}$).

$$\Delta\vec{x} = H^{-1}.\Delta\vec{z} \qquad (2)$$

Linear GPA with ICM inversion has been applied widely to gas path analysis of engines. A valuable overview of this method is given by Smetana [75]. However, due to the nonlinear thermodynamic behavior of engine performance, the linear performance adaptation might not be able to deliver an accurate estimation of engine performance deviation. To improve the accuracy of this linear method, Escher and Singh [76] applied a Newton-Raphson-based iterative method to solved the non-linear relationship between the engine performance parameters and measurements. Gas path analysis using ICM inversion is idealistically simple, offers quick solutions and is capable of performing multiple fault diagnoses. However, this method is limited to detecting the degradation at a small scale. In addition, an inaccurate influence coefficient matrix, measurement uncertainty, and correlated measurements seriously affect its accuracy. Moreover, using this method, the number of measurements (m) must be equal or greater than the number of health parameters (n), (i.e. $m \geq n$), to ensure a unique solution of performance adaptation.

The weighted-least-squares technique is used in many engine gas path analysis systems to increase the diagnostic accuracy in the case of sensor errors [77, 78]. The least square fitting process uses a parametric model to minimize the sum of weighted squared deviations between the actual and predicted measurements using one or more coefficients that are estimated by the fitting process. In addition, the measurement uncertainties associated with the gas path measurements are also considered using a weighting matrix with their respective sample variances. As described by Kamunge [79], the modified FCM and performance model can be written as

$$H^{\#} = (H^T W H)^{-1} H^T W \qquad (3)$$

$$\Delta\vec{x} = H^{\#}.\Delta\vec{z} \qquad (4)$$

where W is the weighted individual matrix. The implementation of this technique in GE's GPA tool, known as the TEMPER program, is discussed in the study by Doel [80]. Similar to the description in the preceding section, a Newton-Raphson-based iterative calculation process can be used. As stated by Li and Korakiantis [81], the non-linear weighted-least-square method is capable of considering the performance nonlinearities of an advanced non-linear diagnostic approach. Kamunge [79] presented a detailed discussion on the non-linear weighted least squares method and highlighted the model capabilities in terms of addressing random measurement noise and fast computation.

Kalman filter employs the system's dynamics model and sequential measurements to estimate the state variables of dynamic systems which are better than the estimate obtained by using measurement alone. The schematic representation of performance-based condition monitoring of gas turbine engine using Kalman filter is shown in **Figure 7** [82].

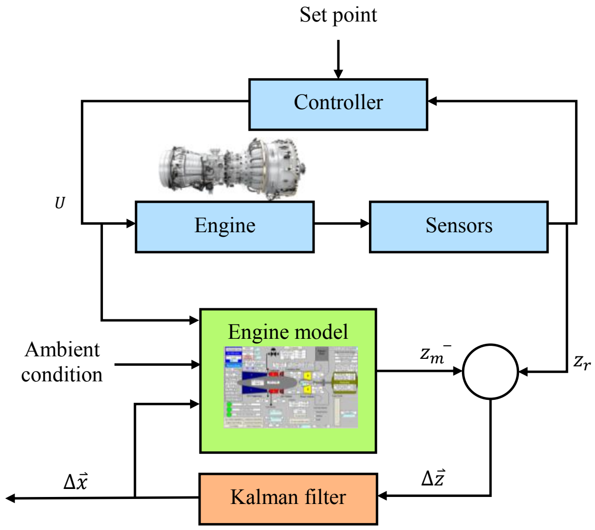

Figure 7. Architecture of engine health monitoring using the Kalman filter technique [83].

Simon et al. [84] states that the discrete linear time-invariant system can be presented by

$$x_{k+1} = Ax_k + Bu_k + w_k \qquad (5)$$

$$y_k = Cx_k + e_k \qquad (6)$$

where k is the time index, x is the engine health vector, u is the control variables, z is the measurements, and w_k and e_k are uncorrelated zero-mean white-noise input sequences corresponding to process uncertainties and measurement noise, respectively. The parameter A denotes the state transition model which is applied to the previous state, B denotes the control-input model which is applied to the control vector, and C denotes the observation model which maps true state space into the observed space. As described by Volponi et al. [85] using this technique, an estimate for the health engine parameters shifts can be obtained by

$$\Delta\vec{x} = \overline{\Delta\vec{x}} + D(\Delta\vec{z} - H.\overline{\Delta\vec{x}}) \qquad (7)$$

where, $\overline{\Delta\vec{x}}$ is the a priori estimate of the engine health deviation, and D is the Kalman gain matrix, referred to as the diagnostic matrix, which can be computed by

$$D = P_0H^T(HP_0H^T + R)^{-1} \qquad (8)$$

where H is engine influence coefficients, R is the measurement covariance matrix and P_0 is a positive semidefinite weighting matrix. The method for generating P_0 and R matrices is thoroughly described by Urban and Volponi [86].

Among the variants of the Kalman filter techniques, the linear Kalman filter (LKF) is the method most commonly used in engine diagnostics [87, 88]. In a significant effort by Kobayashi and Simon, a bank of LKFs was developed in which each filter is designed to detect a specific component, sensor, or actuator fault [89]. In this model, in the case of a particular fault, all filters except the one with the correct hypothesis produced large estimation errors, and thereby the specific fault could be isolated. To maintain the state variable estimates within a user-defined envelope and ensure that they vary slowly with time, Simon et al. [90] effectively incorporated a linear state inequality into the Kalman filtering method.

To decrease the estimation errors that are coupled with nonlinearities, Simon [91] presented a comparison between LKF and two nonlinear Kalman filter-based techniques known as the extended Kalman filter (EKF) and the unscented Kalman filter (UKF) for the purpose of engine health monitoring. Generally, EKF is the nonlinear version of the Kalman filter that linearizes about an estimate of the current mean and covariance. In systems with high non-linearity, the EKF might result in particularly poor performance. Therefore, the accuracy of the model might be more significantly improved using the UKF, which uses deterministic sampling to form a new mean and covariance estimate. This paper concludes that the use of an EKF warrants modeling of the engine dynamics nonlinearity with sufficient accuracy. Use of UKF is not justifiable because it imposes a further computational burden without significant improvement. However, based on the simulation result of a developed non-linear multiple model KF-based approach, Meskin et al. [92] proved improvements in the performance of the UKF over the EKF scheme in terms of fault detection times and functionality and also concluded that the UKF scheme is significantly more robust to large sensor noise.

Applying LKF to performance monitoring poses selected stability problems if few measurements are available [93]. In the case of negative redundancy, i.e. $(m < n)$, a smearing effect is likely to occur, which causes the fault to spread over multiple parameters rather than being correctly isolated [94]. Increasing the number of samples could make the redundancy positive, but because this might be related to nearly the same operating points, it does not represent a set of independent observations, and therefore, the estimation remains unstable. To address the effect of the undetermined problem, a tuning parameter that is a linear subset of the original health parameter is introduced using an optimal transformation matrix [95]. In another study, this tuning is extended to state estimation of the non-linear dynamic system known as undetermined EKF [82].

The genetic algorithm (GA) is a heuristic search and optimization approach that follows the procedure of natural selection. In this method, the interacting variables in the problem are first mixed and encoded to form a series of binary strings to generate numerical chromosomes. A random population of chromosomes is constructed and is subsequently ranked based on a fitness function to determine its accuracy. The fittest string, the elite, is permitted to survive and reproduce. This process can be conducted using genetic operators such as crossover and mutation and leads to the generation of offspring chromosomes and a new higher-quality population. The continuous cycling character of the genetic operators could evolve toward the desired solutions [96].

Conventional optimization for the purpose of gas turbine fault diagnostics was first introduced by Stamatis et al. in 1990 [97]. The GA algorithm adopted in gas turbine fault isolation is based on techniques that use sensor-based and model-based information. As shown in **Figure 8**, the goal is to minimize an objective function, Equation (9) [98], that compares the performance measurements of the actual gas turbine with a set of measurements obtained from an engine performance model, which is subjected to permutation of implanted faults. The solution of the algorithm is a set of implanted faults in a simulator in which the corresponding measurement is closest to the actual measurements and can be effectively applied for purposes of fault isolation [99].

$$OF = \sum_{i=1}^{nm} \frac{|z_i - z_d|}{z_r . \sigma_i} \qquad (9)$$

where $\boldsymbol{z}$ is the measurement vector of the actual engine, $\boldsymbol{z_d}$ is the measurement vector of the performance simulator model in deteriorated condition, $\boldsymbol{z_r}$ is the measurement vector of the performance simulator model in healthy condition, σ is the standard deviation used to account for measurement noise, and $nm\ is$ the number of measurements.

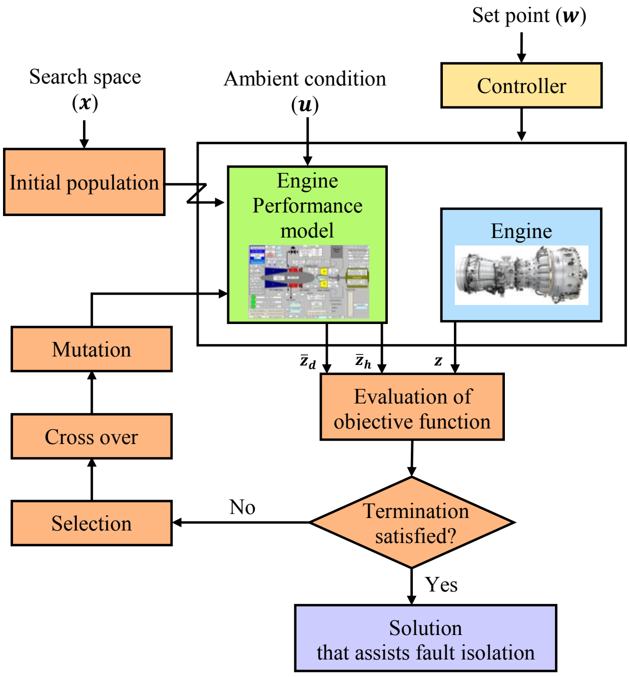

Figure 8. Schematic representation of the fault isolation approach using GA, adopted from [99].

Gulati et al. [100] applied the GA-based technique for a poorly instrumented gas turbine engine (RB199) using the concept of multiple objective point analysis. Sampath et al. [101] validated this method for fault diagnosis in advanced cycle engines (ICR WR21) and reported significant success. Bre et al. [102] presented the concept of on-line diagnostics-based GA for gas turbine engines and highlighted the ability of this technique to detect notably small component deviations even in the presence of measurement uncertainties. However, the work of Sampath and Singh [103] comparing GA with other applicable methods for the purpose of engine health monitoring emphasizes that these advantages occur at the expense of the computation time needed for convergence.

5.2. Data driven methods

Recently, great attention has been focused on the development of data-driven methods, mainly known as computational intelligence-based methods, for engine fault detection and isolation. Due to its capabilities in the modeling of nonlinear dynamical systems, artificial neural networks (ANN) have been extensively exploited and used to achieve fault diagnostics in gas turbine engines. ANN is a black-box model of a nonlinear, multivariable static and dynamic system and can be treated using input-output information measured from the system. The most common ANN includes several layers of plain processing elements known as neurons, the interconnections among them and the weights allocated to these interconnections. The weights store information related to the input-output structure of the network. For a more detailed overview of neural network processing and development, the reader is referred to [104]. The main concepts of using ANN for the purpose of fault detection and isolation in gas turbines are demonstrated in **Figures 9(a)** and **9(b)**, respectively.

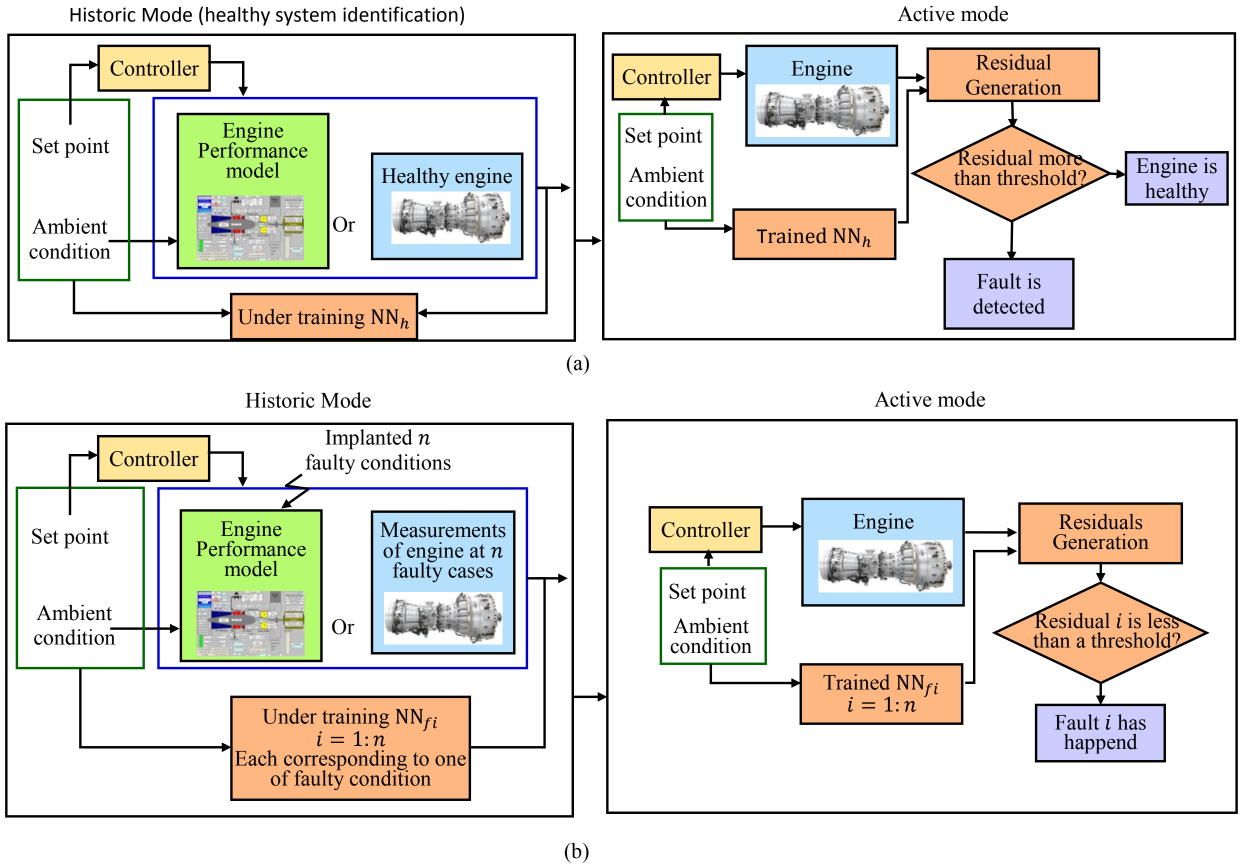

Figure 9. ANN-based approach for (a) fault detection, and (b) fault isolation, adopted from [105-107].

As shown in **Figure 9**, to perform fault detection analysis using ANN, a preliminary phase known as healthy system identification is necessary. The main goal of this phase is to develop networks that are able to accurately represent the behavior of a gas turbine engine in the clean/healthy condition. Subsequently, the outputs of the actual engine and the trained healthy networks are used to generate the residuals. If the residual exceeds a predetermined threshold, the fault occurrence is established in the system. In fault isolation, a bank of neural networks, each corresponding to a particular gas turbine fault, must be trained to act as an identifier of faulty operating conditions. Similar to the fault detection module, these networks can be used in fault isolation through residual generation. Note that in the FI module, the residuals far from zero correspond to the healthy condition or to a fault that is not accounted for in the ANN scheme and those close to zero that cross the thresholds are associated with the faulty condition.

The ability to cope with measurement uncertainties and rapid computational speed has driven a wide range of techniques, and various neural network-based schemes have been developed for fault detection and isolation of gas turbine engines. Although feed-forward back-propagation single neural networks [108] and a modular neural network [109] were successfully examined for engine diagnostic purposes, the concept of generating multiple neural networks for engine diagnostics was first introduced in [110]. This method was further extended by Ogaji [9] who used a multiple neural networks method to isolate sensor and component faults. Fast et al. [111] and Asgari et al. [112] developed ANN-based system identification models that predict the parameters of gas turbines in various conditions and are particularly useful in engine performance health assessment, especially if the real data are only available over a limited operational range. To perform combined mechanical and performance health monitoring, Barad et al. [20] developed a feed-forward multilayered neural network (MNN) with two hidden layers using the popular back-propagation (BP) gradient descent algorithm for network training. The obtained result proves that the ANN-based performance health-monitoring tool is sufficiently robust and delivers an early warning compared with the mechanical parameters. Dynamic neural networks have also been applied to achieve fault detection and isolation of turbine engines. The dynamic ANN-based models proposed in references [105, 106] demonstrate that the problem of dual spool engine fault detection and isolation can be addressed quite effectively using a bank of dynamic neural networks. More recently, Loboda [113] compared the probabilistic neural network (PNN) with Parzen window (PW) and k-nearest neighbor (K-NN) methods for gas turbine fault classification using probability density estimation.

Expert systems apply expert domain knowledge in a computer program to create reasoning for problem solving through an automated inference engine. The ES approach can be adjusted for equipment data interpretation and condition monitoring due to its ability to determine systematic reasoning procedures. This knowledge-based approach is based on evaluation of on-line monitored data using a set of rules learned from past experiences. Liao [114] presented a complete literature review and classification of expert systems. Selected examples of ES use to support gas turbine engine maintenance and diagnostics that highlight its interactivity and user-friendly interfaces are discussed in Spina et al. [115].

The main reasoning methods implemented in ES for machine diagnostic applications are rule-based reasoning, case-based reasoning, and model-based reasoning. A particular ES system that has been used recently for gas turbine diagnosis is TIGER [116]. Although the core of TIGER is a temporal rule-based system, it also uses model-based reasoning for monitoring and diagnostics. In another effort, case-based reasoning (CBR) was applied by GE for engine fault detection at their monitoring and diagnostics center in Atlanta [117]. The modular “plug and play” structure of the CBR system facilitates experimentation and optimization, and in 2004, this system was integrated into the production environment. [117]. The modular “plug and play” structure of the CBR system facilitates experimentation and optimization, and in 2004, this system was integrated into the production environment.

In contrast to the ES, which uses hard-and-fast if-then rules, as explained by Ross [118], fuzzy logic (FL) can be developed based on unclear/uncertain if-then rules. FL supplies an interface that aids experts in translating their qualitative knowledge to solve a problem. The related variables take on fuzzy values that are characterized by a membership function and a sentence. The linguistic variable concept could be interpreted as an elastic constraint on its value [119]. These constraints are spread by fuzzy inference operations. The resulting reasoning procedure has robust interpolation characteristics, which give fuzzy logic a significant potency with respect to the changes in factors such as system parameters and disturbances. The general architecture of an FL-based approach for the purpose of fault isolation is shown in **Figure 10**.

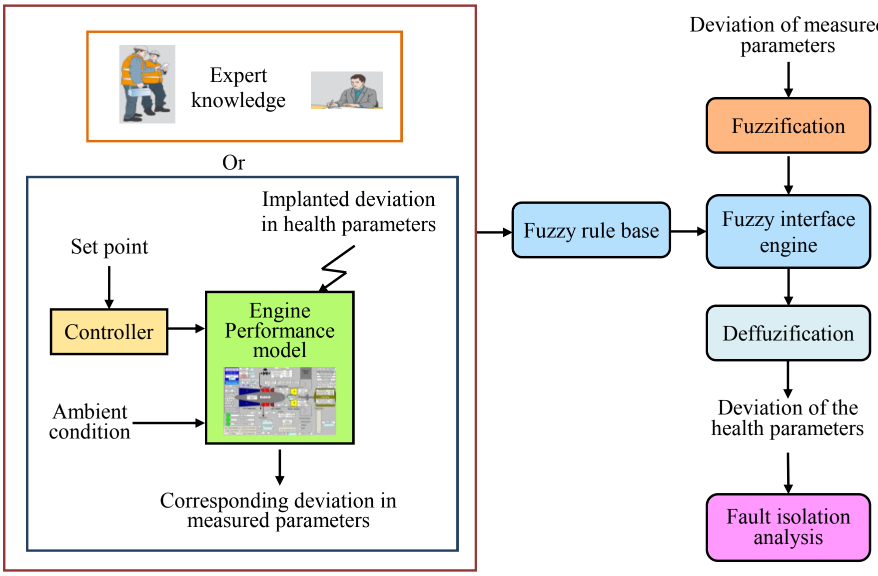

Figure 10. Structure of a FL-based approach for engine fault isolation.

Mohammadi and Montazeri-Gh [120], presented a perfect description of the rule and database generation process aimed at the development of an FL-based engine fault isolation model for a Siemens SGT600 gas turbine engine, a 25.4 MW two-shaft engine with free power turbine. The proposed model is a zero-order Takagi-Sugeno-Kang (TSK) type with 6 inputs and 6 outputs. The inputs consist of a load applied to the power turbine (PW) and deviations of certain measurements, including fuel flow rate, gas generator speed, exhaust temperature, compressor outlet pressure and compressor outlet temperature. The outputs consist of deviation of compressor, gas generator turbine and power turbine efficiency and flowrate, For rule-based generation, the input/output data pairs obtained using the engine performance simulator are replied via the table look-up technique [121].

Several gas turbine diagnostic models have been tested and successfully applied based on FL theory. In 2001, Applebaum [122] applied the fuzzy diagnostic strategy in the development of total health usage and monitoring systems (THUMS) for profitable safety monitoring of gas turbine engines. This work used a fuzzy expert classifier to identify the fault and diagnose the residual trend. Gayme et al. [123] developed an FL rule-based model using heuristics measurements of the gas turbine and designed experiments. The results showed the notable possibility of reaching a credible prediction horizon for fault detection and isolation, even with poor-quality data that included too many gaps. Ganguli [124] applied the FL technique for engine module fault diagnosis and demonstrated a high diagnostic accuracy of 95%. The result from Ogaji et al. [125] proved that the FL approach preserves the non-linearity of the problem and can also cope with multiple gas-path fault isolation problems that occur if more than one single engine component deteriorate simultaneously. Demirci et al. [119] established an automated gas turbine health monitoring system (AEHMS) by implementing fuzzy logic that relied on the expert knowledge and online data, and the entire engine operation was simulated through Matlab and the corresponding fuzzy logic toolbox. Zhao et al. [126] conducted an engine fault diagnostic approach that used a fuzzy logic matrix between the fault symptoms and causations and also considered the principle of maximum membership degree. The results proved that the proposed fuzzy mathematical method produces reliable fault estimation accuracy in gas turbine engines for cases of normal and complex relationships between the fault causes and the symptoms.

5.3. Hybrid methods

Although artificial intelligence systems are important for tackling practical computing problems in model-based methods, each of them faces certain individual limitations. Therefore, it is broadly acknowledged that practical and efficient implementation of gas turbine FDI can be achieved using an appropriate combination of different approaches in a hybrid structure.

Borguet and Léonard [127] used Kalman filter technique, which gives a proper estimation of the health condition for long-time-scale deterioration, together with a secondary adaptive component that searches out sudden changes in performance condition using residual analysis. This auxiliary component implements a generalized likelihood ratio test to detect and estimate abrupt faults and promote model responses to rapid deterioration.

In 2001, Kobayashi et al. [128] investigated a gas turbine diagnostic method using both neural networks and genetic algorithms. In this research, ANN is applied to estimate the engine internal health, and GA is applied to detect sensor bias in measurement uncertainty. In a similar work presented by Sampath and Singh [103], the nested neural network functions were used as a pre-processor or filter to reduce the number of fault classes that are subsequently explored by the GA-based engine diagnostics model. The results showed improvement in the accuracy, reliability, and consistency of the diagnosis.

A method that applies the fuzzy self-organizing neural network to gas turbine engine fault diagnosis was developed by Jiang et al. [129]. In this method, the relationship between the fault cause and fault symptoms is established according to fuzzy mathematics. Two-dimensional mapped pictures of the sample fault are set, and the actual faults are obtained via a self-organizing neural network.

A diagnostic method consisting of a Bayesian belief network (BBN) and Kalman filters was presented in [93] for gas turbine health monitoring. In this proposed approach, a soft-constrained Kalman filter uses a priori information through implementation of the BBN at each time step to estimate the unknown performance parameters. This innovative method improved fault isolation capability compared with the stand-alone Kalman filter.

Verma et al. [130] developed a genetic fuzzy system (GFS) to perform fault isolation from noisy measurements of a gas turbine engine. The proposed model uses GA to decrease the human effort required in fuzzy systems for a trial and error process and makes the development of diagnostic system easier and faster. This inventive model allows rapid development of rule-based if-then fault signatures for different engines. In another study, Xu et al. [131] developed a novel diagnostic method that integrates the wavelet transform and neural networks to resolve the issue of local minima in optimization. In this model, the wavelet basis function assigned to every neuron of the hidden layer is determined by learning. To overcome the lack of samples in gas turbine diagnosis, an integrated method using fuzzy and support vector machines was proposed by Xia et al. [132]. Wang et al. [133] demonstrated a three-step evaluation model for engine health monitoring of gas turbines. The developed model integrates the fuzzy analytic hierarchy process (fuzzy AHP), fuzzy preference programming (FPP) and a technique for ordering the performance by similarity to the ideal solution known as TOPSIS. The fuzzy AHP and FPP methods are used to specify the relative weights of multiple evaluation criteria and synthesize the ratings of the engine, and TOPSIS is subsequently applied to make a final decision on the overall performance of each alternative.

The neuro-fuzzy architecture represents an integration of fuzzy logic and neural network algorithms that use the learning abilities of neural networks with the human knowledge representation abilities of fuzzy systems. The neuro-fuzzy approach has been successfully applied for rotating machinery diagnostics [134]. Recently, this method was used as an enhanced tool for fault diagnostics in gas turbine engines [135]. In 2005, Bettocchi et al. [136] proposed a neuro-fuzzy system for gas turbine diagnostics. In this research, the data generated by cycle programming were used to set up ANNs. The most appropriate neuro-fuzzy system structure for gas turbine diagnostics is selected with respect to computational time and robustness toward measurement uncertainty. Recently, Abbasi et al. [137] used a bank of time-delay multilayer perceptron (MLP) models to perform residual generation and subsequently applied a local linear neuro-fuzzy (LLNF) model to achieve threshold adaptation in the fault detection step.

The authors believe that hybrid methods have a bright future ahead in applications with innovative integration of different methods that are able to resolve each other's imperfections.

Table 4 presents the features, similarities, differences, advantages and limitations of the most applied approaches for performance-based fault diagnosis of gas turbine engines, as highlighted in the literature [16, 79].

Currently, the discussed engine monitoring methods have been applied to different engine platforms, with different levels of complexity, addressing different problems, and using different metrics for evaluating performance. As such it is difficult to perform a one-to-one comparison between the accuracy of the candidate engine monitoring techniques. In a valuable effort and in order to address this shortcoming, NASA Glen Research Center provides a simulation platform called Propulsion Diagnostic Method Evaluation Strategy (ProDiMES) which is publicly available for research on the engine health management [138]. The overall goal was to provide an environment to facilitate the development and comparison of EHM methods against a standard and credible benchmark. Several research efforts have used this platform to compare various engine diagnostic and prognostic methods. For example, Simon et al. [139] presented a comparison between four diagnostic methods that were applied to the Pro-DiMES blind-test-case data set. The compared approaches includes Weighted Least Squares Single Fault Isolation developed by NASA Glenn, Neural Network Single Fault Isolation again developed by NASA Glenn, Kalman-filter based method developed by the University of Lie`ge, and a Generalized Observer/ Estimator developed by Wright State University and the accuracy of fault detection and isolation are extensively discussed.

Table 4
Comparison of the most common engine FDI techniques.

	Method					
Strategy involved	ICM-inversion	WLS	KF	GA	ANNs	FL
Linear (L)/non-linear (NL) [1]	Both L and NL	Both L and NL	Both L and NL	NL	NL	NL
Model required	Y*	Y	Y	N* [2]	N [2]	N [2]
Cope with noise and bias [3]	Y [3]	Y [3]	Y [3]	Y	Y	Y
Need $n \geq m$ [4]	Y	N	N	N	N	N
Single(S)/Multiple(M) FI [5]	MFI	MFI	MFI	SF/ limited MF	SF/ limited MF	SF/ limited MF
Smearing[6]	Y	Y	Y	N	N	N
Fast in on-line (on-wing)	Y	Y	Y	N	Y	Y
Main merits	– Idealistically simple	– Better result for small deviations in presence of noise and bias if compared with ICM inversion	– Efficient in presence of sensor noise and bias.	– Powerful to detect very small health deviations because of its solution refinement capability.	– Good generalization capability. – Robust in the presence of limited information. – Extremely fast convergence.	– Allows the use of linguistic variables. – simpler incorporation of knowledge in comparison to ANNs. – Ability to handle imprecision variables by defining them as fuzzy sets.
Main limitations	– Limited to very small degradations – Requires many measurements – Uncertain in presence of sensor noise and bias	– Need unique expected-value baseline for each engine. – The update is necessary after any change to engine configurations.	– Requires prior knowledge for tuning the covariance matrix. – The risk of divergence due to hypothesis in engine equation estimation.	– Long convergence time. – Possibility of the process stopping at local minimum points.	– Long training time due to unknown optimal network structure. – No way to access the neural networks reasoning. – Difficult to provide confidence level associated with output result.	– Poor generalization capability if compared to ANNs. – Unable to learn since the rules remain fixed after the determination. – Very complex to train the model.

*Y stands for Yes and N stand for No.
(1) Since engine performance is highly non-linear, linear models provide acceptable results only in small deviations.
(2) Although just model based methods need an aero-thermodynamic model of the engine, data driven methods most likely needs a model for data preparation in developing a fault isolation model.
(3) Linear approaches are not able to cope with sensor noise and bias.
(4) The inversion of the ICM needs the number of measurements (n) be equal or more than the number of health parameters (m), otherwise there will be more than one solution.
(5) Some approaches imply that engine deteriorate slowly (MFI) while others imply a fast trend shift due to a single (or multiple) entity going awry (SF/ limited MF).
(6) Smearing is the tendency that spreads-out the faults over a large number of the engine's components.

6. Fault identification

This section presents an overview of the definition, roots, and symptoms of gas path faults in gas turbine engines for the purpose of fault identification. Typically, any fault in a single component or inconsistency in the performance of a group of components can increase machine degradation [140]. Generally, all possible faults of the gas turbine can be classified into four categories, as illustrated in **Figure 11**.

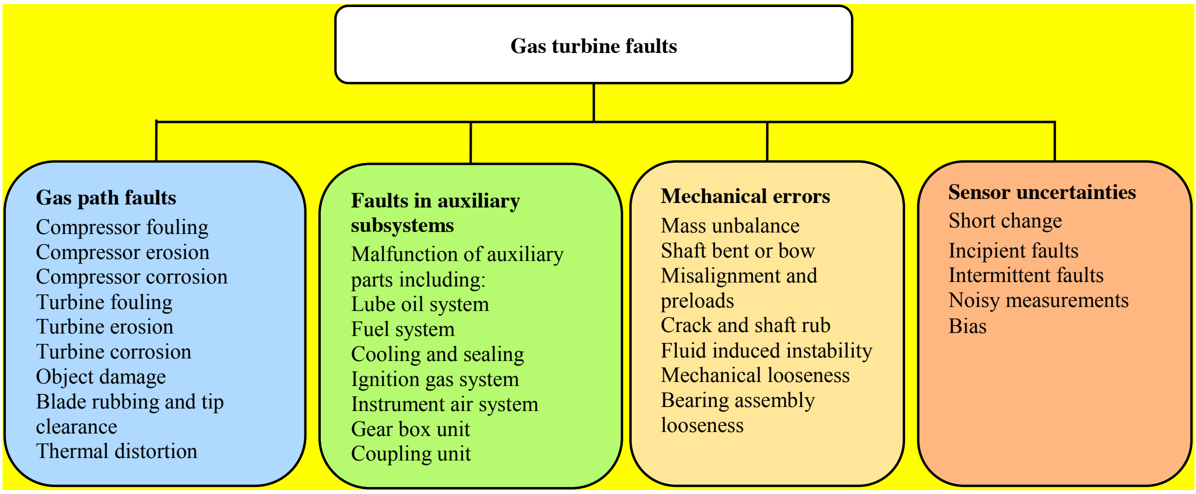

Figure 11. Classification of the most common faults in gas turbine engines.

Fouling, erosion, corrosion, hot section problems, object damage, clearance increase and leakage are the most common causes of gas path deterioration [141]. It should be noted that the common faults in aircraft engines and industrial engines are different to a certain extent [142]. Aircraft engines operate without an inlet air filtration system, and consequently, erosion is one of the key contributors to degradation, especially in the compressor section. Industrial engines use an appropriate air filtration system and are subject to fouling caused by smaller particles. The exception might be engines subjected to water injection in the compressor inlet [143], where an incorrectly sized system can generate water droplets that are sufficiently large to cause blade erosion. However, the effect of a particular fault on the performance of gas turbine is similar, regardless of whether the engine is used in aircraft or industrial applications.

6.1. Introduction to gas path faults

The main gas path faults that are common in gas turbines engines and have an influence on their performance are discussed in the following subsections.

a) Fouling

Fouling is the build-up of air impurities on the compressor blade surface. This phenomenon can result in changes in the blade inlet-angles, airfoil shape and surface roughness, as discussed by Song et al. [144]. Diakunchak [145] states that fouling is the most common cause of compressor deterioration and is known as the source of approximately 70-85% of performance degradation in gas turbine engines. However, fouling is a recoverable deterioration and can be reduced or even eliminated by cleaning to restore the gas turbine engine flow path surfaces to near initial conditions. Manual cleaning [146], grit-blasting [147], and offline and online washing [148-150] methods are various methods that have been proposed to prevent the unfavorable effects of compressor fouling. Many research studies have examined the effect of fouling on characteristic maps of an axial compressor in gas turbines. In one of the recent valuable studies, Yang and Xu [151] used the combination of a linear progression scaling method with the traditional stage stacking technique to investigate the effect of fouling on the performance map of axial flow compressors.

Meher-Homji [152] presented the causes and effects of hot section fouling on gas turbine engines. According to this study, when hot combustion products pass through first stage nozzle, due to the static temperature drop, some of them may deposit on the blades. Since the throat area of the nozzle controls the compressor-turbine matching, a reduction in this area leads to a move away from the design match point. In addition, deposits may also accumulate on the rotating blades. Contaminants that lead to turbine fouling can enter the gas turbine by inlet air, liquid fuel, fuel additives and NOx control injection fluid. Meher-Homji [153] pointed out that since the fuel mass flow rate is typically less than 2% of the air mass flow rate, 1ppm sodium (Na, as major foulants) entering by fuel would have the same effect as just 20ppb airborne salt entering the airflow. This is the main reason that most instructions advise less than 0.5ppm of Na.

b) Erosion

Material removal from the flow path components via abrasive hard particles such as sand and fly ash is known as erosion. Balan and Tabakoff [154] describe how erosion causes performance losses due to the decrease in surface roughness, an increase in blade tip clearance, blunting of the blade leading edge, thinning of the trailing edge and shortening of the blade chord. Hamed, Tabakoff et al. [155] listed the main parameters that have an influence on gas turbine erosion, including ingested particle characteristics, gas flow path and blade geometry, operating condition, and blade material. Particle size has a great influence on the blade impact patterns because larger particles affect the rotor and vane blades and smaller particles tend to follow the flow path [156]. In the turbine section, damage due to erosive particles that enter with the fuel is particularly severe, especially if blockage of the cooling holes occurs. An excessive increase in the blade temperature and creep rupture are the main consequences of this phenomenon. Because the filtration system used in industrial applications can probably remove the bulk of the bigger particles, erosion is more typically a problem in aero-derivative gas turbines [157].

c) Corrosion

Corrosion is the loss or deterioration of material from the flow path component caused by chemical reactions between the component and certain contaminants that enter the gas turbine with the inlet air, fuel, water or steam [158]. Both compressor and turbine components are exposed to aggressively corrosive conditions, and hence, this deterioration is often divided into three forms, including compressor section corrosion, hot section corrosion, and standby corrosion

Acceleration of air in compressor inlet guide vanes causes water vapor to be condensed. In this condition, salt particles get dissolved and may enter to the compressor. The water evaporates as it moves through the compressor and, at times, salt is found deposited on the compressor blades. Experience has shown that the deposits often contain sodium and potassium chlorides. Salty environment leads to pitting corrosion of the blades. This kind of corrosion only happens in compressor section and according to Haskell [159] is rarely experienced after the eighth stage of the compressor as no moisture will survive at a high temperature of this location. Similar to erosion and fouling, corrosion can be controlled with good filtration; however, the right conditions of fog, humidity, or rain can cause migration of the salt through the inlet filter. A much more common attack is caused by offensive atmospheric condition whereas engine operates in marine environments and heavy industrial areas located near chemical plants or industrial cement factories [160].

For a given gas turbine, the specific work of the ideal engine cycle depends on the maximum to minimum temperature ratio. Temperature increase results to increased high-temperature oxidation, hot corrosion, and sulphidation. In this condition, poor selection of material and coating may lead to catastrophic failure. High-temperature oxidation is the chemical reaction between components surface metal atoms and oxygen from surrounding hot gaseous environment [161]. It results in the formation of an external oxide scale that may be protective. However, oxide scales can crack or spall from the substrate surface due to thermally induced stresses when subjected to vibration and start/stop thermal cycles [162]. This phenomenon may also occur on the inner surface of blade cooling passage and result in blade failure. Hot oxidation starts at 810°K but accelerates at higher temperature [153].

Corrosion on engines that are not used for long extended periods is an issue that needs to be addressed by preservation methods [158]. Meher-Homji and Gabriles [163] remarks this kind of corrosion is the result of air moisture and corrosive particles presence in the machine and normally happens during an engine shutdown. In the case that corrosion products accumulate in the blade attachment areas, because of clearance increase, crevice corrosion may take place. In another case, the presence of corrosive material possibly from airborne salt frequently cause corrosion pits on uncoated airfoils, which has the risk of cracking. Standby corrosion reduces the blade fatigue strength significantly which demonstrates symptoms of stress corrosion fatigue as discussed by Sohre [164].

d) Object damage

When an object enters the gas path of a turbine engine, there is a high probability that it will impact rotating or stationary components before being exhausted. This is true for both foreign objects such as stones, hardware, pavement fragments, and birds ingested at the intake with the working flow, which causes foreign object damage (FOD), and domestic objects such as nuts, bolts and pieces of an airfoil liberated within the engine itself, which leads to domestic object damage (DOD) [165]. This damage takes the form of sharp V-notches in the leading edge of blades, especially in the early compressor stages, where these foreign substances impact Nowell, Dini et al. [166]. Notches dimension vary from few micrometers to tens of millimeters, based on the blade construction, particle size, nature of the foreign object and the intensity of impact [167]. Object damage is not a serious problem in industrial gas turbine compared with aircraft. The ease with which object damage can be detected is a strong function of its extent. In some cases, a step change in vibration may be noticeable, in others, a drop in performance may be significant [145].

e) Tip clearance increase (blade rubbing)

Due to the differential pressure across the compressor blades, leakage flow from the pressure surface to the suction surface through the tip clearance area is common. The effect of this leakage on the pressure rise, efficiency drop, and operational stability cannot be neglected [168]. An extensive investigation of axial compressor tip clearance flow and the relevant active control methods was presented by Bae et al. [169]. Kempe et al. [170] proposed an all-fiber, self-calibrating, economical probe capable of near-real-time, single-port, simultaneous blade-to-blade tip clearance measurements with sub-millimeter accuracy in the first stages of a gas turbine. To improve the gas turbine performance, Fabian et al. [171] investigated a control system used to maintain a constant blade tip clearance throughout the entire engine operation.

f) Thermal distortion

In the combustion chamber exit, changes in the radial and circumferential temperature traverse pattern could lead to temporary or permanent deformation [172]. This problem, which could occur due to faults in the fuel nozzle sprays and wrapped combustion chamber components, results in first-stage turbine blades that are untwisted, bowed, burnt or wrapped [173].

Classification of performance-related faults based on their location and whether they are recoverable or not is shown in **Table 5**.

Table 5
Classification of engine gas path faults

Location	Fault type	Recoverable or Non-recoverable
Cold section	• Compressor fouling	Recoverable
	• Compressor erosion caused by particles entered with air	Non-recoverable
	• Compressor pitting corrosion due to salty environment	Non-recoverable
	• Foreign object damage	Non-recoverable
Hot section	• Turbine fouling	Recoverable
	• Turbine Erosion caused by particles entered with fuel	Non-recoverable
	• Turbine hot corrosion and high-temperature oxidation	Non-recoverable
Common	• Domestic object damage	Non-recoverable

6.2. Gas path fault quantification

To perform fault identification or to create a foundation for simulating faults in a computer program, the relationship between physical faults and component deterioration must be determined. **Table 6** presents a brief summary of research that has been performed to quantify this relationship.

Table 6
Quantification of gas turbine faults in the literature.

Fault	Reference	Defected component	Finding: the effect of fault on component performance
Fouling	Fouflias, Gannan et al. [174]	Compressor	• Due to change in aerodynamic shape of blades, compressor efficiency decreases.
	Mund and Pilidis [175]	Compressor	• Due to the accumulation of contaminants, the boundary layers become thicker which leads to reduced air flow capacity.
	Meher-Homji [152]	Turbine	• Due to change in airfoil geometry, the flow capacity and efficiency decreases and the operating line shifts closer to the surge.
Erosion	Hamed, Tabakoff et al [176]	Compressor	• The pressure ratio, mass flow rate, and in particular, the efficiency of the compressor decreases.
	Sugano, Yamaguchi et al. [177]	Compressor	• The efficiency dropped and the surge limit has decreased.
	Diakunchak [35]	Turbine	• Erosion reduces the thickness of airfoil trailing edge which causes increased flow capacity, but it is unacceptable from mechanical integrity considerations. • A 1 % decrease in turbine efficiency due to erosion leads to 3.7% loss in power and 2.7% increase in heat rate.
Corrosion	Boyle [178]	Compressor and turbine	• Increased surface roughness and thicker boundary layers reduce the flow capacity. • A two-stage turbine efficiency losses of 2.5% for a 10.2 μm surface roughness is reported. • Hot section corrosion due to fuel's impurities and additives is typically more severe than compressor section corrosion which is due to salt entered by air.
Tip clearance	Graf, Wong et al. [179]	Compressor	• Increased clearance from 2.9% to 4.3%, leads to a 2.5% loss of efficiency, 20% increase in surge flow coefficient, and 12% reduction in design pressure coefficient. This is mainly due to the leakage flow from pressure surface to the suction surface through the tip clearance area.
	Frith [180]	Compressor	• A 3% tip clearance increase on the axial compressor stages decreases flow capacity by 4.6% and drops the pressure ratio by 3%, and decrease in compressor efficiency by 2.5%.
	Melcher and Kypuros [181]	Turbine	• A 0.25mm change in turbine tip clearance may cause up to 10°C engine exhaust gas temperature and decrease turbine efficiency up to 1.3%
	Radtke and Dibelius [182]	Turbine	• Increasing the radial clearances at the rotors and stators tip from 0.5% and 0.4%, of the blade height, respectively, to 0.8% leads to 0.6%

			decrease in efficiency.
Thermal distortion	MacLeod, Taylor et al. [183]	Turbine	• Both the turbine isentropic efficiency and flow capacity are effected, even though the effect on flow capacity is not as much as an effect on efficiency.

Based on the review presented in **Table 6** and many other references, including [35, 172], Zwebek et al. [184] summarized the effect of various physical faults on component health parameter degradation, as listed in **Table 7**.

Table 7
Effects of various faults on component degradation [184].

Physical Fault	Flow capacity change	Isentropic efficiency change
Compressor fouling	$\Gamma_C \downarrow$	$\eta_C \downarrow$
Compressor erosion	$\Gamma_C \downarrow$	$\eta_C \downarrow$
Compressor corrosion	$\Gamma_C \downarrow$	$\eta_C \downarrow$
Compressor blade rubbing	$\Gamma_C \downarrow$	$\eta_C \downarrow$
Turbine fouling	$\Gamma_T \downarrow$	$\eta_T \downarrow$
Turbine erosion	$\Gamma_T \uparrow$	$\eta_T \downarrow$
Turbine corrosion	$\Gamma_T \downarrow$	$\eta_T \downarrow$
Turbine blade rubbing	$\Gamma_T \uparrow$	$\eta_T \downarrow$
Thermal distortion	$\Gamma_T \uparrow$	$\eta_T \downarrow$
Foreign object damage	$\Gamma_T \downarrow$ & $\Gamma_T \downarrow$	$\eta_C \downarrow$ & $\eta_T \downarrow$

In the fault identification process, it is useful to find a relationship between the faults and their corresponding effects on the engine performance. In this regard, Zwebek et al. [184] provided a representation of component degradation used to simulate the effect of implanted faults on gas turbine performance. In another valuable effort, [185] investigated the effect of different kinds of faults on the engine compressor characteristics and discuss the way of faults modeling in more detail; where the stage characteristics modification factors are formed by considering severity and distribution of the fault.

The effects of main gas path component degradation on gas turbine performance are reported in several research studies. Zwebek and Pilidis [184] investigated changes in gas turbine efficiency, power output, exhaust temperature, and exhaust mass flow by implanting component faults into an engine performance model developed by TURBOMACH, which is the gas turbine performance code of Cranfield University. The obtained results show that degradation in the turbine's isentropic efficiency has the greatest negative impact on engine power and thermal efficiency. The study also reports that the effect of component isentropic efficiency on exhaust flow capacity is negligible, and this parameter is primarily affected by flow capacity changes due to faults such as fouling and erosion. Another research effort [186] studied the effect of selected mechanisms that cause engine degradation, namely, changes in blade surfaces due to erosion and fouling and changes in clearances. Yoon et al. [187] evaluated operation of a micro-gas turbine by implanting deterioration of various components, including the compressor, turbine and recuperate, by changing the component characteristics. The study trained a neural network using the generated deterioration data for the purpose of fault detection and isolation. Kurz et al. [188] performed a study to investigate the effect of deterioration of a given component on measurable engine performance factors that are often used in condition monitoring, including compressor discharge pressure, gas generator speed, firing temperature, and air flow. In another report, the same authors, (Kurz et al. [142]) discussed the degradation mechanism and the impact of component degradation on the performance of two-shaft gas turbine engines because they are used as the compressor drivers for natural gas service. The article highlights that the same level of component degradation might exhibit different relative performance reductions in various ambient conditions.

7. Fault prognostics

Until approximately a decade ago, the focus of engine performance-based health monitoring technologies has been on diagnosis of critical faults. Moving toward an improved insight into engine health, the gas turbine research community has recently decided to incorporate time evolution into monitoring systems by adding prognostic ability. As discussed by Heng et al. [189], prognostics are different from traditional reliability-based methods that rely on event record distributions of identical units to estimate characteristics such as the mean-time-to-failure and probability of reliable operation. In fact, the prognostic approach aims to predict the ongoing degradation of the machine or its components currently under operation. Generally speaking, prognostics are based on the outputs of diagnostics, and therefore, the accuracy is dependent on the diagnosis accuracy. As shown in **Figure 12**, the degradation of an engine can be detected and isolated using diagnostics, and the history of the engine or its component degradation can be fed into the prognostic model.

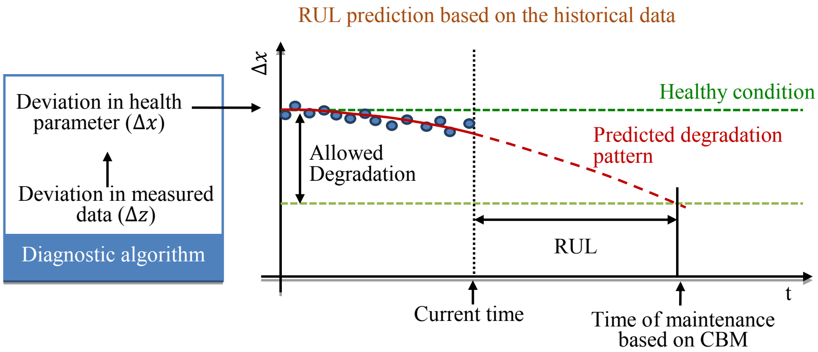

Figure 12. Schematic representation of engine degradation, diagnostics, and prognostics, adopted from [190].

In addition, it should be emphasized that the prognostics accuracy is directly dependent to the employed methods, where generally they can be divided into two main categories: model-based methods and data-driven models. The model-based prognosis attempts to incorporate a model of the engine into the estimation of degradation and the data-driven approaches commonly use historically recorded data to produce prediction outputs. In model-based methods prognostic accuracy is directly coupled to prognostic process. In these methods, the frequency of prognostics should be similar to that of engine model adaptation. This will ensure that the progressive evolution of the engine's health signature is well reflected in the engine model and accurately captured through the diagnostics. For data based methods a critical element of the prognostic process is the quality of data and the complexity of the employed method. Extensive and progressive training of Neural Networks, multiple runs of Genetic Algorithms and retuning data-based algorithms should be performed every time that the operating conditions of the engine are outside the operating envelope initially used for validating the subject methods.

Prognostics can be classified based on several features, including the selected health parameter, time frame, type of degradation, and forecasting approaches.

- A short-term investigation that predicts the future health of the system over a limited time horizon or a long-term investigation that can also forecast the remaining useful lifetime (RUL) or estimate the probability of reliable operation.

- Dependent parameter-based prognostics, which rely on prediction of engine measurements, are related to the global health of the engine, such as gas temperature, shaft speeds, and etc., or independent parameter-based prognostics, which rely on prediction of health parameters such as component efficiency and flow capacity.
- Prediction of the gradual performance deterioration that typically occurs due to a fault such as fouling and erosion or prediction of sudden faults that manifest as instantaneous deterioration due to an event such as foreign object damage. Although the former can be investigated using a forecasting algorithm, the latter can be considered using hazard plots [191]. The focus of this section of the current review article is on gradual deterioration, but one should note that when a sudden fault is detected and isolated, its effect should be considered (**Figure 12**).

Most of the published articles for gas turbine condition monitoring concentrate on fault diagnostics or fault prognostics exclusively. However, as explained in section 7, prognostics are based on the outputs of diagnostics. Hence, if a paper has investigated both issues, it has first discussed the diagnostic and then performed prognostics. Since the concept and approaches in diagnostics and prognostics are different, they can be discussed separately. Therefore the following sub-sections discusses the methods and approaches of prognostics.

7.1. Model-based methods

Gas turbine model-based engine prognostic techniques are mainly developed using Kalman filters or various other tracking filters. As mentioned previously in the diagnostic section, the Kalman filter algorithm takes the current health state and available sensor measurements and generates a virtual sensor that can predict optimal estimates of engine health parameters. Simon et al. [192] has successfully developed a Kalman filter-based model that incorporates linear state inequality constraints for turbofan engine health estimation. Particle filtering by the ability to include system parameters in the state vector for the purpose of system health tracking represents a good solution to failure prognosis problems. Daroogheh et al. [193] developed a fixed-lag dynamic linear model with an adaptive length moving window for time series forecasting using a time-varying ARMA model with fixed and variable model orders. The proposed method is applied for prognosis of gas turbine engine health parameters for the next 60 steps ahead. The obtained results show that even though the mass flow capacity of the turbine is not a good feature for use in prognosis analysis, the failure time can be identified with acceptable accuracy for up to 50 steps ahead by tracking the drops in compressor and turbine efficiency.

7.2. Data-driven methods

Data-driven models rely only on previously observed data to predict the projection of a system state or to match similar patterns in the history to infer RUL. Because sensors are sources of considerable noise, a pre-processor smoothing algorithm can be applied to extract information from historically acquired data. Marinai [191] states that the three most common pre-processor techniques are simple moving average (MA), weighted MA and exponential smoothing. Data-driven models can generally be categorized as statistical models and artificial intelligence models.

Evolutionary/statistical models such as time-series regression, autoregressive moving average (ARMA), and hidden Markov model (HMM) have been extensively applied to engine prognostics problems. Li and Nilkitsaranont [190] applied linear and quadratic regression techniques to the scattered deviation in health parameters, including compressor flow and isentropic efficiency, for prognosis purposes. In this work, given that a constant failure rate that starts at the beginning of an operation is followed by an increasing failure rate, a linear regression model is first applied, and quadratic regression is applied for the time at which a change in failure trend is observed. Recently, Tsoutsanis et al. [43] developed a regression-based method to accurately capture the component degradation pattern for an engine in dynamic conditions. To this end, first, a nonlinear unconstrained optimization method was applied to reconstruct the component characteristic curves to match the resulting simulated measurements with those of the reference engine for each diagnostic window. Second, the developed model was used to diagnose the engine health degradation in sliding windows. Finally, the future degradation trend was accurately captured by local fitting of the linear regression functions at the sliding windows. The accuracy of the proposed prognosis scheme was evaluated using the probability density function (PDF) and RUL metrics. The results show promising prospects for the proposed methodology for accurately estimating and predicting multiple component degradations over time. In another research effort, Marinai [191] presented a method using an ARMA model to forecast the failure risk of a Trent 800 engine for a short-term-ahead time horizon. The results of this study show that ARMA has a remarkable capability for discovering trends and predicting the turning points in the short-term analysis. The accuracy of this method in short-term forecasting is affected by the ability of the analyst. Giantomassi et al. [194] estimated the RUL of turbo-fan engines using the hidden Markov model. The results show that the adopted approach is especially suitable for situations in which a large amount of data is available off-line. Lipowsky et al. [195] presented a novel detection technique based on Bayesian forecasting and dynamic linear models (DLMs). Bayesian forecasting enables the calculation of conditional probabilities, whereas DLMs are mathematical tools used in time series analysis. The combination of the two methods can be used to calculate the probability density functions prior to the next observation or the so-called forecast distributions. The drawbacks of this approach are that several crucial parameters must be determined heuristically, which might lead to uninformative distributions, and once the fault is detected, a ‘‘rule of thumb’’ is involved in determining the gradient change in the prognostic trajectory, which might not be sufficiently accurate. To overcome this problem, Zaidan et al. [196] established a Bayesian hierarchical model to perform inference and inform a probabilistic model of the remaining useful life. The techniques use Bayesian methods to combine two sources of information: historical in-service data across the engine fleet and a once per-flight transmitted performance measurement from the engine(s) under prognosis. The model is improved by applying variational inference to the hierarchical formulation in order to overcome the computational and convergence concerns that are raised by the numerical sampling techniques needed for inference in the original formulation [197]. The proposed technique offered predictive results within well-defined uncertainty bounds and demonstrated several advantages of the hierarchical variant's ability to integrate multiple unit data and address realistic prognostic challenges. Puggina and Venturini [13] suggested an approach based on the Monte Carlo probability distribution to predict the future health status of an engine. The major feature of this technique is that the prognosis can be implemented for both local and global performance parameters, such as fuel flow rate or local temperatures, to estimate the system's future availability.

Artificial intelligence methods such as neural networks are also used by many researchers for the purpose of gas turbine prognostics. Ke-Xu et al. [198] applied a particle swarm optimized neural network to perform a time series prediction of health parameters. Vatani et al. [199] proposed two artificial intelligence methodologies for degradation prognosis of gas turbine engines. The first prognostic scheme was based on a recurrent neural network (RNN) that enables learning related to the engine degradation from the available measurable data, and the second scheme was based on a nonlinear autoregressive with exogenous input (NARX) neural network architecture. It was shown that the NARX network can be trained with fewer data points and that the prediction errors are lower than those of the RNN architecture. In another study, Daroogheh et al. [200] developed a hybrid model to construct observation profiles for future time horizons. In their proposed model, the particle filtering approach is used as a model-based method to compute the engine states and the health parameters, and as a computationally intelligent technique, the artificial neural networks approach is used to forecast the future health scheme of the engine using the obtained observations. A model combining the attributes of neural networks and expert systems was developed by DePold and Gass [201] for trend change detection and prognosis of engines.

As discussed above, to develop and implement a suitable prognostic approach for gas turbine engines depending on the criticality of the monitored engine, various levels of data, historical information, and models are required. **Table 8** gives an overview of the recommended information and models necessary for implementing each of aforementioned prognostic models [202].

Table 8.
Required information, merits, and limitations of various engine prognostics models [202].

	Model-based methods	**Data-driven methods**
Requirements		
Engine model	Required	Beneficial
Failure history	Beneficial	Not-required
Past operating condition	Required	Not-required
Current condition	Required	Required
Identified fault pattern	Not-required	Not-required
Maintenance history	Beneficial	Not-required
Merits and limitations		
Merits	– Are able to incorporate the analytical understanding of the monitored system. – Establish a functional mapping between the drifting parameters and the selected prognostic features [203].	– Are increasingly applied to machine prognostic and have shown improved performances over conventional approaches [203]. – Are able to transform high-dimensional noisy data into lower dimensional information for diagnostic/ prognostic decisions.
Limitations	– It is difficult to catch the system's behavior.	– Are highly-dependent on the quantity and quality of system operating data [204].

8. Concluding remarks and future challenges

Health management and maintenance are the most important concerns for heavy-duty gas turbine equipment owners, and a well-designed maintenance program that optimizes operational costs and maximizes equipment availability should be developed. Several authors have reported on a variety of subjects related to gas turbine condition-based maintenance issues, such as health assessment, diagnostics, and prognostics. Numerous research efforts have emphasized the need for implementing health monitoring in gas turbine maintenance since it creates faster and more reliable information for gas turbine users who refine the maintenance strategy accordingly. Therefore, the main objective of this study was to review and summarize recent scholarly efforts which are focused in the performance-based health monitoring, diagnostics and prognostics of gas turbines. Non-performance-based monitoring methods are briefly described in this review article but not examined thoroughly since they are beyond the main focus of this study. Five areas in need of consideration and improvement are primarily discussed: 1) performance degradation and gas path analysis, 2) performance adaptation and simulation, 3) techniques for fault detection and isolation, 4) principles of fault identification, and 5) prognostic enhancement in health monitoring. The numerous summarized frameworks, procedures, and techniques along with the comprehensive research references introduced in this article can provide a striking platform for experts, students or novice researchers and decision-makers working in the area of gas turbine engines to know the latest releases and state of the art.

In recent years, studies have demonstrated that most research in this area focuses on: 1) condition assessment with only few available measurements, 2) performance prediction and diagnostics in off-design steady and transient conditions, 3) real-time monitoring, 4) multiple component fault diagnostics, and 5) reduction of the negative effects of noise and sensor bias on condition monitoring. Given the plethora of papers in the field, this review article aims to provide insights about where the current research is heading and those issues that attract significant research and development in the short and long term. However, in contrary to the existing reviews, this article aims to highlight the recent trend for performing diagnostics and prognostics with transient data where the condition monitoring systems should capture the fast nonlinear dynamics of the engine at an increased frequency in order to establish a good quality data set for diagnostic and prognostic purposes.

An overview of the references shows that condition monitoring has the potential to play an effective role in the future gas turbine industry as these machines become larger and offshore turbines become more popular. Although proof exists of rapid development in the recent years, certain of the main challenges that must be addressed by the gas turbine research community are summarized as follows:

- Knowledge of the gas turbine deterioration mechanisms is essential for fault isolation and identification. Additional research in this area can enhance the accuracy of diagnostic models.
- Development of tools or methods to extract, process and interpret knowledge, experience, and event data types of information can enhance the monitoring capabilities.
- Development of more effective collection and accurate pre-analysis methods for performance data could yield great improvements in the development of gas turbine performance health monitoring systems.
- Further investigation on development of hybrid diagnostic and prognostic approaches could assist in generating robust tools with fewer deficiencies and additional features.
- The degree of user-friendliness is a major criterion in the development of maintenance strategies. This feature supports the users, many of whom do not have a profound knowledge of the performance of gas turbines or modeling algorithms.
- Finally, additional focus on the development of an integrated sensing, data processing, diagnostic and prognostic system intended to facilitate the application of condition monitoring in real time for shipboard plant monitoring is required for the next generation of intelligent maintenance systems for gas turbines.

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