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Exploring the Landscape of Gas Turbine Health Monitoring through Machine Learning: A Comprehensive Survey

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Abstract: Within today's fiercely competitive industrial landscape, effective condition monitoring, diagnostics, and prognostics play pivotal roles. The digitization of equipment has exponentially expanded data availability across industrial processes, driving the development of advanced techniques that significantly enhance machine performance. This paper delves into a decade- spanning survey of the evolution of condition monitoring, diagnostics, and prognostics, specifically focusing on machine learning (ML)-based approaches for optimizing gas turbine operational efficiency. Through an exhaustive literature review, this publication evaluates the performance of ML models and their applications in the realm of gas turbines. It also addresses key challenges and opportunities in gas turbine research. Ultimately, the synthesis of data collected from various sources coupled with ML techniques demonstrates promising potential in enhancing the accuracy, robustness, precision, and overall performance of industrial gas turbine systems.

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## 1. Introduction

In today’s competitive industry, increasing the reliability, availability, and safety of equipment, while reducing the operational and maintenance expenses are key factors of profitability and competitiveness. Health-monitoring practices have been carried out for a long time; however, over the past decade, the algorithms and their implementation have become more sophisticated. Moreover, the current trend of increasing the use of data collectors in industrial equipment, as well as the development of intelligent tools for condition and fault assessment have led to more effective health management strategies [1]. Remote sensing of plant processes by intelligent tools developed for equipment condition assessment has played a key role in the development of Industry 4.0 [2]. The big amount of data captured by industrial systems contains information about components, events, and alarms related to industrial processes. All these data can provide significant knowledge and information about system processes and their dynamics. This information provides the advantage of process understanding, leading to maintenance cost and machine fault reduction, and thereby an in increase in production and improvement of operator safety [3]. Data analytics using machine-learning techniques is able to treat large amounts of data and acquire online information about the machine’s status. These procedures are mostly used to obtain information from multidimensional time series to identify hidden
patterns and managerial results for strategic decision-making [4].

Condition assessment consists of a systematic inspection, review, and report of the state of the equipment. Inspection procedures have evolved as recent and more effective techniques have been developed, with the increase of data availability. Hence, they can be distilled into three main components: condition monitoring, diagnostics, and prognosis [5]. Firstly, in condition monitoring, the status of the equipment is periodically checked while keeping a record of observations. Monitoring can be developed near the machine or
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remotely, depending on the setup. Data records are collected by several sensors located along the equipment, then returned to the engineering office, where they are analysed and processed to diagnose any unforeseen event.

Secondly, diagnostic systems process the information of the equipment status to determine and identify risks that impact its operational integrity. Usually, a report from experienced engineers is completed in order to plan or recommend some actions to follow in case it is not working as expected. The main purpose of this data analytics process is to make the machine more reliable, available all of the time, and safer, thereby improving its performance [6]. This is complementary to condition monitoring in such a way that one aims to capture the performance of the system, while the other aims to improve it. Thereby, both of the systems need to work accordingly.

Finally, prognosis consists of predicting the future condition of a component and/or system of components. The objective of future condition forecasting is usually defined in terms of the prevention of hard failures of the components or reducing the performance degradation related to the equipment's operation. Failure prognosis puts the focus on forecasting the damage state or failure rate of a component or system of components in an engine, whereas degradation prognosis is associated with the slower decrease of performance throughout its life. This process is a step ahead of both condition monitoring and diagnostics, but at the same time there, is some dependency on how the diagnosis is performed. The relationship among all these processes is represented in Figure 1.

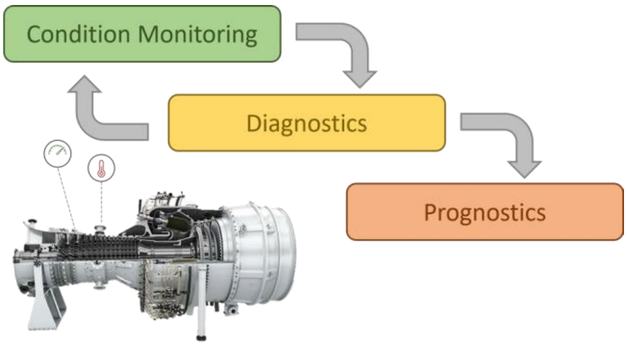

Figure 1. Outline of a gas turbine's condition monitoring, diagnostics, and prognostics.

While condition assessment is almost mandatory to tackle and treat important prob- lems for all industrial equipment, this review is focused on industrial gas turbines (GTs). GTs are some of the most expensive devices in aircraft and industrial applications, where a huge amount of money is invested in operational and maintenance actions [7]. Hence, it is mandatory to have a good health management strategy in order to avoid economic, environmental, and security defects.

The main goal of this paper is to review and discuss the new techniques that have emerged the last decade in the area of machine learning for condition monitoring, diagnosis, and prognosis of gas turbines. In this work, machine-learning techniques refer to algorithms that employ particular real data to learn a proper representation or model parametrisation to solve specific tasks.

The rest of the paper is organised as follows. The methodology employed to select the references for the review is presented in Section 2. In Section 3, the most important concepts of this review are introduced, that is an introduction of GT engines and their maintenance. The most common and simple version of machine-learning techniques that can be found along this study are also introduced. Next, condition monitoring techniques are introduced in Section 4. These are divided into two main groups regarding the aim of the proposed method, health-state-monitoring models, and anomaly detection. Moreover, in Section 5, the diagnostics methods are presented, and they are divided into GT fault detection approaches and sensor fault detection. Prognosis methods are introduced in

Section 6. They are basically a complementary work to condition monitoring and diagnostic methods. Section 7 discuss the strengths and weaknesses of the presented algorithms in the previous sections. Finally, a summary of the presented methods and conclusions are given in Section 8.

2. Methodology of Review

The purpose of the research methodology was to review the evolution of gas tur- bine condition monitoring, diagnostics, and prognostics using machine-learning algo- rithms. In this comprehensive review, a search engine (https://bibliotecnica.upc.edu/en/ discovery/discoveryupc, accessed on 22 June 2021) from our main institution, the Univer- sitat Politècnica de Catalunya, was used. This metasearch tool includes a huge number of collections such as Scopus, Web of Science, and Springer. The search queries aimed to obtain as many publications as possible that would be later filtered in order to ensure essential quality measures.

Figure 2 shows the process followed to accomplish our search methodology. The first step was to identify and collect articles fitting the criteria of this review. The initial search query was: “gas turbine” AND (“soft sensor” OR “machine learning” OR “artificial in- telligence”). As expected, many publications were obtained from the search engine, but the fact that it uses several databases made it easy to find duplicates or documents that did not specifically belong to the researched field. Moreover, the review had a fixed time horizon of the last decade. Thus, publications not satisfying this criterion were discarded in Step 2. Next, a more exhaustive filter was applied in order to find the most significant publications. A further revision of each publication was completed, and many of them were excluded. Three main exclusion criteria were used:

1. Only machine-learning-based algorithms were accepted. The definition of machine- learning techniques is described in Section 1. Hybrid methodologies that included model-based algorithms were also excluded;
2. Documents that were related to the simulation of gas turbines, as well as their design were also excluded;
3. Publications devoted to enhancing the standard control systems of gas turbines using machine-learning techniques were also not accepted.

Finally, the remaining documents were classified into the three main categories, i.e., con- dition monitoring, diagnostics, and prognostics, and were reviewed more extensively.

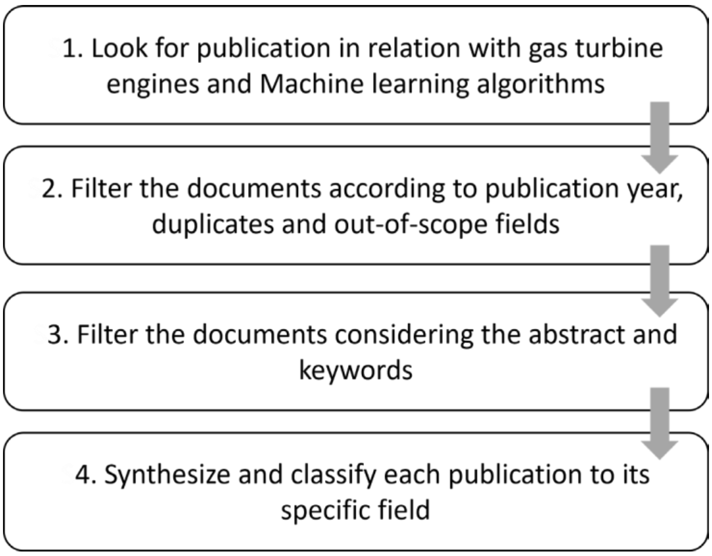

Figure 2. Methodology of research detailed step by step.

The initial search included 2562 documents. During Step 2 and Step 3, a large number of publications were dropped out, resulting in only 96 remaining. Finally, some of these

publications were also excluded in the synthesis and classification process after carefully reading the methodology used. At the end, 66 documents were evaluated. The increase in the number of documents in the last few years draws attention to the potential of these kinds of algorithms and the amount of data available and captured for gas turbines engines.

3. Background

This section is mainly divided into two subsections. First, gas turbine engines and their maintenance are introduced. Then, a quick introduction of the most common and simple versions of the machine-learning techniques found along this study is provided.

3.1. *Gas Turbines*

Gas turbines are a type of internal combustion engine that converts the chemical energy of fuel into electrical power. They are mainly made of three components: compressor, combustor, and power turbine [8]. The main function of the compressor is to provide a sufficient quantity of air to the system to ensure its proper operation. In short, the required inlet air quantity with adequate pressure is compressed at high pressure to provide it to the combustion chamber. Next, the combustion chamber, which contains several combustors, is where the thermal energy is extracted. Pressurised air is mixed with fuel, and by igniting the mixture, the internal temperature is greatly increased. The combustor must be well designed in order to provide a complete combustion process and avoid malfunctioning. Finally, leveraging high temperatures, the turbine is responsible for converting the thermal energy into useful work by expanding the hot gas. The turbine is linked to the compressor via a rigid coupling. Industrial gas turbines in this study were single-shaft systems. Indeed, the turbine ensures the rotational driving of the compressor to convey a process gas.

Several causes have been found that greatly damage industrial gas turbines, giving rise to malfunctioning and deterioration [9]. The only recoverable damage is *fouling*, defined as the adherence of particles to airfoils and annulus surfaces, which leads to changes in the airfoil's shape [10]. Beyond that, several other more harmful damages can affect the gas turbine, such as corrosion, erosion, foreign object damage, and so on. These latter kinds of damage can only be recovered by replacing the affected components. More fatigue factors that are considered harmful to the system performance are the number of starts and stops and the output power set point, among others. A proper condition assessment method is almost mandatory in order to enhance the machine performance and to reduce maintenance expenses.

3.2. *Maintenance*

Maintenance is the process of preserving the good condition of a system to ensure its availability and reliability for a specific period of time or restoring the system to its normal operating conditions [8]. The three main categories of maintenance strategies are: corrective, preventive, and predictive maintenance, sorted in increasing order of complexity [11].

The most straightforward approach to deal with faults is *corrective maintenance*. It is performed only when a component of the system breaks down [12]. Unplanned, run-to- failure, and reactive maintenance are similar ways of naming it [13]. Regarding the cost of interventions and the associated downtime, these kinds of maintenance activities are less effective and the less substantial in comparison with planned corrective actions taken in advance.

Preventive maintenance is performed according to a determined schedule planned in advance, regardless of the health status of the equipment. The plan is based on the advice of experienced equipment manufacturers, historic breakdowns or failure data, operating experience, and the judgement of maintenance staff and technicians. It is also called planned maintenance, and its main goal is to reduce the downtime, increasing the availability of the system, by slowing down the deterioration processes due to engine faults [13]. Although the probability of system failures and the frequency of unplanned emergency repairs can be reduced by preventive maintenance, it cannot fully eliminate the episodes of random failures [14].

Finally, based on equipment health estimation, the *predictive maintenance* strategy aims at detecting possible defects and fixing them before they result in failure [15]. It is a proactive process that requires the development of a system model that can trigger an alarm for the corresponding maintenance [16] instead of taking actions reactively. Currently, The most common methods in industry using this strategy are based on artificial intelligence and other machine-learning techniques [17].

3.3. *Machine Learning*

Machine learning is a general computational algorithmic approach currently applied in a wide range of fields for automated analytical model building. It uses algorithms to automatically learn insights and recognise patterns from data, applying that learning to make increasingly better decisions. These data analytics algorithms are able to deal with a considerable quantity of data and give back some insights about the machine's performance. These methodologies are mostly used to extract knowledge from multidimensional time series to identify hidden structures [4]. These techniques can be applied to a huge number of areas and for several purposes.

3.3.1. Artificial Neural Networks

Artificial neural networks (ANNs) comprise a computing system that attempts to mimic the human brain's neurons. They are based on multiple units that are interconnected and layered [18]. Each unit, called a node, is connected to many other units through edges. Typically, this connection has a weight that increases or decreases while learning proceeds. Furthermore, nodes are aggregated into layers that perform different transformations on their inputs. The signal travels from the input layer to the output layer to perform the computation. According to the application, there are several structures that fit better than others.

Auto-Encoder

An auto-encoder (AE) is a kind of ANN that aims to set the target values so that they are equal to the original input data [19]. It is used for learning an effective encoding of the original data in the form of latent vectors. It is structured mainly into three parts, the encoder, the decoder, and the code. As their names suggest, the encoder is responsible for learning a way to effectively compress the data into a reduced dimensionality representation, while the decoder has the purpose of reconstructing the data by decompressing the encoded representation. The last mentioned part, the code, is a latent dimension formed from the compression/transformation of data where some hidden information can also be found.

Convolutional Neural Network

The convolutional neural network (CNN) is a kind of ANN that applies convolution to any of its layers. Convolution is a mathematical operation that expresses the shape of a function evaluated in another function. In this domain, it can be understood as applying different filters to the data that are tuned while training. The CNN has been widely used in computer vision since there is no need for hand-crafted filters, which makes it more flexible and learn the most relevant patterns [20].

Extreme Learning Machine

Extreme learning machine (ELM) is a particular kind of ANN where the input pa- rameters of the hidden nodes are randomly chosen, and they do not need to be tuned. The output parameters are analytically determined by computing the generalised inverse of the hidden layer output matrices. It has shown good generalisation results together with incredibly fast runs and accurate performance [21].

Generative Adversarial Network

The generative adversarial network (GAN) is a machine-learning framework with an adversarial context where two ANNs confront each other. A *generative* model aims to capture the data distribution of the training data, whereas a *discriminator* model estimates the probability that a sample came from these training data instead of the generative model [22]. Many applications of this algorithm can be listed, such as unsupervised, semi-supervised, and supervised learning with high potential results in sample generation.

Recurrent Neural Networks

A Recurrent neural network (RNN) is a type of ANN that is able to detect temporal patterns in sequential data or time series data. This algorithm has the concept of "memory" that helps to store the states or information of previous inputs and use them to predict the output. It has successfully been applied to language processing, speech recognition, and image captioning [23,24].

3.3.2. Bayesian Model

The Bayesian model is a statistical model that uses Bayesian statistics to express the degree of belief in an event A. The degree of belief is based on prior information or beliefs B, which are updated when new data are introduced to the model [25]. To compute the posterior probability, Bayes' theorem is used,

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

A representation of the Bayesian model is shown in Figure 6, where the prior function is coloured in red, new data introduced to the system is coloured in yellow, and the posterior function is plotted in green.

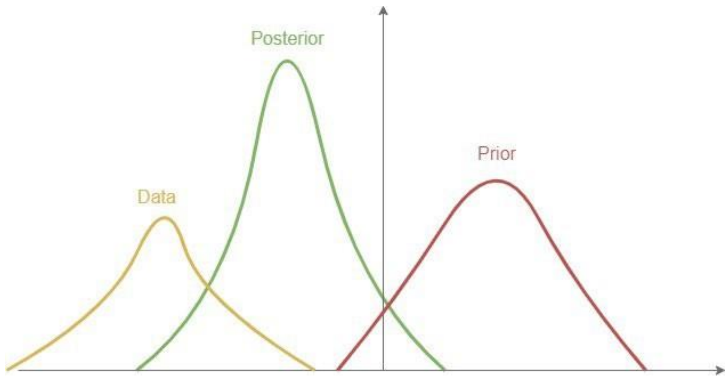

Figure 6. Representation of a Bayesian probabilistic model.

3.3.3. Fuzzy Logic

Fuzzy logic (FL) is an approach to reasoning that is approximate rather than exact [26]. It differs from binary logic because it uses an open and imprecise spectrum of data and heuristics, i.e., assigning a grade between zero and one, which makes it possible to obtain an array of conclusions. This is shown in Figure 7. It is of interest due to the fact that most modes of reasoning are approximate in nature [27]. Fuzzy methods are, currently, commonly used in many different fields such as system controllers, parameter estimation, machine-learning approaches, and so on.

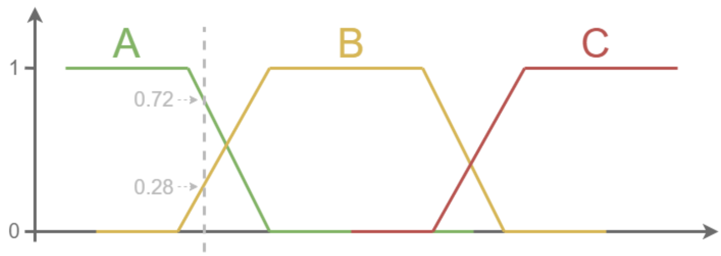

Figure 7. Representation of the fuzzy logic model.

3.3.4. Genetic Programming

Genetic programming (GP) is a type of evolutionary algorithm (EA) motivated by biological evolution that aims to solve a problem starting from a high-level statement of what needs to be performed. It is basically a heuristic search technique that looks for an optimal or at least suitable solution within a defined space [28]. The process consists of recursive operations that generate new solutions that are evaluated based on a fitness value. Figure 8 shows an evolutionary process based on mutation and crossover.

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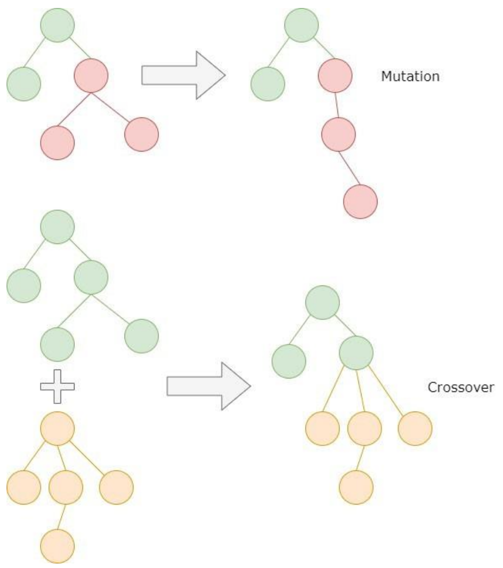

Figure 8. Representation of a genetic programming model.

3.3.5. Clustering

Clustering is a classification method that aims to group samples of a dataset in such a way that the points that belong to the same group are similar according to a certain criterion. This is graphically shown in Figure 9. Some well-known clustering algorithms are the simplest ones, k-nearest neighbours (k-NNs) [29] and k-means [30], the noise-independent density-based spatial clustering of applications with noise (DBSCAN) [31], and hierarchical cluster analysis (HCA) [32], a tree-based representation approach that aims to build a hierarchy of samples.

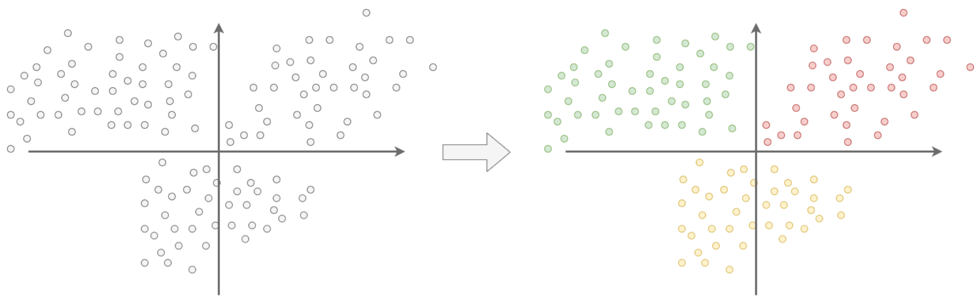

Figure 9. Representation of a simple clustering model.

3.3.6. Linear and Nonlinear Regression

Models Linear Regression

Linear regression methods are the simplest model expressions. They consist of deter- mining the relationship between certain variables linearly. This is performed by drawing a straight line and adjusting to observed data. Several optimisation solvers can be used in order to determine the model parameters.

Nonlinear Regression

Nonlinear regression methods consist of determining the relationship of certain vari- ables by using nonlinear functions. Several methods can be used to optimise their perfor- mance. The nonlinear regression methods presented in this publication are explained next. A well-known technique of nonlinear regression methods is nonlinear autoregres-

sive models. They are a representation of a stochastic process that is used to describe certain time-varying processes regarding only the inputs and outputs [33]. The model representation form is:

$$X_t = \sum_{i=1}^{n} \varphi_i X_{t-i} + b + €_t \quad (2)$$

where $\varphi_{14}, \ldots, \varphi_p$ are the model parameters, b is a constant, and $€_t$ is white noise. In this review, only the nonlinear autoregressive exogenous (NARX) model [34] and nonlinear autoregressive moving average (NARMA) model [35] are shown. The other nonlinear regression model included in this review is the orthogonal least squares (OLS) algorithm. It is an optimisation approach that is able to determine the model structure and estimate the parameters of the unknown system [36]. Figure 10 shows a nonlinear regression model.

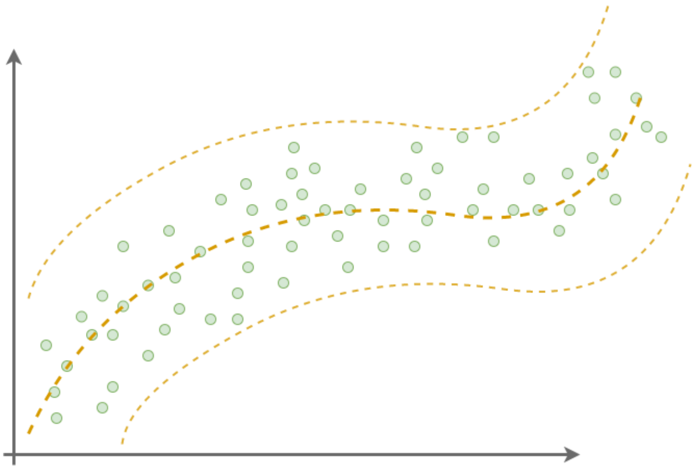

Figure 10. Representation of a nonlinear regression model.

3.3.7. Principal Component Analysis

Principal component analysis (PCA) is a multivariate technique that aims to extract important information from a set of samples by representing them as a set of new orthog- onal variables called principal components. This is observed in Figure 11. The samples are usually observations that describe several inter-correlated quantitative dependent vari- ables [37]. This kind of technique is used in many different applications such as exploratory data analysis, to make predictive models, or for dimensionality reduction.

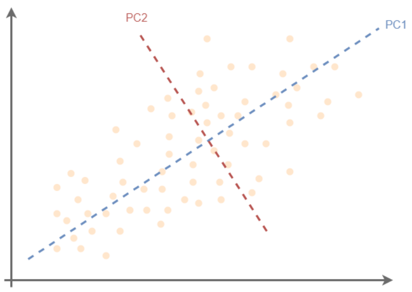

Figure 11. Representation of the principal component analysis model.

3.3.8. Decision Tree Algorithm

The decision tree algorithm is a supervised learning method that, as its name states, has a tree structure representation, as shown in Figure 12, where the nodes represent the features of the dataset, branches represent the decision rules, and leaves represent the possible outcomes. This kind of algorithm has a good performance in discovering features and extracting interesting patterns in large datasets for discrimination and prediction models [38]. Random forest (RF) is an appealing decision-tree-based technique [39].

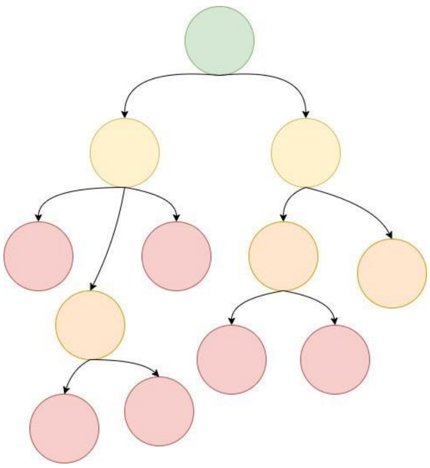

Figure 12. Representation of the decision tree model's structure.

3.3.9. Support Vector Machine

Support vector machine (SVM) is a supervised learning model that consists of defining a decision boundary in the form of a hyperplane, which can easily discriminate and classify the given classes of a dataset [40] in an induced nonlinear higher-dimensional space [41]. A representation of this model is given in Figure 13.

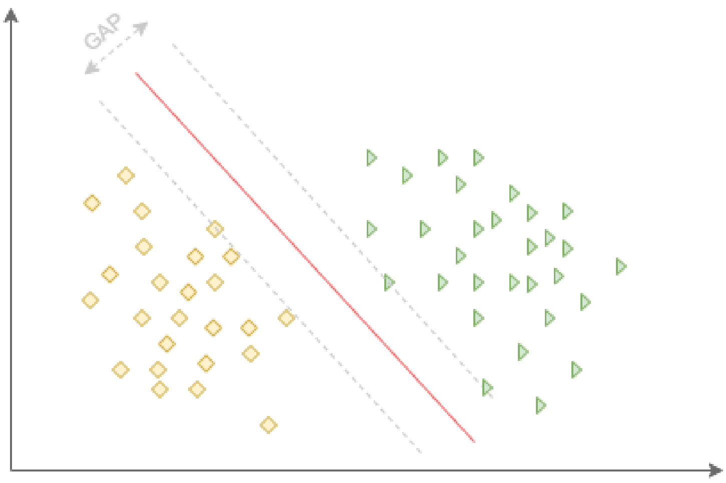

Figure 13. Representation of a support vector machine model.

4. Condition Monitoring

During the last few years, condition monitoring techniques have evolved from visual inspections and manual analysis to more advanced techniques. Thanks to sensors, the most relevant health parameters of gas turbines are constantly being captured, and thereby, on the basis of these data, data analytics methods can treat more sophisticated systems, as well as handle uncertainties due to the stochastic degradation process [42]. The methods proposed in this section for condition monitoring are those approaches that are related to determining the condition of the GT or any of its components, i.e., the health status. Moreover, an important issue that these techniques can also tackle is detecting anomalies in the captured data in order to avoid false alarms and to improve the reliability. Both of the processes, health status monitoring and anomaly detection, are presented next.

4.1. Health Status

The process of going from observed data to a mathematical model has become funda- mental in industry in order to properly identify the health of a system. This issue has been faced from several points of view. Some authors have shown promising results by using the information of the entire system, while some others have broken down the machine into its components and assessed the condition locally. A recurrent neural network (RNN) method was proposed in [43] to identify and model the dynamic performance of a GT with the compliance of the structural and parametric adequacy of an analytical model. The results allowed obtaining an adequate model for any operational mode and showed good perfor- mance for the start-up, ground, and flight modes. In a similar way, in [44], a comparison between an artificial-neural-network (ANN-) and a support-vector-machine (SVM)-based model for monitoring an aero-engine's health status was introduced. The ANN model showed better performance for monitoring purposes, whereas SVM performed better as a classifier of the engine's health status. Moreover, still in the ANN domain, a novel method was proposed in [45] using adversarial training of neural networks based on transfer learning (TL) to enhance the health monitoring system of a GT under varying working conditions. They discussed the issue of the inconsistency of the operational data due to changes in the working conditions and how data-driven condition-monitoring systems became utterly inefficient in some cases. Their results showed promising performance in this operationally changing context and showed that it is possible to train relatively accurate models using the proposed procedure.

Beyond ANNs, some other machine-learning models also show promising results. A variational Bayesian (VB) method was introduced in [46] leading to a Gaussian mixture model (GMM) to be clustered automatically with its mixture components in order to facilitate the discrimination of steady-state and transient machine operation. This procedure can be used in monitoring, but also, it is a convenient pre-processing tool for subsequent diagnosis and prognosis. A comparison of decision tree algorithms in [47] analysed the behaviour of a GT according to temperature evolution. Similarly, but using the one- class approach, a comparative investigation of data-driven approaches based on one-class classifiers was proposed in [48]. One-class classifiers are common algorithms used in several fields in which the models learn to define the boundary of normal and abnormal samples. The common evaluation indexes for machine-learning methods were tested in this work, as well as the sample combinations of the training dataset, the distribution of misclassified samples, and the tolerance to contaminated data. The experimental results showed that these algorithms have good performance on common indexes, but present an enhancement according to the novel evaluation indexes. The conclusion of the study was that the proposed methods can provide decision support in condition-monitoring systems. A significant aspect of a GT's performance is how the machine operates over time.

In the previously introduced methods, many of them are able to treat any kind of operation. However, it is known that start-up is a critical operation in machine deterioration. Hence, further studies of the behaviour of the machine in this operational mode are now intro- duced, as well as a proper machine dynamics performance assessment. Using a NARX method, the behaviour of a heavy-duty single-shaft GT was modelled in [49]. The main aim in this study was to capture the dynamics of the start-up phase. The results showed a satisfactory performance in capturing its behaviour. Working on the same operational state, a method [50] was presented for operation pattern recognition in GTs using multivariate data-mining techniques. The procedure is a modified version of the Fuzzy C-means algo- rithm, incorporating similarity metrics such as a PCA similarity factor. The highlighted results enabled the recognition of normal starts and the existence of a desirable and feasible mode to start the turbine.

From the component point of view, a data-driven approach to generate models using geometric semantic genetic programming (GSGP) to address the problem of modelling key aspects of GT power systems was described in [51]. Based on a few relevant gas turbine parameters, the algorithm proposes a model to monitor other relevant GT variables such as fuel flow and exhaust gas temperature (EGT). The results in the study were consistent with the community benchmarks. In the same sense, using the EGT measure, it was demonstrated in [52] that a CNN can extract relevant information between adjacent EGT values and consider the impact of the EGT profile swirl. It was verified that the effect of the EGT swirl was the key feature to differentiate normal and abnormal GT operations. An intelligent classifier was developed in [53] to monitor and control the combustion quality in power stations using an ANN method. Several image features such as the brightness of the flame, the area of high temperature, or the flame centroid were used to measure and monitor the temperature and the flue gas emission. They also presented an application of estimating the emission of SO_2 [54]. Similarly, also using visual information, the so-called 3D convolution selective auto-encoder (3DCSAE) method was used in [55] to capture the transition from the stable to unstable regime in combustion systems. The model was trained using only completely stable data and completely unstable data, so they showed that the technique is able to properly generalise the condition by identifying the gradual transitions.

Finally, more complex frameworks exist aiming to tackle condition monitoring and to handle some extra issues. In [56], a framework was depicted for modelling, analysing, and predicting the machine behaviour. The study involved both qualitative and quantitative methods. From the qualitative analysis, a Petri net (PN) model was obtained from its equivalent fault tree; in the quantitative analysis, the reliability parameters were evaluated using the vague lambda-tau methodology. The conclusion of the study was that the system reliability of the repairable components can be analysed in a more flexible and intelligent manner. Within the domain of offshore assets' integrity assurance, Reference [57] proposed inferential sensors to predict the status of the machine. They presented high-accuracy predictions of gas turbines' status up to 15 h in advance. The mentioned methods in this section are summarised in Table 1.

Table 1. Summary of the presented methods for health status monitoring using machine-learning models.

Reference	Year	ML Model	Application
	2013	VBGMM	Determine operational change between steady- state and transients
Manjit Verma and Amit Kumar [56]	2014		Qualitative and quantitative analysis for modelling and analysing machine behaviour
Hamid Asgari et al. [49]	2016	NARX	Gas turbine's start-up dynamics' assessment
Cristiano Hora Fontes and Otacílio Pereira [50]	2016	SPCA + Fuzzy C-means	Operational pattern recognition
Nallamilli P. G. Bhavani et al. [53]	2016	ANN	Intelligent sensor to monitor and control combustion quality
Pogorelov G.I et al. [43]	2017	RNN	Dynamic performance assessment
Abshukirov Zhandos and Jian Guo [47]	2017	Decision tree	Behaviour analysis based on temperature evolution
Josué Enríquez-Zárate et al. [51]	2017	GSGP	Model parameters' estimation
Maria Grazia De Giorgi et al. [44]	2018	ANN, SVM	Model comparison for health status monitoring
Jiao Liu et al. [52]	2018	CNN	Abnormal operation detection
Farzan Majdani et al. [57]	2018	ANN	Inferential sensor for machine status assessment
K. Sujatha, G. et al. [54]	2019	ANN + PSO	Exhaust gas estimation
Hossein Shahabadi Farahani et al. [45]	2020	TL	Improvement of health monitoring system
Yanghui Tan et al. [48]	2020	OCSVM, SVDD, GKNN, LOF, IForest, and ABOD	Evaluation of operation conditions
Tryambak Gangopadhyay et al. [55]	2021	3DCSAE	Operational transition detection in a combustion system

4.2. Anomaly Detection

Access to reliable data captured from GT sensors is essential to obtain good monitoring practices. Anomaly detection (AD) has been widely applied to monitor asset operation status, as well as to provide its health status. However, due to the evolution to extreme complex industrial systems, many challenges have arisen for the classical anomaly detection approaches. Therefore, having machine-learning models that are able to automate the construction of AD approaches from available data ease the concern about having a proper AD model. Next, several anomaly detection techniques are presented based on these types of procedures.

A DBSCAN clustering method was proposed in [58] to detect and filter outliers. The results showed that the introduced filtering method is reliable and fast, minimizing the time and resources for data processing. In addition, they showed that the proposed method is able to enhance the performance of ANN-based monitoring, as well as the predictive capabilities.

Another unsupervised learning method was introduced in [59] based on a CNN and AE that effectively identifies anomalies in the monitoring system. The CNN highly reduces the computational cost and decreases the quantity of training data, by its capability of extracting essential features from the spatial input data. The auto-encoder structure identifies any error larger than the usual pre-trained errors. The combination of both is able to treat unusual signals patterns more precisely than other conventional machine- learning methods. Using the same ANN architecture, that is an AE, a re-optimised deep auto-encoder (R-DAE) for gas turbine unsupervised anomaly detection was proposed in [60]. The singularity of this method is that it uses the combination of the simple auto-encoder reconstruction error and hidden features to train a more advanced auto-encoder (re-optimised auto-encoder). The main idea is to have a more discriminative reconstruction error by using more comprehensive information. The results showed an excellent detection performance in a gas turbine sample fleet. In the same line, Reference [61] introduced an AE-architecture-based model to learn robust features from a sample dataset. Then, these obtained features were used as the input to an anomaly detection algorithm using a Gaussian distribution method. In this case, this work did not present a model that directly detects anomalies; instead, it was used to improve the anomaly detection method's performance by having a proper feature detection algorithm in the pre-processing.

Another kind of common algorithm in this field is the one-class methods. In this case, a one-class classifier based on the ELM technique was described in [62]. This algorithm shows promising performance in real-world applications. Another work in this domain was more recently introduced by the same author [63], which enhanced the previous method. A combination of a deep learning (DL) method and a one-class method was employed to perform anomaly detection. Firstly, a denoising AE (DAE) learns the representations or features from multivariate time series sensor measurements. Next, a one-class classifier performs the anomaly detection procedure. The proposed method was compared with other conventional ones, and it significantly outperformed these similar procedures.

Finally, some uncommon methods are also used in the field of AD such as GAN architectures. In [64], an AD method was introduced for the combustion system of gas turbines comparing the performance of three GAN architectures. Experiments showed an unsatisfactory detection under the setting of semi-supervised learning; however, it was significantly improved when some faulty data were included in the training, i.e., supervised learning. This is a novel application of GANs since the most common uses are in image- or video-related problems. Table 2 summarises the presented methods.

Table 2. Summary of the presented methods for anomaly detection using machine-learning models.

Reference	Year	ML Model	Application
Weizhong Yan [62]	2016	ELM	Combustor anomaly detection
Hui Luo and Shisheng Zhong [61]	2017	AE	Improvement of anomaly detection performance
Homam Nikpey Somehsaraei et al. [58]	2020	ANN	Enhancing model performance by filtering and detecting outliers
Geunbae Lee et al. [59]	2020	CAE	Anomalies' identification in a monitoring system
Weizhong Yan [63]	2020	ELM	Enhancement of anomaly detection in a combustor
Rui Xu and Weizhong Yan [64]	2020	GAN	Faulty data detection
Song Fu et al. [60]	2021	R-DAE	Anomaly detection improvement with a novel model

5. Diagnostics

Diagnostic technology aims to analyse the engine performance to identify poten- tial faults and provide an early warning before these faults develop into more complex problems. It is an important part of machine maintenance because having a proper fault detection and diagnosis system can significantly improve safety and reliability.

In this review, diagnosis is treated as complementary to the condition monitoring explained before. The aim of the condition-monitoring process is to identify the health status of the machine, while diagnosis aims to understand the nature of the deviation in the performance. However, in some cases, condition monitoring can also be considered as a part of the diagnostics [65,66].

Gas turbines sometimes operate under unusual conditions, such as frequent start–stop procedures, complex environment conditions, and so on. There are many sensors equipped in a gas turbine for the sake of condition monitoring, as well as for early fault detection. These sensors may fail to return normal signals due to working either continuously for a long time or under harsh conditions. To avoid the misjudgement of the gas turbine detection system due to sensors' failures, it is required to diagnose the sensors' faults from the output signals beforehand.

Next, several machine-learning algorithms are presented in order to have a proper model of both the sensor and machine faults' detection.

5.1. Fault Detection

After a certain period of time, it is inevitable that gas turbines' performance degrades temporarily or permanently due to a long period of working time or harsh operating conditions. Hence, it is mandatory to rely on a robust fault detection model in order to avoid harmful events in the system. Novel machine-learning techniques enable making more reliable models and enhancing fault detection efficiency.

Machine-learning classification techniques were investigated in [67] with further implementation for fault detection in gas turbines. Three methods were compared for GT fault detection in a supervised manner, that is a random forest (RF) approach, k-NNs, and logistic regression, where the most significant performance was shown by the RF classifier on the proposed dataset. However, it was mentioned as a the conclusion that according to the dataset used to perform the study, the results may vary and specific experiments are needed in each case, looking for the one that gives the least mean-squared error, the highest score, and adequate training time.

Using the same model, as in the previous case, an ensemble random forest was pre- sented in [68] for extracting, codifying, and exploiting existing organisational knowledge on GT blade faults' identification. The knowledge was extracted from several digitised signals at many different points in time, as well as from the corresponding health condition of the engine. The results showed a very good performance in GT blade fault identifica- tion, and it outperformed all three alternative classification approaches (neural networks, classification and regression trees, and k-nearest neighbour) in terms of precision and recall. In a similar way, an ensemble framework for fault detection and isolation was pre- sented in [69]. Firstly, the performances of three dynamic neural network architectures were compared, as well as several ensemble methods. The ones that presented the best performances were selected for solving the fault identification task, that is the dynamic radial basis function and the heterogeneous ensemble. To properly identify and classify faults, the residuals of the methods were computed under various engine health conditions.
The results showed significantly better accuracy and a more reliable performance according to non-ensemble techniques.

As mentioned in Section 4, extreme learning machines (ELMs) present good real- world performance in classification modelling. In this case, a new application of ELMs for building a real-time fault diagnostics system in which data pre-processing techniques were already integrated was proposed in [70]. The wavelet packet transform and time-domain statistical characteristics were used for the extraction of vibration signal features; a kernel

PCA was then applied to decrease the redundant features in order to reduce the time of fault identification and improve accuracy; finally, an ELM was used to classify several faults. To evaluate its performance, the proposed approach was compared with SVM on fault detection, and the results showed a faster identification time with similar accuracy in fault classification.

Improving the performance of ELM algorithms, an ELM method optimised by quantum- behaved swarm optimisation (QPSO) and an application to the GT fan engine diagnostic problem were presented in [71]. The introduced Q-ELM technique showed more accurate results than the conventional ANN and other optimised ELM algorithms, as well as the SVM and Bayesian methods. Equally, under the same point of view, a novel engine was introduced in [72] for fault diagnosis using the sparse Bayesian extreme learning machine (SBELM). This methodology addresses fast fault diagnosis without relying on the engine model and treating the effect of noise and uncertainties. The technique was improved by constructing a multi-output classifier framework, which enlarged the detectable fault number and enhanced the reliability of fault diagnosis. Results presented in this study showed superior accuracy compared to the existing data-driven approaches.

Fuzzy methods have shown very good performance in diagnosis with uncertainties, as well as in combination with other techniques. A model was built in [73] by combining Intuitionistic Fuzzy Sets (IFSs) with Fuzzy Petri Nets (FPNs), named the intuitionistic fuzzy fault Petri nets (IFFPNs) model. This work proposed a method that is able to deal with a large amount of uncertain information in the fault diagnosis of gas turbines. The results showed that not only the fault source was detected, but also much fault information such as non-membership and the hesitation degree of the fault. Using fuzzy logic systems as well, Reference [74] introduced interval Type-2 fuzzy logic systems (IT2FLSs) to gas turbine fault diagnosis for the first time. The proposed fault diagnosis and isolation (FDI) system was composed of a bank of IT2FLSs, trained for the detection and assessment of an industrial gas turbine's state and health at various operating conditions using a metaheuristic algorithm. The method presented promising results in performance accuracy and robustness estimation against noise or abrupt sensor failure.

ANNs also are considered in GT diagnosis for fault detection. Different structures and types are used to solve the problem, as well as some combinations with other methods presenting an enhanced performance. In [75], multiple models of parallel dynamic neural networks (DNNs) were introduced for fault detection. The methodology consisted of generating the residuals of multiple DNNs corresponding to several operating modes of healthy and faulty conditions. Next, the fault diagnosis task was addressed according to certain established criteria based on the generated data. A simulated study demonstrated and illustrated the advantages, capabilities, and performance of the proposed method.

Levenberg–Marquardt (LM) and Bayesian regularisation (BR) back-propagation al- gorithms were tested in [76] to train an optimal ANN to detect the drop in compressor flow capacity and compressor fouling in an industrial GT. To assess the model perfor- mance, a *k*-fold cross-validation technique was applied to several model structures using both back-propagation algorithms. The findings showed that the employment of several networks in the form of multi-nets promoted a more reliable diagnosis and ensured the detection at early stages. Regarding back-propagation algorithms, with respect to general performance, BR is more robust and more accurate than LM.

A multi-model robust fault detection and isolation method was proposed in [77] and tested on a single-shaft industrial GT working at various operation points. The model presented in this work was a local linear neuro fuzzy (LLNF) method trained by using a progressive tree-construction algorithm named the local linear model tree, which added robustness to the fault detection stage. In order to discriminate faults, an ANN architecture model was used. The combination of these soft computing techniques showed an effective and straightforward model with successful application to industrial gas turbines.

A hybrid intelligent technique was proposed in [78] aiming to diagnose three simul- taneous faults in two-shaft industrial gas turbines engines. The method was based on auto-associative NN (AANN), which was used as a data preprocessor to reduce the mea- surement noise and extract important features for visualisation and fault diagnosis, and a nested machine-learning classifier, which was used to hierarchically distinguish fault and no-fault conditions, component and sensor faults, and different component faults. Finally, a multi-layer perceptron (MLP) was used to estimate the component fault in terms of flow capacity and isentropic efficiency indices. The results showed good performance and the benefits of integrating two or more methods in engine diagnostics.

Using the CNN's extraction capabilities, a multimodal method was proposed in [79] that assimilated the classification skills of the CNN and BPNN to improve the accuracy of the diagnosis results. The CNN part was used to select and learn hiding attributes in time series properties, whereas the BPNN fit the real distribution of the original sample data. The final diagnosis was given by fusing the information from the two networks. The results showed better and more robust performance than typical and state-of-the-art methods. In a similar way, in [80], a method was introduced to improve visual inspections of cracks and other structural anomalies. The main contribution of this study demonstrated that the classification performance of the CNN architecture model can be significantly boosted by applying filters to image data in the pre-processing phase. The results showed an accuracy of 96.26% on the test set. The developed framework was based on a pipeline that included a pre-processing phase, a sliding window procedure, and the detection of cracks in window patches.

RNNs are good methods to work with temporal patterns, which makes it easy to model systems that depend on previous states. For fault detection, having the knowledge of the prior condition makes the detection easy and more reliable. A framework proposed in [81] improves the processing time and accuracy of the prediction of degraded equipment. The methods used in this approach are multiple RNNs to predict performance and wavelet transform (WT) or empirical mode decomposition (EMD) for feature extraction. This solu- tion presented good results using both methods, EMD and WT, whereas the performance of EMD was slightly better according to the accuracy and lesser processing time. The authors stated that this approach outperformed the existing ones and that this method could be applied in time-sensitive scenarios. Similarly, in [82], a method to accomplish fault detection with only normal data introducing the concept of the normal pattern group was proposed. A group of LSTM machines was used to characterise the measurable healthy parameters of the gas turbines to later identify the gas path faults. Experiments showed that they were capable of properly detecting 13 common faults with a low false alarm rate. Furthermore, promising results have been shown by combining with the RNN method.

A novel hybrid and hierarchical machine-learning-based framework was proposed [83] to perform fault diagnosis. This hybrid strategy consists of a supervised RNN and un- supervised self-organizing map (SOM) approach that has two main features. First of all, the problem of multi-mode and concurrent fault detection and isolation by having no access to prior knowledge of the data labels was faced. Next, an automatic and systematic SOM hierarchical and optimal diagnostic map design was developed. In order to verify the proposed approach, an application to an aircraft gas turbine engine subject to multiple compressor and turbine degradations was diagnosed. All the methods presented in this section are summarised in Table 3.

5.2. *Sensor Faults*

Sensors along a gas turbine system play a crucial role in condition monitoring, as well as in fault detection. Failures in sensor measurements often can result in serious problems affecting machine safety and performance. Therefore, with the emergence of new and more advanced techniques, this field has also been improved to avoid having false alarms and warnings.

A coupling diagnosis method proposed in [84] detects, isolates, and estimates sensor faults. The integration of the square root cubature Kalman filter (SRCKF) and DBSCAN was developed to extract sensor fault features against the process and measurement noise and to detect and isolate the faulty sensors. The estimation scheme to track sensor fault evolution and classification was performed based on the residuals. Experiments demonstrated that this approach is more effective and robust than conventional methods. Using also a coupling diagnosis method, a technique was proposed in [85] based on the wavelet energy entropy (WEE) and SVM for regression (SVR) approaches. The WEE part was used to extract the main signal's features, while the SVR was used to classify the type of faults. The results showed good accuracy, up to 90%, with a shorter diagnosis time. The work presented in [86] aimed to develop an online diagnosis system for gas path sensor faults in GTs. A genetic algorithm (GA) was designed and optimised by the recursive reduced least squares support vector regression (RRLSSVR) algorithm. The reduction technique in the least squares SVM was used to obtain a better generalisation performance and sparseness and exploited an improvement to select the optimal model parameters. An excellent performance in terms of accuracy and sparsity in comparison with the simple least squares support vector regression algorithm was reported, and it serves as useful tool for sensor fault diagnosis and signal reconstruction in turbofan engines.

Table 3. Summary of the presented methods for fault detection using machine-learning models.

Reference	Year	ML Model	Application
Manolis Maragoudakis and Euripides Loukis [68]	2012	RF	Blade faults' identification
Hasan AbbasiNozari et al. [77]	2012	LLNF	Fault detection and isolation working at different operational points
S. Sina Tayarani-Bathaie et al. [75]	2014	DNN	Fault detection from model residuals
M. Amozegar and K. Khorasani [69]	2016	Ensemble ANN	Fault identification framework
Xinyi Yang et al. [71]	2016	Q-ELM	Fault detection using quantum-behaved swarm optimisation
Mohammadreza Tahan et al. [76]	2017	ANN	Compressor faults' detection
Feng Lu et al. [72]	2018	SBELM	Fast fault diagnosis working under noisy and uncertain conditions
D. F. Amare et al. [78]	2018	AANN	Simultaneous fault diagnosis
Xiao-Ling Sun and Ning Wang [73]	2018	IFFPNs	Fault diagnosis with uncertainty information
Jihoon Hong et al. [81]	2019	RNN	Improvement of a degradation detection system
	2019	RF, k-NN, Logistic regression	Supervised fault detection
Mahtab Mohtasham Khani et al. [80]	2020	CNN	Boosting inspection by applying a filter to image data
Morteza Montazeri-Gh and Shabnam Yazdani [74]	2020	IT2FLSs	Fault diagnosis at various operation conditions
Yanyan Shen and Khashayar Khorasani [83]	2020	RNN + SOM	Hybrid strategy to improve fault diagnosis performance
Liang Zhao et al. [79]	2020	CNN + ANN	Multiple neural net fusion for diagnostic enhancement
Mingliang Bai et al. [82]	2021	LSTM	Gas path faults' identification

A one-class clustering algorithm, termed robust hierarchical clustering, for novelty identification was proposed in [87]. The method consists of creating a uniform cluster across sensors in the absence of novelties. Thereby, in the presence of novelties, the associated sensors are clustered distinctly. To evaluate the method, it was compared with similar reported techniques [88], and it showed a much faster performance. The application proposed in this work was used for identifying emerging fault models in a sensor network of industrial GTs.

Finally, as expected, ANN algorithms also take part in solving this problem. In [89], a fault diagnosis method based on a BP neural network was designed for sensor failure detection, and the integrated verification of the model and algorithm on a full digital simulation platform was conducted. Two main sensor faults were addressed, offset and drift, and the analysis and the comparison of the simulated results confirmed the good performance and consistency of the method. A summary of the analysed models is presented in Table 4.

Table 4. Summary of the presented methods for sensor fault identification using machine-learning models

Reference	Year	ML Model	Application
Sepehr Maleki and Chris Bingham [87]	2019	Hierarchical clustering	One-class sensor fault detection
Linhai Zhu et al. [84]	2020	SRCKF + DBSCAN	Sensor faults' identification in harsh conditions
Rongzhuo Sun et al. [85]	2020	RNN	Coupling diagnosis method for sensor fault identification
Yu Hu et al. [86]	2020	GA-RRLSSVR	Online diagnosis for gas path sensor faults
Ying Liu et al. [89]	2020	ANN	Sensor fault detection and verification in a digital simulation platform

6. Prognostics

Estimating and forecasting the degradation of GTs are important issues to tackle, which allow a dynamic planning that only takes action when needed. In this way, this is beyond diagnostics to reduce unexpected events and undesired operation conditions while reducing maintenance costs and maximizing the profit by increasing the availability of the system. To do so, the performance prognosis of GTs deals with the prediction condition of a GT at some future time based on past records, the operating conditions, and detected faults.

In this review, the predictive methods presented below were based on both health state prognostics, putting the focus on predicting the status of a GT by treating the system as a whole, and single components' and parameters' prognostics.

A constrained linear regression method was proposed in [90] for predicting the degra- dation of micro-gas turbines over time. First of all, the degradation was estimated from time-dependent variables; next, it was forecasted using only running hours. The method was successfully evaluated on several trial systems and showed a good correlation with the corrected power.

In [91], the problem of the health monitoring and prognosis of aircraft gas turbine engines was treated. Two different dynamic neural networks, the NARX neural network and Elman NN, were designed to capture the dynamics of two main types of degrada- tion, compressor fouling and turbine erosion. After an extensive comparison between the methods, the results showed that the Elman NN outperformed the NARX model.

In [92], the use of a particular type of weighted loss function was extended, namely asymmetric loss functions, to investigate its performance in the prediction of the remaining useful life (RUL) of a gas turbine engine. It was shown that in some cases, the use of this kind of loss function enhanced the prediction in some deep-learning architectures.

A Bayesian hierarchical model was established in [93] to perform inference and inform a probabilistic model of the RUL. The suggested technique provided forecasting results within well-defined uncertainty bounds and proved several advantages of the hierarchical variant's ability to integrate multiple unit data to face realistic prognostic challenges.

The prediction of gas turbines' performance for power generation was the concern in [94]. Two surrogate models based on high-dimensional model representation (HDMR) and an ANN were conceived of from real operational data to forecast the operating features of the air compressor and turbine. Experiments showed a good performance in both full- and part-load on confidential operation data.

In [95], a framework was proposed to identify short-term and long-term degradation and relate them to more complicated components' degradation. The methodology consisted of a multistage predictive model that incorporated orthogonal least squares (OLS) learning and the multi-criteria decision-making (MCDM) approach for selecting the inputs and the model structure, as well as regression methods for power and EGT prediction. Experiments showed good prediction performance.

Four different algorithms were tested in [96] to predict the electrical power generated by gas turbines. The parameters used for the prediction were the ambient temperature, ambient pressure, relative humidity, and exhaust vacuum. The aim of predicting the electrical power was to increase and maximise the profit. The results showed the best performance with the random forest algorithm.

The work in [97] examined and compared various machine-learning approaches to develop a predictive model, which could forecast hourly full-load electrical power. Two main purposes were set for this study: firstly, the best subset configuration or combination to obtain the most influential parameters for the prediction; secondly, the most efficient and accurate machine-learning model to successfully predict the full-load electrical power. In a similar way, introducing an ANN architecture in the regression, in [98], an ANN model was used to predict the electrical power of a power plant in an efficient and accurate manner. The data and the study of the best subset were similar to those mentioned before, but for the regression, a successful ANN structure was implemented.

In [99], a method was developed to estimate and predict the EGT of a gas turbine. The methodology uses multigene genetic programming (MGGP) to estimate the EGT based on six other six GT parameters in any operating condition and a nonlinear autoregressive exogenous (NARX) neural network for one-step-ahead prediction. The results showed an excellent prediction made for different flight missions.

A prognostic approach based on a multiple-input and single-output (MISO) fuzzy logic model was suggested in [100] to estimate the pressure difference across a GT filter house in a heavy-duty power-generation system. The associated results revealed that the proposed fuzzy logic model returned very small deviations and showed a higher predictive performance than conventional multiple regression methodologies.

A method to predict the performance of a GT combustor using real-time data from an industrial gas turbine was proposed in [101]. In order to optimise the efficiency of the ANN-based predictive model and to determine its structure, a sensitivity study of the input parameters, that is the main parameters of the turbine, was also conducted. The results showed that the prediction well matched the real operating data. Moreover, the method could predict complicated and difficult combustor operating characteristics.

A multi-polynomial regression (MPR) and an ANN model were compared in [102] for the computation of the relationship between the EGT and RPM for a gas turbine. The RPM was considered as an input quantity, whereas the EGT as the output parameter of an experimental gas turbine. The results employing an ANN model presented more satisfactory results than those using the MPR. Moreover, a study to obtain the best ANN structure was also conducted. Table 5 presents a summary of the mentioned models in this section.

Table 5. Summary of the presented methods for prognostics using machine-learning models.

Reference	Year	ML Model	Application
Pınar Tüfekci [97]	2014	Several ML algorithms	Full-load electrical power prediction
Martha A. Zaidan et al. [93]	2015	Bayesian hierarchical model	RUL inference
S. Kiakojoori and K. Khorasani [91]	2016	NARX, Elman NN	Estimation of compressor fouling and turbine erosion dynamic degradation
Apeksha Wankhede and Vilas Ghate [98]	2018	ANN	Electrical power prediction
Iman Koleini et al. [102]	2018	MRP, ANN	EGT prediction based on shaft velocity
Divish Rengasamy et al. [92]	2020	DNN, CNN, LSTM	RUL prediction
Zuming Liu and Iftekhar A. Karimi [94]	2020	HDMR + ANN	Compressor and turbine operation characteristics prediction
Thambirajah Ravichandran et al. [95]	2020	OLS + MCDM	Short- and long-term degradation estimation
Salama Alketbi et al. [96]	2020	RF	Electrical power prediction
Maria Grazia De Giorgi and Marco Quarta [99]	2020	MGGP + NARX	EGT prediction
Sabah Ahmed Abdul-Wahab et al. [100]	2020	MISO fuzzy logic	Pressure difference of GT filter estimation
Yeseul Park et al. [101]	2020	ANN	Combustor performance prediction
Tomas Olsson et al. [90]	2021	RNN	Micro-GT degradation prediction

7. Comparative Analysis of ML Models

Table 6 provides a comparative study of the advantage and limitations of the presented ML methods for the condition monitoring, diagnostics, and prognostics of gas turbines. In this table, the accuracy and complexity of the models, the ability of the method to treat uncertainties, the computational time, and the model performance under noisy conditions (robustness) are summarised. Furthermore, some remarks that are considered important for each method are specified in the observations.

The assessment of this comparison was performed according to several methods presented above regarding every model and its application in each specific case. It should be noted that there can be variants and different parameter setting in the methods that can enhance or decrease the model's quantitative performance. Therefore, the presented table was constructed based on the average performance of model in different kinds of applications.

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Table 6. Comparative study of the presented machine-learning-based models.

Algorithms	Accuracy	Model Complexity	Treat with Uncertainties	Computational Time	Robustness	Observations
ANN accurate data	Reasonably high	Reasonable	Low	Reasonably low	Reasonably low	The performance can be improved with a large amount of
AE	High	Reasonably high	Reasonable	Reasonably low	Reasonable	Good generalisation
properties CNN	High	High	Reasonable	Reasonably high	Reasonable	-
ELM	Reasonably high	Reasonably low	Low	Low	Low	-
Low	High	Reasonably low		Reasonable	Reasonable	-
High	High	Reasonably low				
High	Reasonable	Reasonably high		Reasonable	Reasonably high	Large amount of and sequential data
				Reasonable	Reasonably high	-
Clustering datase	Reasonably high	Reasonable	Reasonable	Reasonably high	Reasonably high	The performance can be improved by having an accurate
Decision Tree	High	Reasonable	Reasonable	Reasonably low	Reasonably high	-
High	Reasonably high	Reasonably high		Reasonably low	High	Generalisation properties with a reasonable amount of data; expertise in the field is needed
High	High	Reasonably low		High	High	-
L and NL Regression	Reasonable	Low	Low	Low	Reasonably low	Regulation can help to generalise the solution
Low	Low	Reasonably low		Low	Low	It works well only with linear data. Good performance in pre-processing data
SVM	Reasonably high	Reasonably low	Reasonable	Low	Reasonably low	The performance can be improved by using more sophisticated kernels

8. Summary and Conclusions

This review provides a thorough survey on the last decade of contributions and developments in the condition monitoring, diagnostics, and prognostics of gas turbines using machine-learning models. An introduction to GT engines was provided at the beginning of the document. The most standard and common machine-learning techniques that can be found in this study were also introduced. More detailed examples and results for more specific techniques can be found in the corresponding section. Table 7 gives a summary of the publications analysed, classified by the corresponding topic. Some of the references were duplicates due to more than one topic being treated in that specific paper.

Table 7. Classification summary of reviewed publications.

Algorithms	Condition Mon	itoring	Diagno	stics	Prognostics
ANN	[44,45,53,54,56,57]	-	[69,75–79]	[89]	[91,92,94,96–98,101,102]
AE	[42,55]	[59–61,63]	-	-	-
CNN	[52]	[59]	[79,80]	-	-
ELM	-	[62,63]	[70–72]	-	-
GAN	-	[64]	-	-	-
RNN	[43]	-	[82,83,103]	-	-
Bayesian Models	[46]	-	-	-	[93]
Clustering	[48]	[58,63]	-	[84,87,88]	[96]
Decision Tree	[47,48,56]	-	[67,68]	-	[96]
Fuzzy Logic	-	-	[73,74]	-	[100]
Genetic Programming	[51]	-	-	[86]	[99]
Linear and Nonlinear Regression	[49]	-	-	-	[90,91,95]
PCA	[50]	-	-	-	-
SVM	[44,48]	-	-	[85]	-

GT condition monitoring considers the continuous process of measurement, analysis, filtering, and anomaly detection of the system itself and its components. The increase in the availability of data and the new emerging techniques show a significant improvement in this field. The further study of condition monitoring feeds the diagnosis section by making more accessible fault detection. Using measurements of the system performance, the analysis of the faults is more straightforward and presents promising results. In addi- tion, new techniques have been proposed to ensure proper signal measurements. Reliable measurement is an important issue to tackle since all captured data come from sensors. Thereby, due to the significant improvements in AI and ML for feature extraction and pattern recognition, most of the recent research has adopted this methodology for GT diagnostics and sensor fault detection.

The historical evolution of GT conditions, the extracted performance features and pattern recognition techniques, as well as proper records of failure events shape the basis for future fault prediction techniques. Both classical approaches and more advanced algorithms were shown in the section about prognostics. They are able to predict from the general health state of the system to single parameters' evolution.

Despite the techniques having been improved greatly in the last decade, some chal- lenges must still be faced. According to Table 6, working on noisy conditions and uncer- tainties is still a huge challenge to tackle. Some algorithms attempt to solve this issue by including more complex terms in the model expression. It has been shown that combining several methods to independently tackle different problems to be solved enhances the performance and improves the robustness. However, because of unbalanced data, a lack of quality data, or not enough system information, the performance is not as accurate as would be expected. This is a clear future research line for these kinds of algorithms.

Another important issue to tackle is the online performance. Most of the methods proposed are able to properly detect anomalies and system performance deviation by analysing data either when the failure has occurred or in simulation software. Further research is needed to integrate all this information in real time, as well as to have a proper recommendation action system.

Finally, the number of simultaneous events that can be detected is still a challenging task. This has been improved thanks to ensemble methods that present a better performance in task parallelisation than simple methods, but which focus on a few failures or unexpected machine events.

To sum up, the digitalisation of GTs and the use of machine-learning techniques enable enhancing the accuracy and efficacy of the algorithms, leading to an improvement of the system performance. However, a clear future research line remains, and important challenges need to be faced. Treating uncertainties, enhancing the model's robustness, and reducing the computational time of complex methods must be the focus for the next generation of algorithms.

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