



Gas Turbine Performance Monitoring and Operation Challenges: A Review

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Highlights

- This paper presents the elements affecting the efficiency of gas turbines.
- Reviews about machine learning monitoring system for gas turbine emission predication.
- Reviews about the available monitoring system solutions for gas turbines.

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Abstract

Gas turbines efficiently produce high amounts of electrical power hence they have been widely deployed as dependable power generators. It has been detected that the performance of gas turbines is a function of plenty of operational parameters and environmental variables. The impacts of those variables on the said performance can be mitigated using powerful monitoring techniques. Thus, extra maintenance costs, component defect costs, and manpower costs can be illuminated. This paper has enlisted the factors impacting gas turbine efficiency. It has also reviewed multiple monitoring solutions for the said impacting factors, It has been concluded that all types of sensors have ignored errors in their work, which may exacerbate the problems of malfunctions in gas turbines due to the critical environment in which they operate (heat, fumes, etc.); however, the machine learning-based monitoring systems excel in addressing such problems. The most cost-effective and accurate monitoring task can be achieved by using machine learning and deep learning tools.

1. INTRODUCTION

Gas turbines convert the working gas, more likely, air into high temperature and high-pressure gas which is subsequently used for turning the turbine engine [1]. Thermodynamic energy is converted into mechanical energy that is used in electrical power production. Three essential parts participate in the production of power in the SPP, namely: gas compressor, combustion chamber, and turbine/engine [2]. A gas turbine involves another vital process called combustion energy production that is used for heating the so-called working gas. A combustion chamber is a vital part of the GPP; it is used for compensating the lost energy of working gas after it departs the compressor [3,4]. The power quality of the gas turbine is realised under multiple considerations related to the working mechanisms of each part in the GPP. The power enhancement of gas turbines was the focal point of a large number of researchers; it is mainly performed by enhancing the pre-turbine process (at the compressor and combustion chamber sections) [5]. Inlet air is cooled down before entering the compressor to boost the output power at a high ambient temperature which was proposed in [6]. From this point, performance enhancement techniques are imposed by adaption of mechanical chillers for cooling down the air before passing to the compressor [7]. It is worth saying that the running cost of deploying chillers is relatively high; according to [4], it make up 30% of the power production cost. Gas emission from the turbine is another disturbing and performance degrading factor. According to [8], gas emission is related to ambient inlet air temperature. It was reported that low ambient inlet air temperature leads to an increase in the carbon emission from the turbine. As reported in [9], the type of fuel used in the combustion process is of direct impact on the level of gas emission (i.e., carbon emission). Since the gas emission is correlated with multiple concerns of turbine output quality,

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such as ambient inlet air temperature, ambient out air temperature, ambient air pressure, ambient humidity, etc., a proactive approach is proposed for forecasting the emission of two gases, i.e., Nitrogen oxides and Carbon monoxide. Upon successful forecasting of emissions, troubleshooting can be performed to prevent future damages. A natural air gas turbine is preferred since it has a low gas emission level as compared to diesel and oil fuels [4,10].

The energy demand has dramatically increased in recent years due to population growth which is linked to economic and industrial growth [11]. In other words, the larger the population, the larger the loads rise due to factory/industrial and residential power requirements. Gas turbines in GPP/stations are termed by their rapid installation and good power outcomes (amount) if the impact of fuel/raw material is neglected. Other than the fuel cost, gas power plants are the most rapid and efficient in power demand fulfilment. The expansion of power systems is associated with unpleasant occurrences such as maintenance/troubleshooting high cost and the redundant disposal outcomes such as burned fuel and gas emission treatment costs. More specifically, in gas power plants, gas emission is considered the most disturbing technical problem and is participating in many subsequent performance degradations. Risks of gas leakage/emission can include the following dangers: poison, fire, and injury caused from machinery performance [12]. In 2003, in the Kaixian city of China, 243 people were killed, and 100,000 people evacuated due to gas blowouts [13]. A smart/intelligent system was developed in [14] for monitoring the pollution in urban air due to the existence of gas power plants. Conventional monitoring systems that depend on human power for diagnosing and reporting errors are no longer standing with the tremendous expansion of the power system. Deploying sensors made from semiconductor materials for detecting gas leakage has a major drawback in terms of poor gas sensitivity [15]. An emission is a sign of low ambient temperature, which leads to a low rotation of the turbine blades and, hence, the lowering of the amount of output power. On the other hand, gas emission from the GPP is the biggest environment violating factor. Technically, three main strategies have been adopted in the literature for controlling the emission in the GPP, namely: Periodic measurements, continuous emission monitoring, and proactive emission control. In the first technique (i.e., Periodic measurements), costly tools and equipment are to be used for monitoring emissions from the turbine in a periodical fashion, more likely every week. This technique is reported by its high cost as well as having no sufficiency for tackling the ground reality of the emission problem (emission may occur at any time and trigger another bigger issue). On the other hand, continuous emission monitoring may be performed using expensive monitoring systems such as SCADA, which itself is susceptible to faults and errors. A proactive approach to emission control and prevention is a promising low-cost alternative depending on computer vision to tackle such asseverating trouble. The proactive approach is implementable by adopting smart machine learning and deep learning paradigms for predicting the future status of emissions. However, the problem is yet to be brought to a standstill since the big standard organisations such as the European Committee for Standardisation (CEN) have not yet approved the approach despite the existence of condensed research activities in the same interest. The performance of proactive forecasting approaches is still disputed and susceptible to more developments.

2. GAS TURBINE OPERATIONAL CHALLENGES

Gas turbines (GTs) work under rigid conditions such as fog, dust, salt, etc., moreover, frequent stop-start operations are also amongst the harsh environments where GT is functioning as sensors which are meant to control and monitor the GT process, it has been widely equipped in different types of machinery and sub-systems of GTs. Generally, the performance of sensors undergoing such harsh environments is degrading if left to run for long terms. The errors in sensing devices are causing GT malfunctions and operational errors. GTs are generally susceptible to various types of faults. More specifically, the fault of gas turbine sensors is considered one of the essential operational troubles. This kind of fault is categorised into five groups, namely: step fault, drift fault, pulse fault, noise fault, and periodic fault. Those categories are discussed in [16–18] and [19]. Fault monitoring is essential to clear the sensor's fault. Similarly, two methods are determined for the sensors' health diagnosis. Those methods are model-originated and data-originated. The model originated method is based on mathematical analysis that is meant for mathematical fault diagnosis model establishment, whereas, the data originated method depends on data technology, such as machine learning, for fault type assessment [17], [19–22]. A combination of machine learning, i.e., support vector regression (SVR), and an analytical approach, i.e., wavelet energy entropy (WEE), are used

for the fault diagnosis of sensors [19]. Features and attributes of faults are extracted from the sensor's output using WEE, whereas SVR is used for classifying the extracted features. A 7000 kW GT is used for collecting log data for constructing a sensing database under various operation conditions. The same database is used for performance evaluation of the coupling approach; results have shown that WEE is contributing to reducing the sensing time by up to 90%. The data mining-based sensor diagnosis approach makes use of whole historical sensing information obtained from GT units. Such methods (machine learning) are utilised for training on sensing data and, hence, to be used for testing where both results can be compared to evaluate the efficiency of the method [23,24]. Figure 1 depicts the process of data-oriented-based detection of internal faults in GTs. Fault diagnosis using a data-originated approach has multiple advantages such as, the model is trained by real data (historical sensing data); hence, it yields a good and reliable sensing process close to real-world sensors. In [25], feature extraction is vital for sensing efficacy using data-originated approaches. Conventionally, the Fast Fourier Transform (FFT) is used for performing frequency analysis of the data and for producing the frequency domain representation of them. Wavelet, on the other hand, can produce more reliable features by generating a time-frequency presentation of original data so that both information from the time domain and frequency domain are being used for attribution of the data. The artificial neural network (ANN) is amongst those tools that outperform sensor fault diagnosis.

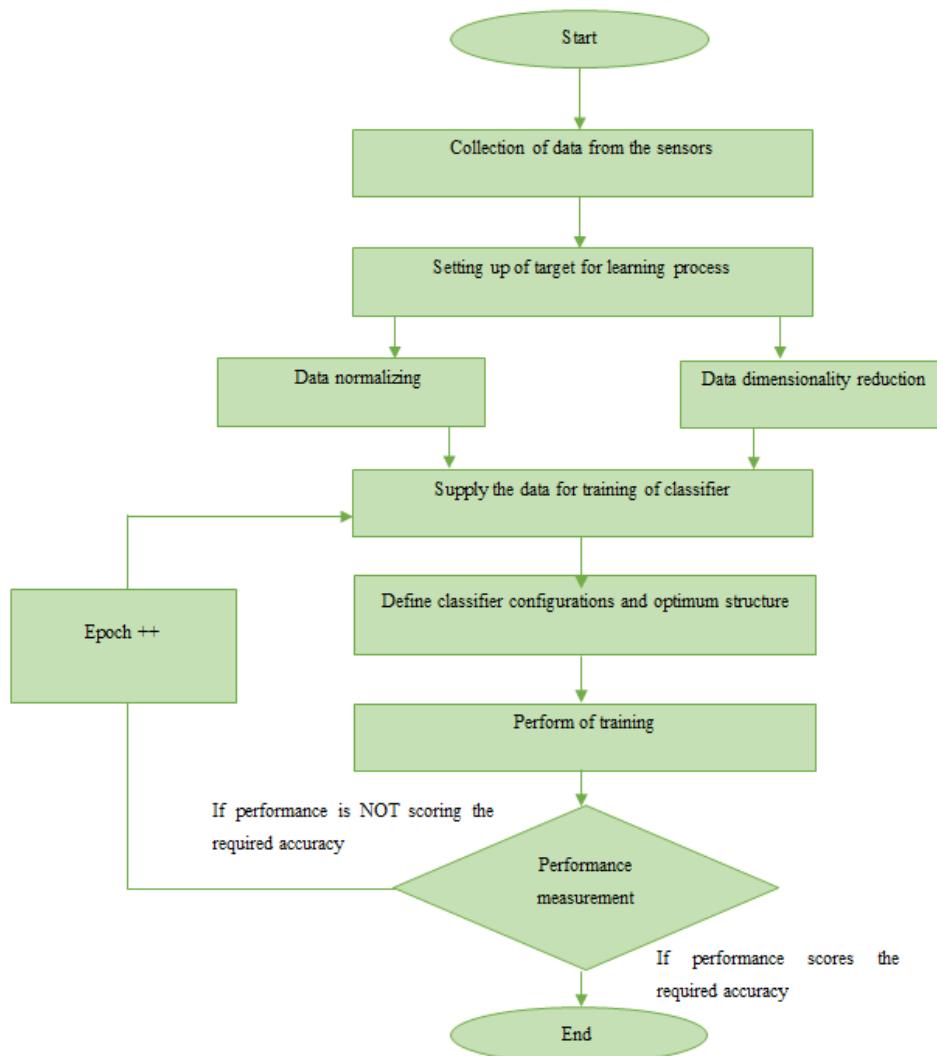


Figure 1. Depicts the process of data-oriented-based detection of internal faults in GTs

In [16], features complexity can be reduced by using the so-call dimensionality reduction approach, which eliminates some features to mitigate the load on the classifier and to produce results quickly. The abruptly occurring fault and drifting incipient fault are identified using the multi-scale analysis [18]. Sensor faults

have be decomposed in [17] using wavelet singular entropy and wavelet energy entropy. The problem of the mentioned approach was that both could identify whether the sensing signal was faulty but they could not recognise the type of fault.

3. GAS TURBINE INTERNAL FAULTS

The degradation of the GT components is leading to a crucial impact on engine availability, economic worth of GTs, as well as the reliability of GTs in power generation. The only way for tracking those degraded components is by tracking the gas path inside the GT. Accurate and quick diagnosis of GT degraded components (especially when multiple components are degraded at the same time) is a challenging task due to the lack of measurement tools and tracking systems that work inside the GT complex. Getting into this problem poses another challenge related to the cost of machinery and economic worthiness. They are considering that gas turbine life-cycle expenditures are higher than the purchasing budget. For example, the initial cost of the gas turbine from a Siemens V94.3A model is 2.86 million Euros, whereas the life cycle (forty-year plan of maintenance [26]) of expenditures from the same gas turbine costs 51.34 million Euro. The same indicates that GT expenditure might reach 18 times more than the initial budget of the same model. Monitoring engine conditions and applying appropriate maintenance schemes are, in turn, reducing the maintenance and life cycle expenditures of the GTs [27,28]. The gas path analysis (GPA) demonstrated in [29] has remained a sustainable technology for accessing the degraded components of the GT and assessing its conditions. The GPA was introduced for the first time in 1969 by Urban [30]. This technique is widely used for the condition monitoring of GTs, and is said to have an implicit impact on maintenance [26]. Both economic and aerodynamic performances are impacted by the degradation level of turbine components; more degradation may yield the so-called loss of performance in GT engines [31]. In [32], degradation types that seem popular, such as hot section damage, erosion, fouling, object damage, rubbing wear, etc., are demonstrated. Those degradations are common and widely monitored in most of GTs. Some of the most common types of gas turbine degradation are fouling, erosion, corrosion, rubbing wear, hot section damage, seal damage, and object damage [32]. Moreover, degradations are sub-divided into two groups, namely unrecoverable degradations and recoverable degradations [33]. It reported that engine (internal) fault diagnosis methods are categorised into three sections as mentioned in [34,35], namely data-oriented, model-oriented, and a hybrid approach. The model-oriented approach requires broad knowledge of the GT model and subsystems where the model for internal faults can be simulated using that exported knowledge. This approach is suspected to present different challenges due to the GT model complexity. On the other hand, the data-oriented model is reserved for high fault detection accuracy; it has employed neural networks [36] or other deep learning approaches [37]. The accuracy of the data-oriented approaches is subject to the training phase performance. Other models have gained significant attention in the internal fault diagnosis of the GT engine, such as an object-oriented artificial neural network. Such approaches are made to pave the road for limited monitoring data availability [33,38]. The hybrid approaches are, on the other hand, made to tackle the challenges faced in both model-oriented and data-oriented technologies. It is more likely desired for achieving high accuracy in less time where none of the previous models permits. Since the hybrid model is made from a combination of two different methods from the previous models to meet the desired enhancement of the performance, the trade-off between the performance metrics is termed as some methods are more about real-time applications where less processing time is being provided, and others are more about the accuracy (throughput) and that is essential for other types of applications that are promoting high throughputs. The sensing device fault detection model in GTs based on sensor signal monitoring is illustrated in Figure 2.

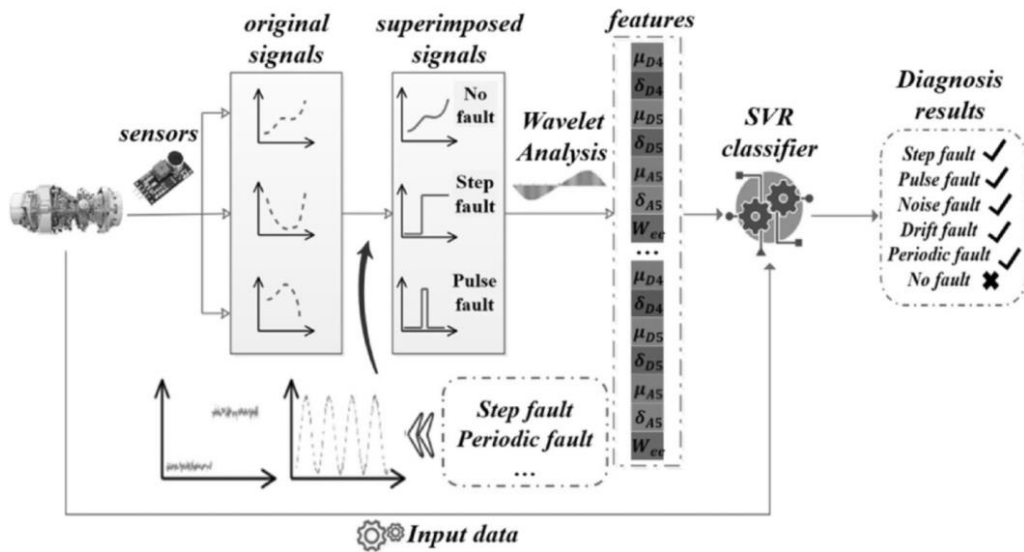


Figure 2. Sensors fault detection through sensors signal monitoring [39]

4. COMBUSTION CHAMBER MONITORING

Gas turbines, along with their noticeable performance in the energy sector, are reliable and fast establishing plants. The new century is witnessing a noteworthy expansion in GTs of mini size, which has become strategically essential in the energy production sector. The internal units of the GTs are very complex and require high-quality export systems for surveillance and control of each, which is practically not possible. When considering the costs of expert systems and other considerations, GT internal unit monitoring can be said to be complex as per the ground reality. As well, the development of diagnostic and prognostic systems is essential for the continuous GT performance to fill the gap of manpower limitation in surveillance tasks. Diagnostic and prognostic systems are widely propagated in mini GTs.

GTs work on the principle of combustion operations that include multiple geometrical and physical parameters. That makes the combustion process which takes place inside the gas chamber of the turbine a very complex process. It is also complicated to be monitored. The heat flux impacting the walls of the gas chamber is an integral operand. This heat flux variation impacts the distribution parameters, spatial and temporal, which control the combustion process. This variation may lead to undesired occurrences such as loss of performance of the combustion process which impacts the generation level of the gas turbine. Malfunctioning, such as burner error and flame instability, is caused due to combustion process instability. Appropriate monitoring of those changes/variations, in turn, participates in maximising the performance of the gas turbine and maintaining high efficiency. Burner and flame distribution monitoring are the most targeted operations to maintain a good combustion process. The research conducted in this regard is illustrated in Table 1.

Table 1. GT internal chamber monitoring technologies and their problems

Reference	Challenge	Solution	Research gap
[40]	The complexity of gas combustion monitoring in GTs	Using temperature profiles of downstream gas	Cost of implementation and accuracy defect
[41]	The difficulty of combustion modelling where a swirl angle cannot be accurately measured	Using laser imagining operations is used for tracking the combustor process.	Cost of implementation and accuracy defect
[42]	Swirl angle measurement problem	Numerical modelling of the	Good accuracy but high computational cost

		combustion system using (CFD).	
[43]	Combustion system monitoring	ANN for developing black box and white box for GT subsystem modelling	High accuracy and still under development

5. SWIRL CHARACTERISTICS

Downstream gas temperatures in GTs in different patterns can be compared to maintain smooth operations of the combustion system. Theoretically, the essential heat parameter used for monitoring GTs is the outlet temperature of the combustor. But, the outlet temperature of the combustor is typically too high and cannot be measured directly using conventional sensors, all owing to the secondary parameters being located downstream of the combustor outlet, such that the inter-duct temperature (IDT) and exhaust gas temperature are considered key variables for the maintaining, monitoring, and controlling of the gas turbine engines [44]. In gas path studies in the combustion system, the dynamic complexity is taking place when considering gas propagation through the turbine. The turbulence in the motion of the combustion system products inside the path of the turbine in the form of spiralling clusters results in the so-called swirl [45]. The spiralling cluster's motion inside the gas turbine must be in a straight line to avoid the swirl impact. To monitor the back data of the combustion system product movement for judging its conditions and health status, it is mandatory to evaluate the swirl angle at the time of using the temperature profiles of the downstream gas [40]. In [41], laser imagining operations were used for tracking the combustor process of the turbine, which determined the swirl angle. Laser imaging is an expensive approach but, on the other hand, does not yield an accurate status of the combustion system conditions. Alternatively, numerical modelling of the combustion system is made using the model of computational fluid dynamics (CFD) [42]. Other than their high accuracy and performance, CFD models are proven to be high computational cost consumers. An artificial neural network (ANN) is used for developing the black box and white box models for monitoring the system and achieving good outcomes. The satisfactory result of those approaches is owed to their non-paramedical and nonlinear configurations [43]. An artificial neural network (ANN) is widely popular as a data-oriented approach for monitoring systems in multiple sections inside the GT, yielding high accuracy and satisfactory outcomes wherever it is applied.

6. DYNAMIC BEHAVIOUR MODELLING

So far, the popularity of artificial neural networks has widely increased in mechanical applications and industrial areas. A large number of industrial applications are now modelled using the artificial neural network. It has been relied upon (ANN) by those applications due to its high-speed approximation and capability of learning complex nonlinear problems taking place in the mentioned sector. It is also known for its flexibility of solutions provided for industrial applications. A monitoring system is one of those interesting applications where ANN is applied. Several methods, including fault diagnosis, modelling, and systems optimisations, are illustrated in [46]. Those works were performed between 2007 to 2017; the most required material that ANN demands to operate is data in large amounts, and it also demands a proper input parameter configuration. Speed and temperature property instantaneous prediction at flow structures are proposed in [47] using an ANN-based prediction model. The results obtained from the proposed model are shown to be enhanced more than the results of the maxed dynamic model. The dynamic power signature in the welding process was monitored using the ANN, and the results were compared with those obtained from the regression model. However, the performance of both were compared, and the results showed that the ANN model is more reliable in terms of data quality [48]. A locomotive system maintenance approach based on ANN is proposed in [49] to monitor the level of lubricating oil in the system. This approach is said to be low-cost and for real-time applications. ANN is used in [50] for monitoring of power grids (smart grids) for power system performance enhancement. This approach overcomes the limitations of the conventional existing monitoring technologies by providing fast and reliable results. A hidden output feedback-based Elman neural network (OHFEN) is used for the detection of faults in a gas turbine by investigating the blade's conditions of the turbine [51]. The approach can state whether the blades are

running smoothly or not. In [52,53], the ANN model was made for the implementation of a multi-neural network diagnosis model for gas turbine status assessment. Two types of optimisation algorithms were applied to the multi-stage neural network to enhance the accuracy of the diagnosis. Those algorithms were the Bayesian regularisation and Levenberg–Marquardt. A twin-shaft 18.7 MW gas turbine engine was used for the collection of training data used in this experiment. Faults of gas turbines such as pre-chamber exhaustion and bearing tilt pad wear early-stage detection was performed using the group of sensors that collected the data from the gas turbine in hierarchical form. The collected data were applied to self-organised map neural networks (SOMNN) [54]. Other experiments of ANN in industrial applications, more specifically in the gas turbine, are illustrated in Table 2.

Table 2. Research of ANN based GT applications

Reference	Application	Model
[55]	Fault detection and isolation of gas turbine engines	Dynamic neural network (DNN) with multilayer perceptron (MLP) and support vector machine (SVM)
[56]	Start-up phase of a single shaft gas turbine simulation	Non-linear autoregressive models
[57]	Gas transport network	Artificial neural networks (ANN) and the fuzzy inference system (FIS)
[58]	Control the heating process of a steam turbine	Artificial neuron system
[59]	Fault detection in a gas turbine and to control their dynamic behaviours	Adaptive neuro-fuzzy interference system (ANFIS)
[60]	Fault detection and isolation in an aircraft gas turbine engine	Neural network bank based on the time delay neural network TDNN and dynamic neural model (DNM)
[61]	Operating conditions of a steam turbine optimisation	Inverse artificial neural network
[62]	Fault detection and isolation in a dual spool gas turbine engine	Dynamic neural network (DNN)
[20]	Fault diagnosis in a GT engine	Dynamic neural network (DNN)
[63]	Microturbine gas modelling	ANN
[64]	GT monitoring with optimal mechanical performance	ANN
[65]	Modelling of microturbines.	ANN
[66]	Classifying data for GT validation	ANN
[8]	GT multi-model approach for industrial applications	ANN
[67]	High throughput GT diagnostic system	ANN

Presently, the processed monitoring field hung on distinct functions provides a set of solid tools to enhance operations of the processed outfit and to guarantee the optimal proportion of cost/ quality. One of the main exercises in the processed manufacturing of fault decisions is vibration monitoring in rotating machines which is still a hot motif in maximum processed sectors [20, 51, 68]. The plan of the observed configuration will give the beginning data for a demonstrative methodology for these machines to guarantee their protection against fineness and to assess their energetic conduct precisely. The conventional modelling approaches of this type of machine cannot present their dynamic behaviours verbatim due to the considerably nonlinear exact complications of comparable systems [53,56], [69–71]; on the other hand, they're high procedures. Therefore, there is a fabulous expanded must for creating unused approaches to guarantee the exact displaying of the distant inside miracles of comparable configurations. This is the case of gas turbines, which are subject to several unstable marvels, which are hourly nasty to interpret because of the problems of their dynamic complications and their operating context [52,72].

7. APPLICATION SCOPES

The aero-dynamic impacts on the gas turbine are illustrated in [73,74], where there are impacts of various aero-dynamics on the engine and other turbine parts causing degradation. The correlation of aero-dynamic factors with the overall efficiency of the gas turbine is listed in [37,75]. Aero-dynamics such as blade corrosion, erosion, and fouling [76,77] have been found to affect the performance of the blades' aero-dynamic behaviours, which affect the turbine tip clearance and triggers the so-called parasitic phenomenon [78]. Other degradation impacts can be seen more easily when increasing the flight cycle that damages (disturb) the gas path and ruin the gas path components; the same degradation level has remained difficult to be realised [33,79]. To tackle those impacts (most of the reported impacts) and increase the life of the gas turbine, sensor-based monitoring has been proposed [80-82]. Other researchers have proposed to revise the design of the hybrid-electric propulsion and ultra-high bypass ratio [83-85]. In [86], it was found that on-board monitoring and control systems may greatly enhance the life and performance of the gas turbine.

8. INTELLIGENT SYSTEMS FOR GAS TURBINE MONITORING

The expansion of data in various fields has incurred the need for smart and lost fewer methods for processing. Machine and deep learning tools are feasible options. Table 3 demonstrates the most populated AI tools used in different areas for monitoring through smart data processing. Machine learning tools have been used to classify the sensor reading features. Feature extraction is required whilst using machine learning tools for this purpose. However, with deep learning tools, the feature extraction stage is dispensed. Higher accuracy of monitoring is obtained by using deep learning such as a neural network. To adopt any machine learning or deep learning tool, insensitive and highly risky applications such as gas turbine monitoring, the accuracy of those tools must be optimised to a level that they can be reliable in their allotted tasks.

Table 3. Activity monitoring and classification accords with previous research works

No.	Method	Purpose	Dataset	Features	Preprocessing	Impression
[87]	DNN	Customer-firm behaviour	Real data from customer smartwatch or computer	Stimuli-Organism-Response theory	--	Conceptual framework of artificial intelligence, and both solicited and unsolicited online customer engagement
[88]	ANN, CNN, LR, SVM	AI implementation in commercial banks	Loan information; Credit card transactions	Findings suggest that by using AI, commercial banks can reduce losses in lending, increase security in processing payments, automate compliance-related work, and improve customer targeting		
[89]	RCNN	Improving the efficiency of IMS to reduce road accidents	Image data: CDD [24]; HPD [25]; SFD [16]; WSCD [18]	Feature less	--	Upon indication of the accident, feedback is sent to Rescuer
[90]	ANN-FPGA	Biodiversity assessment	Voice data	Vocal behaviours from different creatures including humans	Data targets are population model, climate, and diversity	--

				and animal		
[91]	Pilot study	The popularity of AI in the academic librarian community	Survey questionnaires resulted in data	--	--	A pilot study is considered an alternative to evaluate human response/behaviours to a particular event
[92]	Pilot study	Intelligent personal assistants using AI for sensing, thought, and action	Survey questionnaires resulted in data	--	--	Found that artificial autonomy-based AI is crucial for IPA
[93]	KNN, MLP, RF, GSOM	Detection, analysis of deep emotional intensity, emotion transitions, emotion latent representations, and profile-based emotion classification	Digital conversation platforms	Anxiety (climate change anxiety, panic attack), Bipolar (mood stabilizer, anger outburst), Self-harm (suicidal thought)	Word2Vec technique to capture semantically similar terms used for the eight basic emotions proposed by Plutchik	Unsupervised learning approach where we curate an emotion vocabulary based on the emotion expressions used in a related context
[94]	KNN	Learning activity patterns of home occupants	Raw sensor values formatted either as integer or floating-point data types. Furthermore, each data value is associated with a timestamp (YYYY-MM-DD HH:MM:SS) value to	--	--	--

			indicate the time point at which the value was recorded			
[95]	SAE-OCCCH	Abnormal activity detection (e.g., fall) using a smart watch	Smartwatch dataset (private)	--	SAE for artifact reduction in the sensing signal	--
[96]	Analytical study	Post-earthquake search and rescue using a wearable device	--	--	--	Remote sensing information fed from a wearable device is used for post-earthquake trapped victims' search and rescue
[97]	HMM, SVM, KNN, RF	Sleep disorder detection	Smartwatch, smartphone	Noise energy, noise entropy, MFCC coefficients	WT filtering	The accelerometer and heart rate monitor sensors on the smart watch and the sound level sensor on the smartphone are activated And used for data generation

8.1. Deep Learning Classifier

Alternatively, neural networks have gained special attention in this regard due to their classification performance and their diagnosis accuracy; hence, neural networks are widely used for sensor fault diagnosis. Figure 3 demonstrates the learning and prediction process of artificial intelligence, i.e., deep learning-based monitoring in GTs. Dynamic neural networks have been used for the detection of signal abnormality through performing input-output mapping of sensor data. A general regression neural network (GRNN) is used for auto-detection network fabrication that represents the optimised architecture of the fault diagnosis of sensors through the exhaust inlet temperature of the gas turbine [19]. A Sparse Bayesian extreme learning machine (SBELM) is presented in [98], where the multi-output classifier was established using a signal-output classifier using the sparse technology of the extreme learning machine. Different kinds of activation functions are presented in [99] for designing a mini-cost multi-layer perception model. Such a model consists of several hidden layers (can be a single hidden layer also) as well as input and output layers. A support vector machine is applied to diagnose faults in GT sensors [100]. It is understood that supervised learning algorithms such as SVM differ from the multi-layer perceptron, i.e., artificial neural networks (ANN), in terms of accuracy as well as the time of classification. Thus, both types of learning are

meant for the classification of features provided by feature extraction paradigms. Knowing that feature extraction approaches are enriched with mathematical complexity increases the processing cost, i.e., processing time. Another approach is proposed using support vector data description (SVDD) for the classification of data without needing most statistical data and feature extraction work. This approach has been applied to the error diagnosis of helicopter drive train components [101]. Another application of machine learning (coupling) has been used in the aerodynamic modelling of aero-engines. The support vector machine is coupled with a stochastic gradient descent to perform the aerodynamic modelling [102].

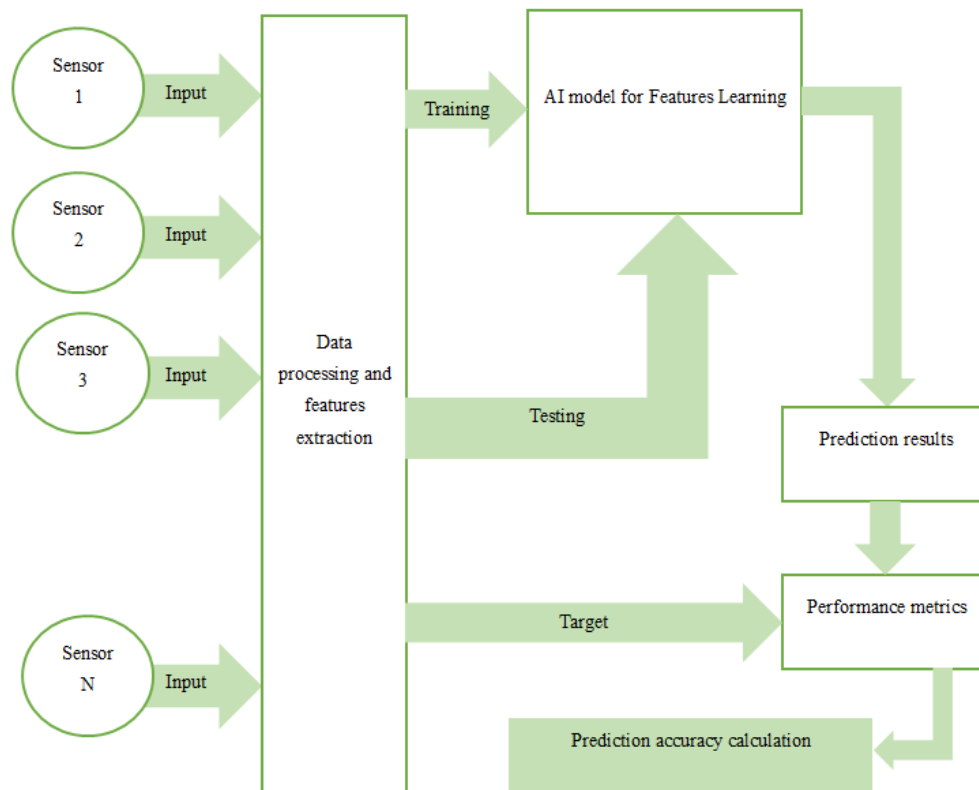


Figure 3. Monitoring process using AI methods in gas turbines

9. CONCLUSION

Gas turbine performance is limited by internal and external factors. However, sensors are used for remote monitoring of the internal gas turbine chamber where harsh environments with high pressure and high temperatures exist. The tolerance of the said sensors may not be enough to maintain efficient monitoring. The faulty sensors impose error challenges which may worsen the fault problems. On the other hand, the pressure and thermodynamic properties of the turbine are also have a noteworthy impact on the performance. As illustrated in the previous sections, machine learning-based monitoring systems are outperform others in tackling such complex problems. Prediction of future events is the main objective of deploying the machine learning predictors. It is also used to track sensor performance as well as the prediction of more appropriate parameters and decision-making in gas turbine maintenance and operation control. Artificial neural networks provide an interesting solution for tackling problems associated with gas turbines. This paper has shown that ANN memorisation, adaptation, and problem learning capacities provide strong functions for the control and monitoring system of the gas turbine. In any case, the most vital advantage that can be attributed to neural network control and monitoring tasks in gas turbines is the estimation and modelling of vibration indicators by problem learning. ANN technology does not demand the explicit (straightforward) knowledge of complicated mathematical models; instead, ANN demands reliable operating sources of data and a strong optimization approach. This paper has shown that intelligent models are having an outstanding impact on gas turbine monitoring. They have been utilised for different subsystems; monitoring of internal gas chambers, turbulence analysis, thermodynamic parameter

monitoring, and sensor quality monitoring. The most cost-efficient and accurate monitoring task could be achieved using machine learning and deep learning tools as illustrated in the previous sections.

CONFLICTS OF INTEREST

No conflict of interest was declared by the authors.

REFERENCES

- [1] Li, J., Ying, Y., "A Method to Improve the Robustness of Gas Turbine Gas-Path Fault Diagnosis Against Sensor Faults", *IEEE Transactions on Reliability*, 67: 3–12, (2018).
- [2] Yazdani, S., Salimipour, E., Moghaddam, M. S., "A comparison between a natural gas power plant and a municipal solid waste incineration power plant based on an energy analysis", *Journal of Cleaner Production*, 274: 123158, (2020).
- [3] Liang, Y., Cai, L., Guan, Y., Liu, W., Xiang, Y., Li, J., He, T., "Numerical study on an original oxy-fuel combustion power plant with efficient utilization of flue gas waste heat", *Energy*, 193: 116854, (2020).
- [4] Bao, J., Zhang, L., Song, C., Zhang, N., Guo, M., Zhang, X., "Reduction of efficiency penalty for a natural gas combined cycle power plant with post-combustion CO₂ capture: Integration of liquid natural gas cold energy", *Energy Conversion and Management*, 198: 111852, (2019).
- [5] Matjanov, E., "Gas turbine efficiency enhancement using absorption chiller. Case study for Tashkent CHP", *Energy*, 192: 116625, (2020).
- [6] Kwon, H. M., Kim, T. S., Sohn, J. L., Kang, D.W., "Performance improvement of gas turbine combined cycle power plant by dual cooling of the inlet air and turbine coolant using an absorption chiller", *Energy*, 163: 1050–1061, (2018).
- [7] Hashmi, M. B., Majid, M. A. A., Lemma, T. A., "Combined effect of inlet air cooling and fouling on performance of variable geometry industrial gas turbines", *Alexandria Engineering Journal*, 59: 1811–1821, (2020).
- [8] Guteša Božo, M., Valera-Medina, A., Syred, N., Bowen, P. J., "Fuel quality impact analysis for practical implementation of corn COB gasification gas in conventional gas turbine power plants", *Biomass and Bioenergy*, 122: 221–230, (2019).
- [9] Caposciutti, G., Baccioli, A., Ferrari, L., Desideri, U., "Impact of ambient temperature on the effectiveness of inlet air cooling in a co-digestion biogas plant equipped with a mGT", *Energy Conversion and Management*, 216: 112874, (2020).
- [10] Majdi Yazdi, M. R., Ommi, F., Ehyaei, M. A., Rosen, M. A., "Comparison of gas turbine inlet air cooling systems for several climates in Iran using energy, exergy, economic, and environmental (4E) analyses", *Energy Conversion and Management*, 216: 112944, (2020).
- [11] Sanchez, E. Y., Represa, S., Mellado, D., Balbi, K. B., Acquesta, A. D., Colman Lerner, J. E., Porta, A. A., "Risk analysis of technological hazards: Simulation of scenarios and application of a local vulnerability index", *Journal of Hazardous Materials*, 352: 101–110, (2018).
- [12] Volponi, A. J., "Gas turbine engine health management past, present and future trends ", *Journal Eng Gas Turbines Power*, 136: 1–25, (2017).

- [13] Lu, F., Jiang, J., Huang, J., Qiu, X., "An iterative reduced KPCA hidden markov model for gas turbine performance fault diagnosis", *Energies*, 11: 1–21, (2018).
- [14] Dong, M., He, D., "Hidden semi-Markov model-based methodology for multi-sensor equipment health diagnosis and prognosis", *European Journal of Operational Research*, 178: 858–878, (2007).
- [15] Pourbabaee, B., Meskin, N., Khorasani, K., "Sensor Fault Detection, Isolation, and Identification Using Multiple-Model-Based Hybrid Kalman Filter for Gas Turbine Engines", *IEEE Transection, Control System Technology* 24: 1184–1200, (2016).
- [16] Salahshoor, K., Kordestani, M., Khoshro, M.S., "Fault detection and diagnosis of an industrial steam turbine using fusion of SVM (support vector machine) and ANFIS (adaptive neuro-fuzzy inference system) classifiers", *Energy*, 35: 5472–5482, (2010).
- [17] Chen, K.Y., Chen, L.S., Chen, M. C., Lee, C. L., "Using SVM based method for equipment fault detection in a thermal power plant", *Computers in Industry*, 62: 42–50, (2011).
- [18] Lemma, T. A., Hashim, F. M., "Wavelet analysis and auto-associative neural network based fault detection and diagnosis in an industrial gas turbine", *BEIAC 2012 - 2012 IEEE Business, Engineering & Industrial Applications Colloquium*, 978: 103–108, (2012).
- [19] Chen Jiao, Wang Yong-hong, W. S., "Application of wavelet singular entropy in periodic fault detection of sensors on gas turbine", *Noise and Vibration Control*, 31: 103-108, (2011).
- [20] Zhang, Z., Weng, S. L., Wang, Y. H., "Application of wavelet analysis in fault diagnosis with gas-turbine sensors", *Dongli Gongcheng/Power Engineering*, 26: 245-250, (2006).
- [21] Yu, B., Liu, D., Zhang, T., "Fault diagnosis for micro-gas turbine engine sensors via wavelet entropy", *Sensors*, 11: 9928–9941, (2011).
- [22] Sina Tayarani-Bathaie, S., Sadough Vanini, Z. N., Khorasani, K., "Dynamic neural network-based fault diagnosis of gas turbine engines", *Neurocomputing*, 125: 153–165, (2014).
- [23] Jiao, C., Yong-hong, W., Shi-lie, W., "Application of general regression neural network in fault detection of exhaust temperature sensors on gas turbines", *Proceedings of the CSEE*, 32: 92–97, (2009).
- [24] Lu, F., Jiang, J., Huang, J., "Gas Turbine Engine Gas-path Fault Diagnosis Based on Improved SBELM Architecture", *International Journal Turbo Jet Engines*, 35: 351-363, (2016).
- [25] Matuck, G. R., Barbosa, J. R., Bringhenti C., Lima I., "Multiple faults detection of gas turbine by mlp neural network", *American Society of Mechanical Engineers*, 48821: 1–7, (2017).
- [26] Navi, M., Davoodi, M. R., Meskin, N., "Sensor fault detection and isolation of an industrial gas turbine using partial kernel PCA", *IFAC-PapersOnLine*, 28: 1389–1396, (2015).
- [27] Zhang, Y., Bingham, C. M., Yang, Z., Gallimore, M., Ling, W. K., "Sensor fault detection for industrial gas turbine system by using principal component analysis based y-distance indexes", *Processing 2012 8th International Symposium on Communication Systems, Networks and Digital Signal Processing (CSNDSP)*, Poznan, Poland, 1–6, (2012).
- [28] Jan, S. U., Member, S., Lee, Y. D., Shin, J., Koo, I., "Sensor Fault Classification Based on Support Vector Machine and Statistical Time-Domain Features", *IEEE Access*, 5: 8682-8690, (2017).

- [29] Camerini, V., Coppotelli, G., Bendisch, S., “Fault detection in operating helicopter drivetrain components based on support vector data”, *Aerospace Science and Technology*, 73: 48-60, (2017).
- [30] Ren, L., Ye, Z., Zhao, Y., “A modeling method for aero-engine by combining stochastic gradient descent with support vector regression”, *Aerospace Science and Technology*, 99: 105775, (2020).
- [31] Evaluations, E., Rinaldi, F., “Exergetic, Economic, and Environmental Evaluations and Multi-objective Optimization of an Internal-Reforming SOFC-Gas Turbine Cycle Coupled with a Rankine Cycle”, *Applied Thermal Engineering*, 108: 833-846, (2016).
- [32] Wojcik, W., “Energy applications in industry”, *Fuel Energy Abstracts*, 44: 37-40, (2003).
- [33] Hanachi, H., Liu, J., Kim, I.Y., Mechefske, C. K., “Hybrid sequential fault estimation for multi-mode diagnosis of gas turbine engines”, *Mechanical Systems and Signal Processing*, 115: 255-268, (2019).
- [34] Talebi, S. S., Tousi, A. M., “The effects of compressor blade roughness on the steady state performance of micro-turbines”, *Applied Thermal Engineering*, 115: 517-527, (2017).
- [35] Urban, L. A., “Gas turbine engine parameter interrelationships”, Second Edition, Hamilton Standard Division of United Aircraft Corporation, United States, 53, (1969).
- [36] Safiyullah, F., Sulaiman, S. A., Naz, M.Y., Jasmani, M. S., Ghazali, S. M. A., “Prediction on performance degradation and maintenance of centrifugal gas compressors using genetic programming”, *Energy*, 158: 485-494, (2018).
- [37] Kang, D. W., Kim, T. S., “Model-based performance diagnostics of heavy-duty gas turbines using compressor map adaptation”, *Applied Energy*, 212: 1345-1359, (2018).
- [38] Sogut, M. Z., Yalcin, E., Karakoc, T. H., “Assessment of degradation effects for an aircraft engine considering exergy analysis”, *Energy*, 140: 1417-1426, (2017).
- [39] Hanachi, H., Mechefske, C., Liu, J., Banerjee, A., Chen, Y., “Performance-Based Gas Turbine Health Monitoring, Diagnostics, and Prognostics: A Survey”, *IEEE Transactions on Reliability*, 67: 1340-1363, (2018).
- [40] Tsoutsanis, E., Meskin, N., Benammar, M., Khorasani, K., “A dynamic prognosis scheme for flexible operation of gas turbines”, *Applied Energy*, 164: 686-701, (2016).
- [41] Dixon, R., “Real-Time Diagnostic Method of Gas Turbines Operating Under Transient Conditions in Hybrid Power Plants”, *Journal of Engineering for Gas Turbines and Power*, 142: 1-10, (2020).
- [42] Jos, D., Orozco, R., Jos, O., Palacio, C. E., Almaz, O., Pii, O., Date, R., Date, R., Date, A., Jos, D., Orozco, R., Jos, O., Palacio, C. E., Almaz, O., “A new methodology of thermodynamic diagnosis, using the thermo-economic method together with an artificial neural network (ANN): a case study of an externally fired gas turbine (EFGT)”, *Energy*, 123: 20-35, (2016).
- [43] Tang, S., Tang, H., Chen, M., “Transfer-learning based gas path analysis method for gas turbines”, *Applied Thermal Engineering*, 155: 1-13, (2019).
- [44] Korbicz, J., Koscielny, J., M., Kowalczyk, Z., Cholewa, W., “Fault diagnosis: models, artificial intelligence, applications”, Second Edition, Springer Science and Business Media, New York, 922, (2012).

- [45] Martinez-Garcia, M., Zhang, Y., Wan, J., McGinty, J., “Visually interpretable profile extraction with an autoencoder for health monitoring of industrial systems”, 2019 4th IEEE International Conference Advanced Robotics and Mechatronics (ICARM), Toyonaka, Japan, 649–654, (2019).
- [46] Hermeth, S., “Mechanisms affecting the dynamic response of swirled flames”, PhD thesis, Institut National Polytechnique de Toulouse, France, 1–217, (2012).
- [47] Bulat, G., Jones, W. P., Navarro-Martinez, S., “Large eddy simulations of isothermal confined swirling flow in an industrial gas-turbine”, *International Journal of Heat and Fluid Flow*, 51: 50–64, (2015).
- [48] Boxx, I., Arndt, C. M., Carter, C. D., Meier, W., “High-speed laser diagnostics for the study of flame dynamics in a lean premixed gas turbine model combustor”, *Experiments in Fluids*, 52: 555–567, (2012).
- [49] Cadorin, M., Pinelli, M., Vaccari, A., Calabria, R., Chiariello, F., Massoli, P., Bianchi, E., “Analysis of a micro gas turbine fed by natural gas and synthesis gas: Test bench and combustor CFD analysis”, *Proceedings of ASME Turbo Expo*, 1: 627–636, (2011).
- [50] Muthuraman, S., Twiddle, J., Singh, M., Connolly, N., “Condition monitoring of SSE gas turbines using artificial neural networks. Insight Non-Destructive Test”, *Condition Monitoring*, 54: 436–439, (2012).
- [51] Ardabili, S. F., Najafi, B., Shamshirband, S., Bidgoli, B. M., Deo, R. C., Chau, K. W., “Computational intelligence approach for modeling hydrogen production: A review”, *Engineering Applications of Computational Fluid Mechanics*, 12: 438–458, (2018).
- [52] Xie, C., Wang, J., Li, H., Wan, M., Chen, S., “Spatial artificial neural network model for subgrid-scale stress and heat flux of compressible turbulence”, *Theoretical & Applied Mechanics Letters*, 10: 27–32, (2020).
- [53] Zhao, D., Wang, Y., Liang, D., Ivanov, M., “Performances of regression model and artificial neural network in monitoring welding quality based on power signal”, *Journal of Material Research and Technology*, 9: 1231–1240, (2020).
- [54] Altıntaş, O., Aksoy, M., Ünal, E., Akgöl, O., Karaaslan, M., “Artificial neural network approach for locomotive maintenance by monitoring dielectric properties of engine lubricant. Meas”, *Journal International Measurement*, 145: 678–686, (2019).
- [55] Menke, J. H., Bornhorst, N., Braun, M., “Distribution system monitoring for smart power grids with distributed generation using artificial neural networks”, *International Journal Electrical Power Energy System*, 113: 472–480, (2019).
- [56] Zhuo, P., Zhu, Y., Wu, W., Shu, J., Xia, T., “Real-time fault diagnosis for gas turbine blade based on output-hidden feedback elman neural network”, *Journal Shanghai Jiaotong University*, 23: 95–102, (2018).
- [57] Zhang, Y., Bingham, C., Garlick, M., Gallimore, M., “Applied fault detection and diagnosis for industrial gas turbine systems”, *International Journal Automation and Computing*, 14: 463–473, (2017).
- [58] Amozegar, M., Khorasani, K., “An ensemble of dynamic neural network identifiers for fault detection and isolation of gas turbine engines”, *Neural Networks*, 76: 106–121, (2016).

- [59] Asgari, H., Chen, X.Q., Morini, M., Pinelli, M., Sainudiin, R., Spina, P. R., Venturini, M., "NARX models for simulation of the start-up operation of a single-shaft gas turbine", *Applied Thermal Engineering*, 93: 368–376, (2016).
- [60] Marjani, A., Baghmolai, A. M., "Analytical and numerical modeling of non-isothermal and steady-state gas transportation network and the comparison with the results of artificial neural network(ANN) and fuzzy inference system (FIS)", *Journal of Natural Gas Science and Engineering*, 36: 1–12, (2016).
- [61] Nowak, G., Rusin, A., "Using the artificial neural network to control the steam turbine heating process", *Applied Thermal Engineering*, 108: 204–210, (2016).
- [62] Nadji, H., Ahmed, H., Abdellah K., Chaibet, A., "Faults detection in gas turbine using hybrid adaptive network based fuzzy inference systems", *Diagnostyka*, 17: 3–17, (2016).
- [63] Sina Tayarani-Bathaie, S., Khorasani, K., "Fault detection and isolation of gas turbine engines using a bank of neural networks", *Journal Process Control*, 36: 22–41, (2015).
- [64] Hamzaoui, El. Y., Rodríguez, J. A., Hernández, J. A., Salazar, V., "Optimization of operating conditions for steam turbine using an artificial neural network inverse", *Applied Thermal Engineering*, 75: 648–657, (2015).
- [65] Sadough Vanini, Z. N., Khorasani, K., Meskin, N., "Fault detection and isolation of a dual spool gas turbine engine using dynamic neural networks and multiple model approach", *Information Sciences (Ny)*, 259: 234–251, (2014).
- [66] Sina Tayarani-Bathaie, S., Sadough Vanini, Z.N., Khorasani, K., "Dynamic neural network-based fault diagnosis of gas turbine engines", *Neurocomputing*, 125: 153–165, (2014).
- [67] Nikpey, H., Assadi, M., Breuhaus, P., "Development of an optimized artificial neural network model for combined heat and power micro gas turbines", *Applied Energy*, 108: 137–148, (2013).
- [68] Barad, S. G., Ramaiah, P. V., Giridhar, R. K., Krishnaiah, G., "Neural network approach for a combined performance and mechanical health monitoring of a gas turbine engine", *Mechanical Systems and Signal Processing*, 27: 729–742, (2012).
- [69] Bartolini, C.M., Caresana, F., Comodi, G., Pelagalli, L., Renzi, M., Vagni, S., "Application of artificial neural networks to micro gas turbines", *Energy Convers Management*, 52: 781–788, (2011).
- [70] Palmé, T., Fast, M., Thern, M., "Gas turbine sensor validation through classification with artificial neural networks", *Applied Energy*, 88: 3898–3904, (2011).
- [71] Fast, M., Assadi, M., De, S., "Development and multi-utility of an ANN model for an industrial gas turbine", *Applied Energy*, 86: 9–17, (2009).
- [72] Joly, R.B., Ogaji, S.O.T., Singh, R., Probert, S.D., "Gas-turbine diagnostics using artificial neural-networks for a high bypass ratio military turbofan engine", *Applied Energy*, 78: 397–418, (2004).
- [73] Gwashavanhu, B., Heyns, P.S., Oberholster, A.J., "Shape principal component analysis as a targetless photogrammetric technique for condition monitoring of rotating machines", *Measurement*, 132: 408–422, (2019).

- [74] Roghanchi, P., Kocsis, K. C., “International Journal of Mining Science and Technology Quantifying the thermal damping effect in underground vertical shafts using the nonlinear autoregressive with external input (NARX) algorithm”, *International Journal of Mining Science and Technology*, 29: 0–7, (2018).
- [75] Zhuo, P., Zhu, Y., Wu, W., Shu, J., Xia, T., “Real-Time Fault Diagnosis for Gas Turbine Blade Based on Output-Hidden Feedback Elman Neural Network”, *Journal Shanghai Jiaotong University*, 23: 95–102, (2018).
- [76] Asgari, H., Chen, X.Q., Morini, M., Pinelli, M., Sainudiin, R., Spina, P. R., Venturini, M., “NARX models for simulation of the start-up operation of a single-shaft gas turbine”, *Applied Thermal Engineering*, 93: 368–376, (2016).
- [77] Gomez, J. L., Khelif, I., Bourdon, A., André, H., “Angular modeling of a rotating machine in non-stationary conditions : Application to monitoring bearing defects of wind turbines with instantaneous angular speed”, *Mechanism and Machine Theory*, 136: 27–51, (2019).
- [78] Hadroug, N., Hafaifa, A., Kouzou, A., Chaibet, A., “Dynamic model linearization of two shafts gas turbine via their input / output data around the equilibrium points”, *Energy*, 120: 1–10, (2016).
- [79] Kobayashi, H., Gotoda, H., Tachibana, S., “Nonlinear determinism in degenerated combustion instability in a gas-turbine model combustor”, *Physica A*, 510: 345–354, (2018).
- [80] Tahan, M., Muhammad, M., Abdul Karim, Z. A., “A multi-nets ANN model for real-time performance-based automatic fault diagnosis of industrial gas turbine engines”, *The Brazilian Society of Mechanical Sciences and Engineering*, 39: 2865–2876, (2017).
- [81] Benyounes, A., Hafaifa, A., Guemana, M., “Gas Turbine Modeling Based on Fuzzy Clustering Algorithm Using Experimental Data”, *Applied Artificial Intelligence*, 30: 29–51, (2016).
- [82] Ben ahmoune, M., Ahmed, H., Guemana, M., “Vibration modelling improves pipeline performance, costs”, *Oil Gas Journal*, 113: 98–100, (2015).
- [83] Glenn, N., “Aircraft turbine engine control research at NASA Glenn Research Center”, *Journal of Aerospace Engineering*, 26: 422–438, (2013).
- [84] Sharma, O. P., Epstein, A. H., Greitzer, E. M., “Influence of Compressor Deterioration on Engine Dynamic Behavior and Transient”, *Journal of Turbomach*, 122: 477–484, (2014).
- [85] Tang, S., Tang, H., Chen, M., “Transfer-learning based gas path analysis method for gas turbines”, *Applied Thermal Engineering*, 155: 1–13, (2019).
- [86] Bai, M., Liu, J., Chai, J., Zhao, X., Yu, D., “Anomaly detection of gas turbines based on normal pattern extraction”, *Applied Thermal Engineering*, 166: 114664, (2019).
- [87] Li, J., Ying, Y., “Gas turbine gas path diagnosis under transient operating conditions : A steady state performance model based local optimization approach”, *Applied Thermal Engineering*, 170: 115025, (2020).
- [88] Liu, J., Li, Z., Hanachi, H., “A physics-based framework for online surface roughness assessment for high-pressure turbines”, *Chinese Journal Aeronaut*, 34: 135–156, (2020).
- [89] Tahan, M., Tsoutsanis, E., Muhammad, M., Karim, Z. A. A., “Performance-based health monitoring,diagnostics and prognostics for condition-based maintenance of gas turbines : A review”, *Applied Energy*, 198: 122–144, (2017).

- [90] Litt, J. S., Simon, D. L., "A Survey of Intelligent Control and Health Management", *Journal of Aerospace Computing, Information, a Communication*, 1: 543–563, (2004).
- [91] Hanachi, H., Mechefske, C., Liu, J., Banerjee, A., Chen, Y., "Performance-Based Gas Turbine Health Monitoring, Diagnostics, and Prognostics: A Survey", *IEEE Transactions on Reliability*, 67: 1340–1363, (2018).
- [92] Wang, C., Li, Y. G., Yang, B. Y., "Transient performance simulation of aircraft engine integrated with fuel and control system", *Thermal Engineering*, 114: 1029–1037, (2017).
- [93] Spang, H., A., Brown, H., "Control of jet engines", *Control Engineering Practice*, 7: 1043–1059, (1999).
- [94] Connolly, J. W., Chicatelli, A., Garg, S., "Model-based control of an aircraft engine using an optimal tuner approach", *Joint Propulsion Conference & Exhibit, Atlanta, Georgia*, 4257: 1–14 (2012).
- [95] Flamm, J. D., Bonet, J. T., " Overview Of ERA Integrated Technology Demonstration (ITD) 51A Ultra-High Bypass (UHB) Integration for Hybrid Wing Body (HWB)", *Aerospace Sciences Meeting*, 7: 1–22 (2016).
- [96] Hung, J.Y., Gonzalez, L. F., "Progress in Aerospace Sciences On parallel hybrid-electric propulsion system for unmanned aerial vehicles", *Progress in Aerospace Sciences*, 51: 1–17, (2012).
- [97] Dinc, A., "NOx emissions of turbofan powered unmanned aerial vehicle for complete flight cycle", *Chinese Journal Aeronaut*, 33: 1683–1691, (2020).
- [98] Adibhatla, S., Ding, J., Technologies, U., Hartford, E., Garg, S., Griffith, S., Karnofski, K., Company, T.B., Payne, N., Simon, D., Wood, B., Hartford, E., Propulsion, A., Management, H., Networked, M., Hardware, C., Architecture, S., Engineer, P., Chief, B., Control, I., Branch, A., Manager, T.P., Controls, H.I., Engineering, P.S., Control, I., Branch, A., Engineer, P., Systems, D., "Propulsion Control Technology Development Needs to Address NASA Aeronautics Research Mission Goals for Thrusts 3a and 4" , *Joint Propulsion Conference, Cincinnati, Ohio 4732*, (2018).
- [99] Sun, R., Shi, L., Yang, X., Wang, Y., Zhao, Q., "A coupling diagnosis method of sensors faults in gas turbine control system", *Energy*, 205: 117999, (2020).
- [100] Perez-vega, R., Kaartemo, V., Lages, C. R., Borghei, N., "Reshaping the contexts of online customer engagement behavior via artificial intelligence : A conceptual framework", *Journal of Business Research*, 129: 902–910, (2020).
- [101] Li, C., "Microprocessors and Microsystems Biodiversity assessment based on artificial intelligence and neural network algorithms", *Microprocess*, 79: 103321, (2020).
- [102] Sun, R., Shi, L., Yang, X., Wang, Y., Zhao, Q., "A coupling diagnosis method of sensors faults in gas turbine control system", *Energy*, 205: 117999, (2020).