Journal of the Brazilian Society of Mechanical Sciences and Engineering (2021) 43:403
https://doi.org/10.1007/s40430-021-03121-2

REVIEW

Recent trends and challenges in predictive maintenance of aircraft's engine and hydraulic system

Khalid Khan[1] · Muhammad Sohaib[1] · Azaz Rashid[1] · Saddam Ali[1] · Hammad Akbar[1] · Abdul Basit[1] · Tanvir Ahmad[1]

Received: 15 December 2020 / Accepted: 23 July 2021 / Published online: 2 August 2021

Abstract

Predictive maintenance (PM) strategies are based on real-time data for diagnosis of impending failure and prognosis of machine health. It is a proactive process, which needs predictive modeling to trigger an alarm for maintenance activities and anticipate a failure before it occurs. Various industries have adopted PM techniques because of its advantage in increasing reliability and safety. But in the aviation industry, expectations for safety are increased due to its high cost and danger to human life when an aircraft fails or becomes out of service. Flight data monitoring systems are regularly implemented in commercial operations using artificial intelligence (AI) algorithms, but there is limited work specific to safety critical systems such as engine and hydraulic system. This paper provides a survey of recent work on PM of aircraft's' hydraulic system and engine, identifying new trends and challenges. This work also highlights the importance of PM and state-of-the-art data pre-processing techniques for large datasets.

Keywords Artificial intelligence · Condition monitoring · Machine learning algorithms · Predictive maintenance · Remaining useful life

1 Introduction

Reliability and availability are a basic requirement of all machines. This is especially true for industrial and commercial machines. However, wear-out and eventual system failure is unavoidable in industries, which makes an adequate monitoring system a necessity for reducing failure rate and maximizing lifetime of equipment. In most industries, the oldest maintenance strategy "fix it when it breaks" is used. Unscheduled maintenance costs in an industry contribute from 15 to 60% of the total production cost, depending on the type of industry [84]. Estimation of failure before its occurrence is mandatory for life-critical systems which includes elevator, electrical systems, gas thermostats and aircrafts to avoid catastrophic accidents.

There are three methods of maintenance in practice, namely **corrective maintenance** [131, 134, 136, 137], **preventive maintenance** [48] and **predictive maintenance** [147].

Corrective maintenance is performed after the unexpected breakdown of a machinery. It is the unscheduled maintenance of an equipment, while *Preventive* maintenance is performed at a pre-designated time, usually provided by the manufacturer or can be based on past failure data. Critical machine parts are replaced or serviced before their complete failure due to fatigue, wear and tear. It is performed while the equipment is still working so that it does not break down unexpectedly. *Preventive* maintenance can result in increased maintenance costs if it is performed when not required. *Predictive* maintenance which is a type of pf preventive maintenance is performed by monitoring the condition or health of equipment and servicing or replacing parts in an optimal scheduled way. Due to rapid development in monitoring equipment, machine condition over time can be accurately monitored. Prognostics techniques are then used to anticipate a failure before it happens through forecasting the remaining useful life (RUL) of a machinery.

This paper focuses mainly on this maintenance technique. Any abnormal performance of a plant equipment may result in significant losses, due to which on-time maintenance has received an increasing attention globally [66].

Technical Editor: Monica Carvalho.

✉ Khalid Khan
Engrkhaliduet@gmail.com

[1] TDF, University of Engineering and Technology Peshawar, Peshawar 25000, Pakistan

PM market was $1498 M in 2016 and is expected to expand to $10,962 M by 2022 [4]. Over time, aviation industry has shown growth in annual traffic which is predicted to increase by 4.4% per annum (Forecast).

Prognostic and Health Management (PHM) in aviation industry is expected to expand, which will have a significant influence on aircraft maintenance to make sure that old aircraft is in safe operating condition. By 2036 an additional 41,000 plane deliveries will need to be fulfilled in order to meet service needs for both passengers and cargo. To accommodate these demands, civil aviation authorities and airlines are investing in airport infrastructure, route expansion and fleet capacity. Figure 1 shows the aircraft delivery forecast from 2013 to 2032.

Hence, identifying the faults in advance has become an essential practice in industries. Traditional maintenance techniques, i.e., corrective and preventive maintenance, are inefficient in terms of time and money and are not based on real time data [18]. Scheduling of maintenance tasks based on condition monitoring and performance degradation curve is gradually replacing traditional maintenance methods [80]. PM helps in increasing system safety, minimizing downtime [40] and ensuring efficient production [17]. Maintenance activities can take up about 13% of the total operating cost [52] in the aviation industry. With increase in complexity and automation of aerospace systems, susceptibility to faults is increased. Any minor fault in the absence of prior actions can result in taking the aircraft outside the normal working condition, thereby resulting serious damage to aircraft parts, even midair failure or crash. Such crucial instances are avoided by using fault-tolerant flight control (FTFC) techniques, some are which are proposed in the work of Yu and Jiang [148].

A major cause of accidents and casualties in aviation industry is engine failure [108]. Engine is the main element of an aircraft which produces thrust for propulsion, driving various subsystems and also powers the hydraulic unit [57]. Most importantly, hydraulic system provides hydraulic fluid to an actuator or servo system which converts this energy into mechanical work and generates the power required for moving an aircraft component or flight control [31]. Hydraulic servo system is widely used in aerospace because of the advantages it offers in rapid response, high density of driving power and high precision [153]. Control surfaces like elevators, ailerons and rudders are controlled by hydraulic actuators and therefore is a central part for the flight control system (FCS). Exhaustion of the actuators can be dangerous, which can affect aircraft performance and also endanger flight safety [51]. The aerospace industry is adopting proactive maintenance instead of reactive to reduce maintenance cost and operational downtime by increasing the useful life of aircraft components.

Prognostics techniques have been developed using different AI techniques for estimation of remaining useful life (RUL) [155]. PM techniques can broadly be classified into physics/model-based and data-driven approaches [27, 125, 127]. Physics-based predictive maintenance techniques are solely based on expert knowledge, whereas data-driven approaches use AI algorithms to extract meaningful information from the data [122]. AI techniques and data mining techniques (which is a specific AI technique) are being applied in different fields, i.e., healthcare [135], E-commerce [22], financial data analysis [102, 142], online retail and marketing and telecommunication industry [26, 105, 130]. The focus of this paper is on PM in aviation industry specifically aircraft's hydraulic and engine systems. Extensive research has been carried out to analyze flight data of aircraft's, which can help in shaping predictive analytic in aviation [74]. Data mining techniques can be beneficial for calculating the RUL of equipment before failure; hence, it

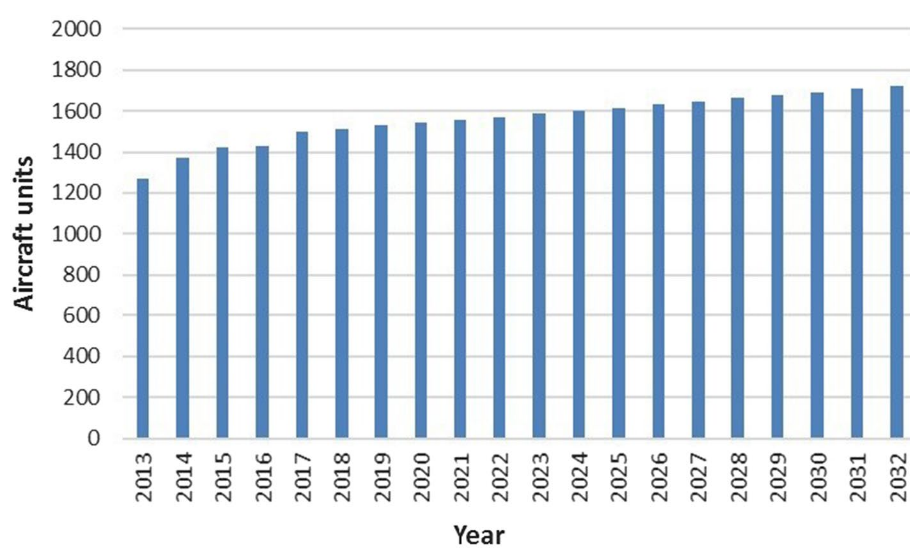


Fig. 1 Aircraft delivery forecast (2013–2032)

can be fixed on time before final failure [9, 10]. Mechanical systems usually fail due to fatigue, while most of the catastrophic failures occur due to cyclic loading of moving parts of machinery; hence, monitoring of aircraft structures has become mandatory during the aircraft service life [101].

2 Research methodology

A survey has been conducted to find out about the increasing research interest in predictive maintenance of an aircraft. As research within this area is of practical importance, the scope of this investigation covers the period between 2000 till 2018. To accomplish the study aims, this research is based on reviewing a variety of journal articles, all of which are directly related to system health management concepts and its deep learning application. A literature search was conducted using Google Scholar. The primary descriptor used is "machine learning", combined with ''system health management", ''condition monitoring" and ''fault/failure detection". A summary of this survey is presented in Fig. 2.

During all the years studied for this review as indicated in Fig. 3, the most widely used AI techniques were neural networks and support vector machines. As indicated in Fig. 3, other important techniques used for health monitoring are simple statistical techniques and model-based approaches.

Fig. 2 Number of papers published on aircraft maintenance each year

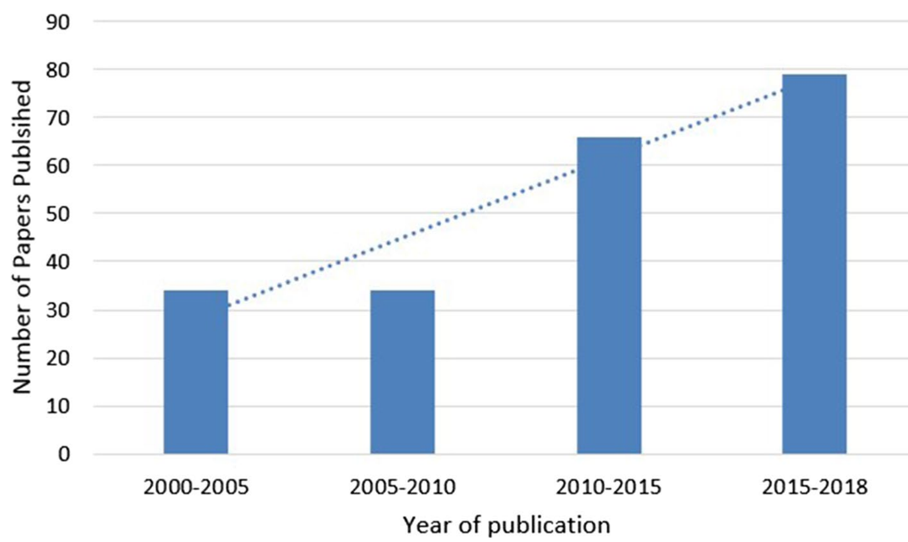
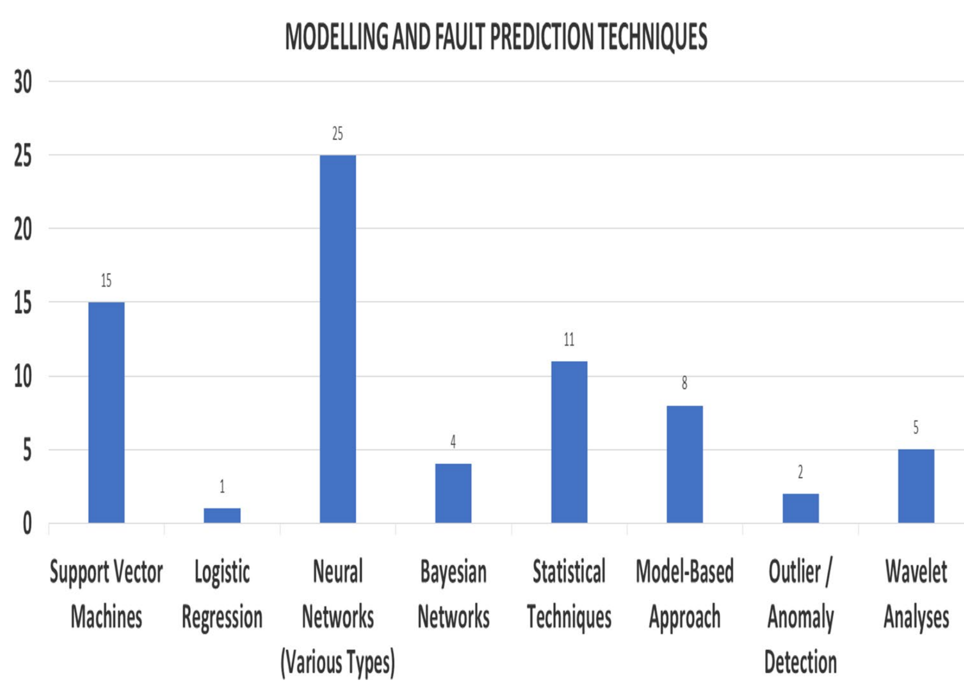


Fig. 3 Number of published papers reviewed



A detailed literature review on prognostics benefits, approaches, applications and challenges is presented in [37]. Challenges and opportunities for rotor crafts and general aviation are reviewed and identified in [47]. An understanding of different predictive maintenance techniques and its latest trends in all sort of industries is provided in [111]. A review of latest flight scheduling, fleet assignment and planning processes of commercial aircraft is given in [38]. Benefits of using AI in prognostics in different industries are highlighted in the literature survey summarized in [110]. A review on aircraft health management system in [59] focuses on different functional areas for diagnosis of engine faults.

To the best of author's knowledge, a review paper is not published in recent years, which covers predictive maintenance technologies specific to aircraft's' engine and hydraulic system. An effort is made through this review paper to provide insights of latest predictive maintenance techniques in aircraft's' engine and hydraulic system for filling the gap and provide direction for the future work in this area. In addition, this paper also presents original research contribution in Sect. 10 where AI techniques are utilized to predict failure in aircraft hydraulic system and engine.

The paper is structured in the following manner: Sect. 1 briefs about the recent trends in the maintenance procedures practiced in the modern industries. Section 2 presents a significant role of aircraft's engine and hydraulic systems in the overall safety of the fleet. Section 3 presents an overview of the recent trends in model-based data driven approaches; Sect. 4 is about fault prognosis. Section 5 is discussing engine's operational safety and quality; Sect. 6 encompasses the application of predictive maintenance in addressing the condition monitoring, while Sect. 7 concludes the paper.

3 Importance of hydraulic system and engine for aircraft safety

Maintenance of key aircraft components such as engine, hydraulic system and actuators is still based on preventive and corrective maintenance scheduling. To match today's competitive aerospace market, innovative maintenance solutions must be optimized for aircraft maintenance ensuring maximum service life and safety of the aircraft. Utilizing predictive maintenance approaches in an aviation industry is the need of the hour. An aircraft system is complex and consists of many interconnected systems, including electrical system, engine, hydraulic system and other subsystems. Maintenance of an aircraft engine is the most critical, time consuming and, above all, expensive part. It takes approximately 30% of the total maintenance cost of an aircraft [30].

Development of prognostics for an aircraft engine is widely studied because of its operational reliability, safety and maintenance costs [106]. On the other hand, hydraulic system being a key component of an aircraft is used to control landing gear, surface system and brake system. The hydraulic system enables an aircraft to take off, maintain control during cruise and land [32]. Use of hydraulically powered components depends upon the complexity of aircraft. In a small aircraft, use of hydraulic system might be limited for activating wheel brakes, but in larger complex aircraft, operation of key components relies solely on the hydraulic system [85].

Condition-based maintenance (CBM) and fault detection technology for an aero-engine are not new and have been developing since 1950s. These techniques have evolved from simple and offline diagnosis to more sophisticated real-time monitoring and intelligent systems [6]. CBM monitors real-time condition of a system and determines what maintenance needs to be done. A complete architecture for CBM systems should cover the range of functions from data collection through the recommendation of specific maintenance actions. The different steps of according to CBM framework are given in Fig. 4.

An aircraft component replacement based on data mining techniques in [69], has developed a model which receives real-time data from commercial aircraft and signals an alert when a component is required to be replaced. A predictive maintenance model for aircraft having flight data from subsystem, i.e., environmental control system, a propulsion system, a flight control system, an electrical system and a hydraulic system, is developed in Ethington et al. [39]. Statistical features from sensory data are extracted for defining threshold number for future flights using ensemble of machine learning classifiers [39]. Ensemble classifiers used are Naive Bayes, support vector machines (SVMs), learned decision trees and neural networks (NNs).

4 AI-based diagnostics

AI-based diagnosed techniques can be categorized into two classes: data-driven and knowledge-based [24, 118]. Data-driven approaches are based on heuristic processing of available measured sensor's data, while knowledge-based techniques utilize expert/domain knowledge which is obtained using accelerated life tests to model system's behavior. Knowledge-based approaches are more accurate and effective when the mathematical model of the system, in addition to different fault models are available. However, when system complexity increases it becomes difficult to find explicit mathematical models. This problem is especially emphasized for the case of aircrafts, where the complexity of the system makes it challenging to have an accurate mathematical model. In this case, data-driven techniques have proven to be useful [87]. Efficient monitoring in modern industries

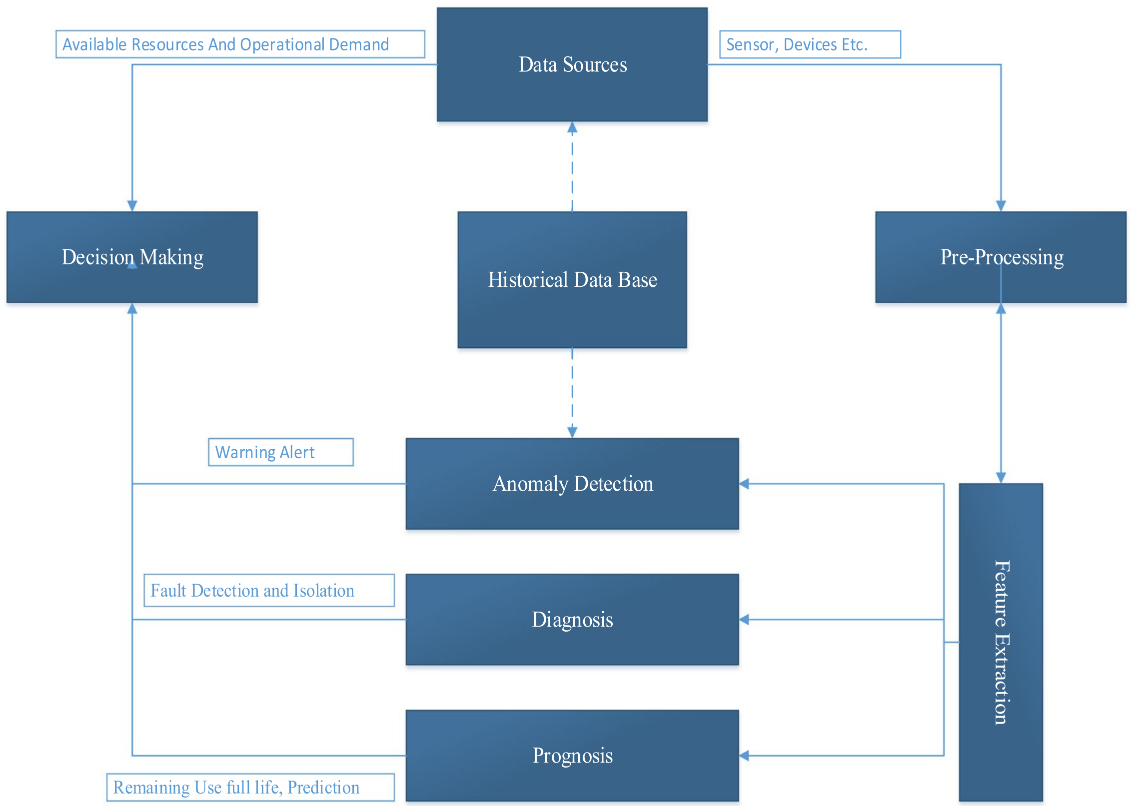


Fig. 4 CBM architecture adapted from Bonissone et al. [16]

is helping researchers to develop more sophisticated data driven approaches.

In this section, various techniques used for failure detection in different fields are explained. The use and benefits of different data pre-processing and machine learning algorithms in predictive maintenance are also highlighted. Figure 5 illustrates some of the AI approaches that have been used for PHM applications over the years.

4.1 Knowledge-based approaches

Knowledge-based approach also called physics-based models and work on extensive knowledge of the physics and domain knowledge for each of the possible failure modes for different types of systems and requires relatively less training data [114]. A detailed review of knowledge-based fault detection and diagnosis for aerospace systems can be found in [83], wherein a nonlinear generic model is presented for actuators and sensor's data. Another diagnostic approach is presented in the case of electrical machines, where modeling stator winding insulation is presented in [8]. A generic exponential model is used to fit data points for least mean square minimization which can forecast the RUL of the insulation lab [8]. Possible solutions using integrated machine health monitoring system based on AI are presented in [81]. Model for prediction of defect propagation in bearings is developed in Li et al. [71]. A rotor shaft crack growth model for prediction of its health condition and RUL using Forman law of linear elastic fracture mechanics is presented in [94]. Fatigue crack growth is usually the main cause for equipment failure. Particle filtering presented in [20] is used for the estimation of RUL of equipment subject to fatigue crack.

4.2 Data-driven approaches

Data-driven approaches analyze sensory data using heuristic processing or AI without going into details of physics behind the failure modes. Such algorithms have shown better performance for fault detection and isolation [41]. Fuzzy similarity-based prognostics model based on data-driven concept is proposed for estimation of the RUL of equipment subject to fatigue cycles [29]. Machine learning algorithms such as neuro-fuzzy systems capture the system dynamic behavior quickly and accurately [132]. Support vector machines [115] offer the advantage of reduced input space, and a small number of support vectors can be used to construct the classifier and predictor models, making it faster and robust. Recurrent neural networks [21] are used in prognosticating time-series data with ease and success. An automated approach for ore grinding mills liner inspection is explored in [1]

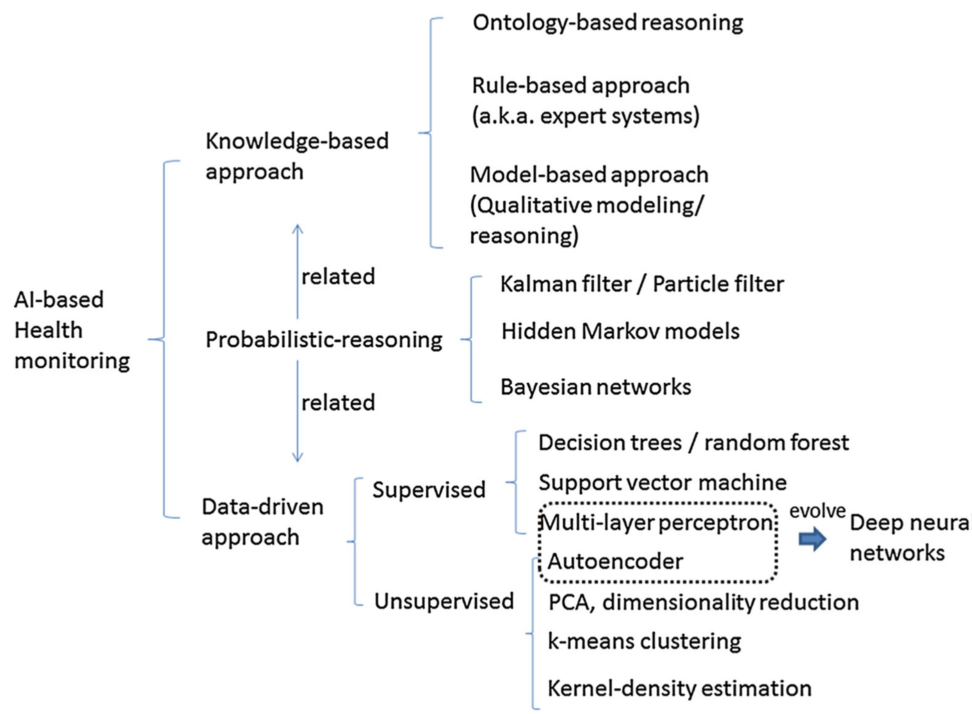


Fig. 5 Categorization of AI-based techniques for PHM applications

which eliminates inspection delays and provides even better inspection than human eye of the most experienced professional, thus saving time and cost. Artificial neural network is used for detecting faults in the induction motor bearings in [120]. Clark transformation is used for extracting features and dimensionality reduction which are the characteristics of bearing defect [33]. CBM systems are implemented on most of the wind turbine which reads data from the turbine and send it to supervisory control and data acquisition (SCADA). A framework for the techniques developed for diagnosis and prognosis of the faults, based upon SCADA data, is provided in [131, 134, 136, 137]. Machinery prognosis strategy based on data-driven techniques is developed in [92] for industry application utilizing Dempster–Shafer regression [99] and multi-step-ahead time-series prediction models.

Stochastic process (Wiener process) is combined with a data analysis method (principal component analysis) for modeling the degradation curve of the components in [67]. An efficient method based on neural network for prognostics and health management is presented in [97]. Dimensionality reduction technique called neuro-scale has been used for effective visualization of the data [76]. Kalman filter is used to ensemble multi-layer perceptron and radial basis function networks for estimation of RUL [76]. Triple correlation techniques for damage detection of composite structure are proposed in [117] by correlating higher and fundamental harmonics of vibration signals.

Artificial neural networks also known as nonlinear algorithms are widely used for machine learning approaches in prognostics which establishes a relationship between input and desired output for optimal performance [113]. Another widely used machine learning algorithm is based on outlier/anomaly detection that develops a model for normal operation of the system and sends an alert when new data crosses the model's threshold indicating an anomaly which maybe an indication for upcoming failure [15, 25]. A Bayesian network-based approach is used in [25] for fault diagnosis of a centrifugal compressor because of its capability to develop a probabilistic relationship.

A major advantage of using an unsupervised machine learning algorithm for fault diagnosis is that it does not need feature selection and signal processing. Deep neural networks have been used in [64] for detection of bearing failure on raw time-series sensor data and have achieved classification accuracy of 100%. An autoencoder known as variant of deep learning has been used in [61] for automatic feature extraction from a vibration signal to intelligently diagnose the health condition of a machine.

4.3 Fusion approaches (data and knowledge based)

Knowledge-based approaches use mathematical models and expert knowledge for modeling a machine behavior. Data-driven approaches rely on transforming sensor data into a behavior model, which requires large training datasets. Hybrid models combines different algorithms from both data-driven and model-based modeling for developing robust health assessment techniques [34, 126]. Fusion prognostic of data-driven and experience-based approaches is presented in [139] to improve the system state forecasting accuracy and prediction of RUL of an aircraft gas turbine based on real-time sensors data. An artificial neural network has been used for estimation of the battery's state of charge using measured current and voltage in [54]. ANN is combined with an unscented Kalman filter (UKF) to reduce the errors in neural network [54]. A hybrid prognostic approach based on Weibull distribution and artificial neural network is presented for estimating RUL of rolling element bearings derived from vibration signals [3].

5 Fault prognostics of aircraft's engine for operational safety and quality

Fault diagnosis and prognosis of hydraulic system has gained increasing importance in energy, industry and automobile engineering [12, 35]. Hydraulic system of an aircraft provides high-pressure fluid for the control of an aircraft enabling it to take off and land [32]. Hydraulic pump is the heart of a hydraulic system, which converts mechanical power to hydraulic power [49] and also provides a stable supply of high-pressure oil for driving the actuators [137]. Aircraft hydraulic pump works under high pressure and temperature and is therefore susceptible to multiple faults [32]. Estimation of RUL of piston pump is mandatory for effective use of the hydraulic system.

Research on hydraulic fluid contaminant sensitivities of major components has been conducted since the 1970s, which helped in establishment of the fundamental mathematical modeling for failures caused due to contamination of all kinds of hydraulic components [42]. Contamination in the hydraulic fluid causes approximately 70% to 80% of hydraulic system failures [154]. A mathematical model for RUL prediction based on contaminant sensitivity for the aviation hydraulic piston pump is presented in [133]. An adaptive-order particle filter is effectively used in [123] for RUL prediction of hydraulic pump. Degradation trend in [112] is used for monitoring aircraft's hydraulic pump by using a state recognition method based on wavelet packet norm entropy during complicated operational condition. RUL prediction of a hydraulic system can be performed by using output pressure of hydraulic pump with noise [45, 46]. Wavelets analyses can be used for efficiently extracting noise and fault characteristics from actual signals of a hydraulic pump [100]. Fault feature in every frequency band and energy of various frequency components can be extracted and used as input to a neural network [100]. A prototype for aircraft's hydraulic pump in [19] includes feature extraction, signal processing and estimation of degradation curve for the pump sensory and in-flight processing data.

Health monitoring based on real-time data and fault messages from aircraft is rarely studied. These messages contain important information about when a sensory signal exceeds a predetermined threshold [11]. Event logs are studied and used in a wide range of applications [107]. These logs can help effective implementation of predictive maintenance in aviation industry [65]. Degradation messages can be used for predicting hydraulic system failures in a commercial aircraft [50]. The aim is to estimate remaining time until fluid level of hydraulic system reaches unacceptably low values based on degradation messages using a particle filter framework [95]. Hydraulic actuators provide controls for elevators, ailerons and rudders having the ability to alter aircraft movement. PCA is used for dimensionality reduction followed by fault diagnosis of aileron actuators using SVM [103]. Nonlinear dynamic mathematical model for coupled model of hydraulic actuator and aero-servo-elasticity followed by modeling of different kinds of failures is presented in [144]. Numerical simulation of loss of control for ailerons is explored to provide feasibility of the proposed method [144]. Faults in landing gear hydraulic retraction have been diagnosed from multi sensor signal using SVM and have used stacked de-noising auto encoders for feature extraction [75].

Convolutional neural network is a useful option for developing aircraft health management system for sensor data from hydraulic pump, fuel tank and actuator displacement [70]. Deep learning can be implemented for recognizing patterns from training data and identifying failure based on threshold conditions of hydraulic system. For example, aircraft hydraulic pump failure is predicated using gray forecasting model [73]. Similarly, real-time data from three aeronautical hydraulic systems are used for developing health monitoring system for hydraulic fluid leakages.

To predict upcoming failures of the turbine's hydraulic pumps of aircraft, multiple outlier detection method, ST-DBSCAN, is used and has proven to be the best suited method for this use case [88]. In order to detect the health status of the aircraft based on the actual flight data, this article proposes an anomaly detection for the aircraft hydraulic system by the autoencoder (AE) model with the long short-term memory (LSTM) layers, called LSTM-AE anomaly detection model. In general, the AE is a practical unsupervised or semi-supervised algorithm that can be used to handle unlabeled data. The LSTM is a variant of recurrent neural network (RNN) and realizes information mining of time-series data by three specific gate transmission mechanisms. Based on the fusion of the two advantages, the proposed LSTM-AE can effectively solve the problem of detecting the health status of the aircraft based on actual flight data [140]. A linear degradation model is used to characterize the underlying degradation process of the air-conditioning system (ACS), for which only a small number of performance parameters are available. Given the computed Health Index (HI), Bayesian estimation method is used to for system health state estimation and prediction [63]. Another paper proposes an unsupervised deep stacked autoencoder (DSAE) model for the multi-stage and multi-parameter aircraft system and the LSTM layer is used to mining sequence information in quick access recorder (QAR) data of a flight [141]. A long short-term memory network-based autoencoder (LSTM-AE) is proposed for complex aircraft system fault detection and classification, which makes use of the raw time-series data from heterogeneous sensors; the case study results show that the computed HI can effectively characterize the health state of the aircraft system and different fault types can be identified with high confidence, which is helpful for line fault troubleshooting [91].

5.1 Aircraft's engine: operational safety and quality

Engine being the main power source constitutes about 40% of the failures is of significant importance for developing fast and accurate predictive maintenance solutions [2]. In order to increase operational safety and quality, reliable operation of critical engineering systems such as aircraft engines is of utmost importance [14]. Reliability can be defined as frequency and probability of system failures [96]. Development of engine diagnostic system for safe operation of an aircraft is essential to detect and isolate engine faults in advance. Among AI algorithms, ANN [121] and SVM [59] are widely used techniques [145]. Advantage and disadvantage of different machine leaning approaches, i.e., filter, Bayesian belief network, generic algorithms, neural network and fuzzy logic systems, are discussed in [128]. A hybrid model based on integration of particle swarm optimization (PSO) and SVM for predicting RUL of aircraft engines is presented in [90]. PSO is used to adjust kernel parameters in the SVM training phase for increasing the regression accuracy.

Wear is one of the major causes for early failure in all types of engine faults [79]. SVM with kernel function of radial basis function based on oil spectral analyses for prediction of wear trend for an aircraft engine system is used in [79]. A stacked sparse autoencoder [55] and logistic regression based on deep learning is proposed in [80] for RUL prediction of an aircraft engine. Kalman filter is successfully used for estimating aircraft engine's RUL in [13]. Similarly, Kalman filter is used to determine deviation in engine speeds, temperature and pressure from a predetermined nominal state [129].

ANN is a useful tool for detecting trends and identifying patterns in complex data [28]. Use of ANN for engine fault diagnosis increases the success rate considerably [78]. In the recent years, extreme learning machine has gained significant attention because of its ability of faster learning relative to conventional ANN [56]. Extreme learning machine for pattern recognition of aero-engine faults is used in [146] to get favorable results. Fault detection and isolation system for on-board sensors using extreme learning machine with memory principle is presented in [77]. Hilbert–Huang transform is combined with SVM for engine fault diagnosis [131, 134, 136, 137]. Automated failure diagnosis in aviation maintenance using AI is proposed in [149] for reliability and safety of the overall system. Detection of faulty component(s) in an aeronautical turbo-shaft engine using deep belief network is explored in [72] and has achieved an accuracy of 96.84%.

Interpretable aircraft engine diagnostic based on separating binary indicators using a standard forward feature selection algorithm is developed in [104]. The main goal of the experimentation in [104] is to reduce health indicators, which act as inputs to a Naive Bayes classifier and increases its accuracy. Signal denoising of a jet engine health using optimally weighted recursive median is provided in [124]. Degradation pattern learning using neural network is used for estimating RUL of an aircraft engine in [124]. Simulation data of battery and turbofan engine degradation obtained from National Aeronautics and Space Administration (NASA) data repository are used in [87] for predicting RUL using discrete Bayesian filter. Degradation dataset of an aircraft gas turbine engine having two potential failure modes generated by C-MAPSS [44] is used for modeling and prognostic analysis [23].

A new approach based on genetic programming for aircraft jet engine-condition monitoring is proposed in [89]. Exhaust gas temperature is used as a condition indicator for accurately diagnosing faults in the engine [89]. Gas-path diagnostic of aero-engine for effective engine-condition monitoring is reviewed in [82]. Health parameters of gas-path components are used for accurate fault diagnosis based on square root unscented Kalman filter in aero-engine [151]. Shaft data from Rolls-Royce Trent (aircraft engine type) are used to develop a static model using SVM for detection of novel events, which reflect changes in vibration spectra [53]. Regression analyses combined with SVM are used in [150] for engine health condition monitoring by taking into consideration four engine parameters, namely fan speed, fuel flow and exhaust gas temperature.

6 Original contribution

A machine learning approach has been used for condition monitoring by analyzing hydraulic data of aircraft. This dataset consists of control commands, actuation system information and aileron/elevator position. These parameters are monitored in order to identify significant changes, which can be possible indications of a developing fault. Selection of parameters that are sensitive to system's condition is a crucial step in performing condition monitoring of a machine. Statistical analysis has been used to detect change in mean or variance based on statistical distribution of the data for condition monitoring [116, 152]. The deviation of data parameters from an identically and independently distributed normal distribution creates an alert indicating failure [86]. One way of extracting failure patterns from dispersed and high-dimensional data is to perform statistical analysis [93]. Statistical analyses have been effectively used in [109] for condition monitoring of a hydraulic system and RUL prediction of electro-mechanical cylinder. Some of the preliminary results of this research work based on statistical analyses using primary data are presented in this section.

Aircraft's performance changes with change in altitude [5, 98]. Engine faults and deviation from normal operation are noticeable in the take-off mode when the engine is working at high temperature and pressure [7]. For this purpose, hydraulic system data have been divided into three segments, i.e., before flight, in flight and after flight. The classification included division of all flight data into before flight data, in flight data and after flight data. This division was performed using the parameter 'Weight on Wheel (WOW)'. The traditional feature extraction algorithms which include time, frequency and time–frequency analysis [58] are used in this work. Time-domain methods rely on features extracted from time waveform, e.g., mean, variance, kurtosis and skewness [143]. Frequency-domain analysis begins with transforming signal into frequency domain using Fourier transform [62]. Time–frequency methods include Hilbert–Huang transform, wavelet and short-time Fourier transform analysis [68]. After data division, nine time-domain statistical features [60, 119] have been extracted from each segment of the data. These features include maximum, minimum, average, variance, skewness, kurtosis, mode, standard deviation and median.

Hydraulic system dataset consists of different tail numbers, all of them having same hydraulic unit. Fault sheet provided with dataset indicates faults on a specific date, which is used for labeling of files. SVM has shown its superior ability for fault diagnosis in a number of studies [36, 138]. SVM capabilities are explored in this research for condition monitoring of a hydraulic system using statistical features. The model was trained on both normal and faulty data and shows an accuracy of 78%, but when it is tested on unseen data its accuracy drastically drops to 49%. Details of the SVM results are given in Table 1.

These results show that the model performs poorly, and the accuracies are low as described in the above table. This brought us to the conclusion that the models were not properly differentiating between normal and faulty files. A solution to this could be to find out a procedure where rows are labeled as normal or faulty, instead of the complete files. The next step should be to plot the time-series graphs of the whole data, compare the faulty and normal data and analyze it, notice the trends and try to detect anomalies. Based on the plots, there could be a possibility to label rows instead of complete files as normal or faulty.

Table 1 SVM results

Model	Predictions	Test set accuracies
Support vector machine (RBF kernel)	Total tests	23,735
	Correct predictions	11,678 (49.20%)
	Incorrect predictions	12,057

Plotting the labels against time gives valuable information that can be used to find trends, detect anomalies and predict future values. Using this method, the plots for the labels (hydraulic pressures) can be analyzed. This method is based on the idea that a label has certain operating normal conditions, upper and lower limits and some averages. If the plots of the labels do not conform to their normal behaviors, conditions and limits, fault prediction and detection can be easily performed. This method does not require extensive domain knowledge about the features since they are not taken into consideration. But still, it requires the following values:

1. Average values during normal operations.
2. Upper and lower limits of the average normal operations.
3. Maximum and minimum limits of the operating hydraulic pressures.

From the plots, the following observations can be made.

- For normal data, the rolling mean line (yellow) stays within its upper and lower bounds with rare occurrences of deflection from its limits.
- For normal data, the number of spikes that shoot above the upper limit and/or below its lower limit is also very rare. These trends can be observed in Fig. 6.
- For faulty data, the rolling mean/moving average is observed to divert from within its upper and lower limits. Diverting above indicates that the hydraulic average pressure is greater than the required and vice versa. This phenomenon is represented by red dots.
- For faulty data, the number of spikes that overshoot its upper and lower limits is large. These over-shooting spikes are marked with black dots. These trends can be observed in Fig. 7.

When the fluid is passed/retracted from/to an actuation system, pressure surge is created shown by spikes in Fig. 8. Operation of hydraulic pumps/units within certain upper and lower limits is considered safe. Deviation from these limits can be caused by faults in the hydraulic unit such as leakages, contamination or over-pressurization. Since most of the fault-inducing processes are a continuous phenomenon,

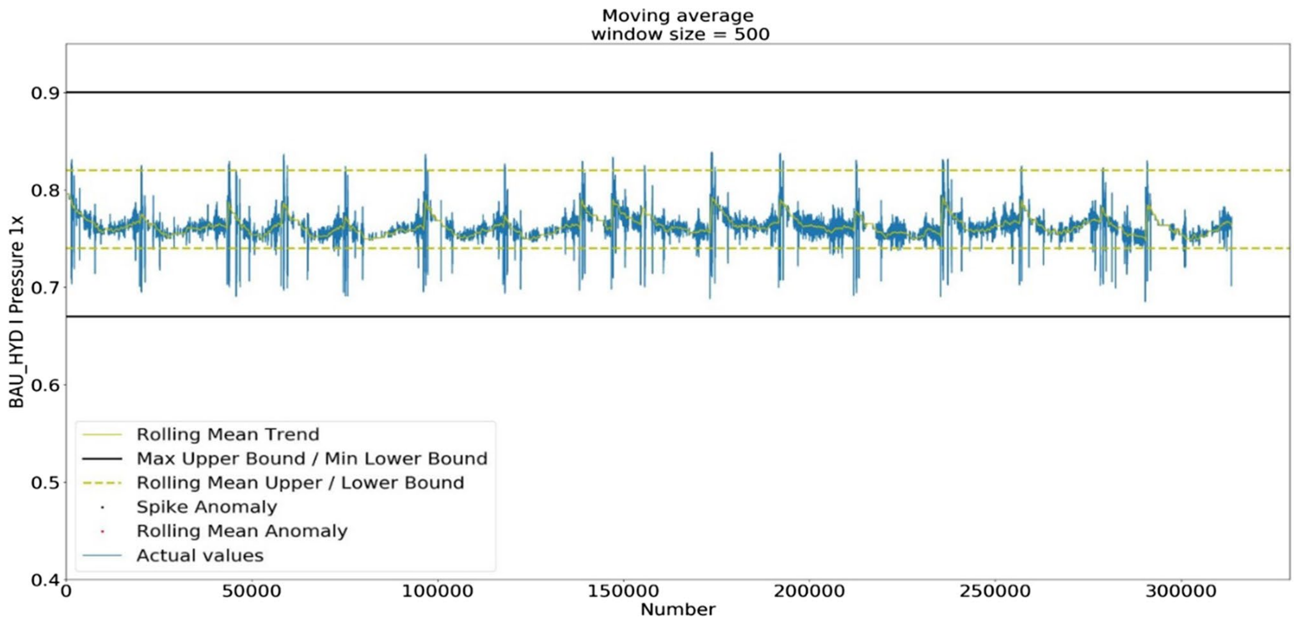


Fig. 6 Normal operations of hydraulic pressure 1 ×

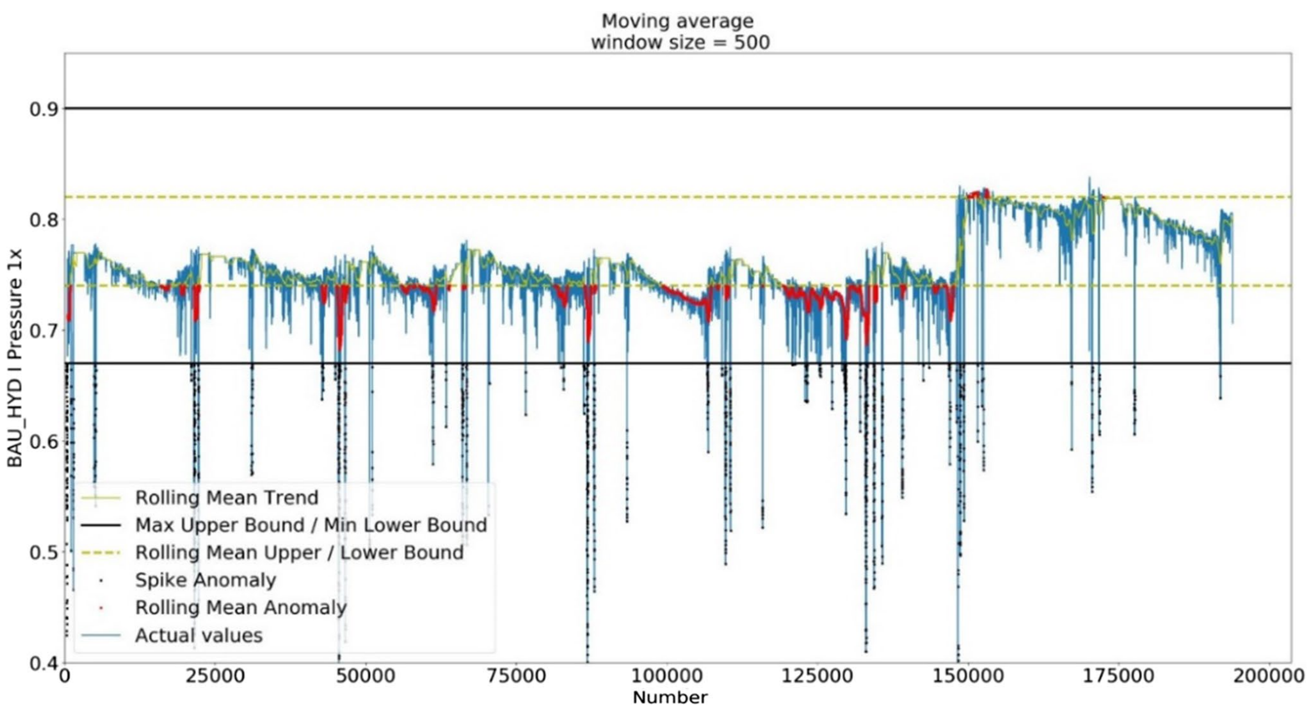


Fig. 7 Anomaly detected in hydraulic pressure 1 ×

it is difficult for a pilot to report the subtle changes/anomalies that lead toward them. Extreme and continuous observations are required to measure the changes over time.

Two sets of upper and lower bounds have been provided with hydraulic system dataset by the manufacturer, whereby one of the sets was defined for normal operations (yellow dotted line), while the other was for extreme/stressful operations (black solid line). Pressure values of hydraulic units (blue color) have been plotted against time. A window size of 250, 500, 750 and 1000 has been tested to measure the average operational pressures in which window size = 500 has shown best results in capturing the anomaly

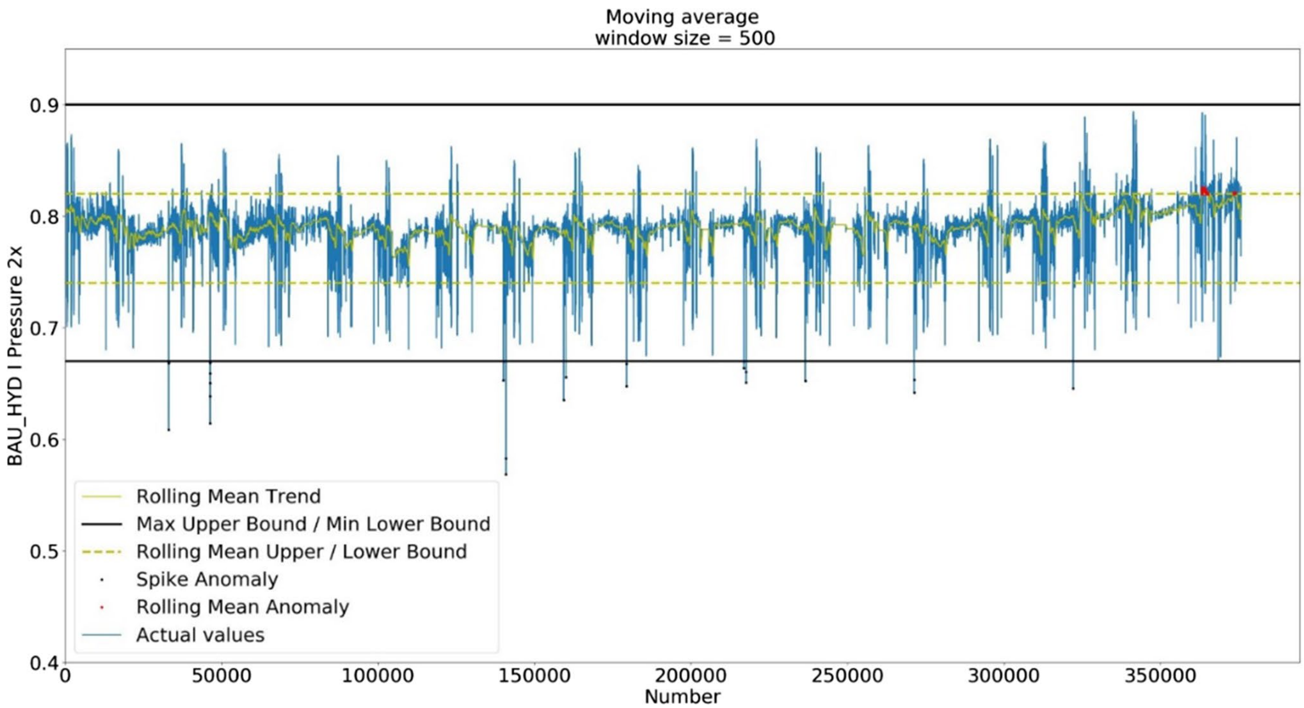


Fig. 8 Normal operations of hydraulic pressure 2 ×

pattern. Yellow solid line in Fig. 9 depicts moving average, and yellow dotted line acts as limits for normal constant flow of hydraulic fluid. Black line acts as a limit for spikes considered as over-pressurization (above) or under-pressurization (below). A normal operation hydraulic pressure 1 × and 2 × can be seen in Figs. 6 and 8, respectively.

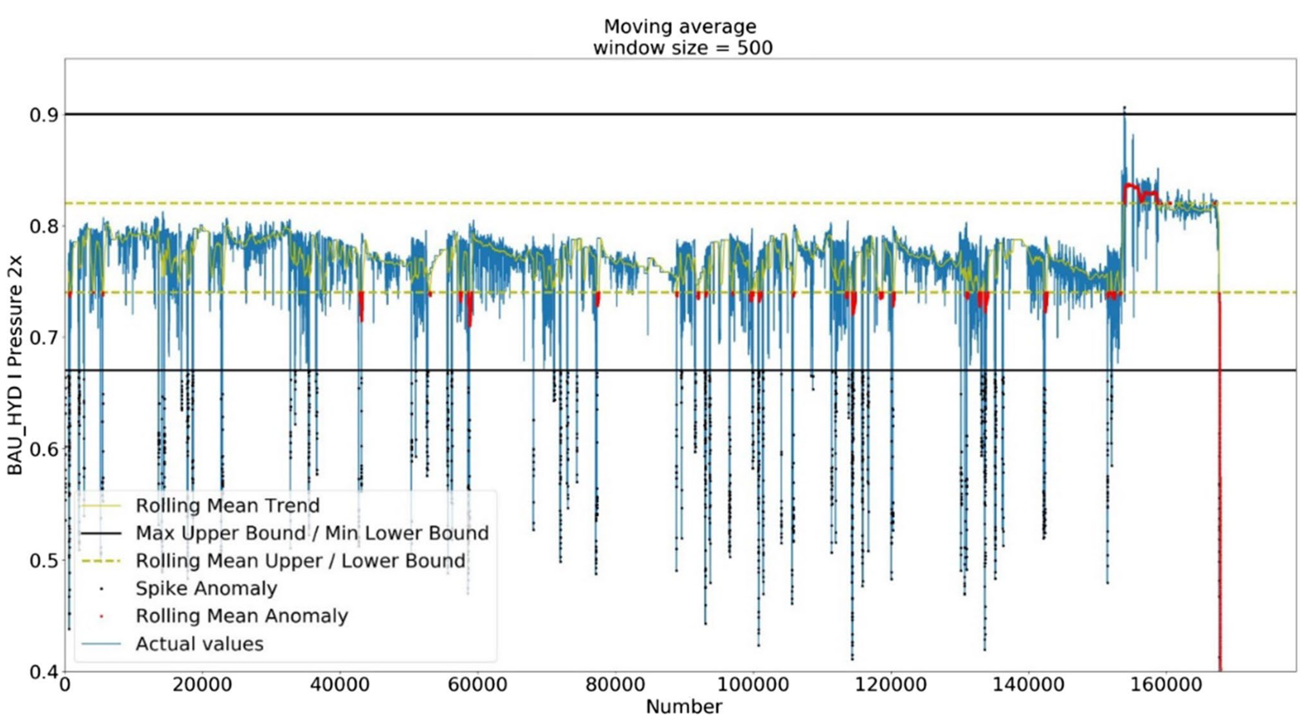


Fig. 9 Anomaly detected in hydraulic pressure 2 ×

Table 2 SVM results after relabeling

Model	Total labels	Correct labels	Incorrect labels
SVM	1106	1080	26

Table 3 Training and testing results of single flight

Training MSE	Testing MSE engine 2	Testing MSE engine 3
0.00028117	0.00217895	0.00193086

Fault operation of hydraulic pressure 1 × is identified when the yellow moving average crosses the yellow dotted line marked by red color as shown in Fig. 7. Similarly, Fig. 9 depicts faulty operation of hydraulic pressure 2 × which is characterized by increase in number of black dots on spikes when high pressure values cross black line.

This helps identify new limits for the dataset operating upper and lower limits from the graphs. Once the new limits were found out and the time-series graphs were plotted with the new limits, we moved on to the process of labeling the whole data. Now, instead of whole files being labeled as normal or faulty, we have specific rows that are labeled accordingly. We used these data to train SVM model and predict the labels of a third file to test their performance. The results for the trained model are shown in Table 2.

From the results above, it can be concluded that the models are now correctly identifying the faults with an accuracy of around 90%, which is quite an acceptable range.

This section demonstrates the results of the EGT prognostic model. For this model, EGT is used as main parameter to be estimated and 12 parameters are taken as input which are considered to have a correlation with EGT. We have nine engines with a series of flight data. Each of the engines has its own settings and conditions under which they operate which makes them different. For this reason, a prognostic model for every engine is developed. The final performance of the model is measured by examining the residuals. Residual values are the difference in the observed values and the estimated values of the quantity, EGT in our case.

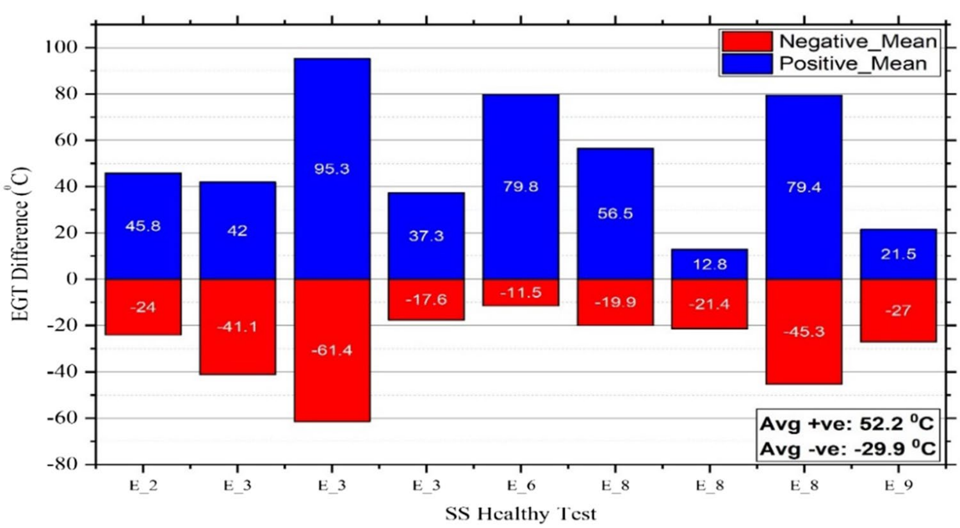
6.1 Training results of EGT:

This section explains the training and testing results of single flight from the healthy data. A single flight from this dataset is selected and a model is trained on it and then tested against data from various flights of different engines to measure its performance (Table 3).

Figure 10 presents the residual errors of all the single flights from our dataset. There are a total of nine different results from 9 flights selected from the data. The bars in Fig. 10 show the difference in the measured values and the actual values from our model. These differences are further divided into positive and negative differences. It can be clearly inferred from the graph that differences in the actual and predicted values are significantly high (except E_8). The model is not able to correctly predict from this training data; therefore, this is not a good approach.

Figure 11 plots the actual EGT values versus the predicted EGT values, while Fig. 12 shows the normalized error in the prediction of EGT by the model. The blue line is the actual EGT, whereas the red line plots the predicted EGT values over time. As is evident from the graph, the two plots are quite like each other which, indicates an accurate prediction for most part. But there are also a few peaks, where the two EGT values are apart, indicating the error. These peaks occur whenever the pilot acts on the throttle in an abrupt manner, which causes the fuel flow rate to increase that results in the extreme EGT values. In such cases, the neural network cannot predict the EGT values correctly and hence the high error rate.

Fig. 10 EGT results for different engines



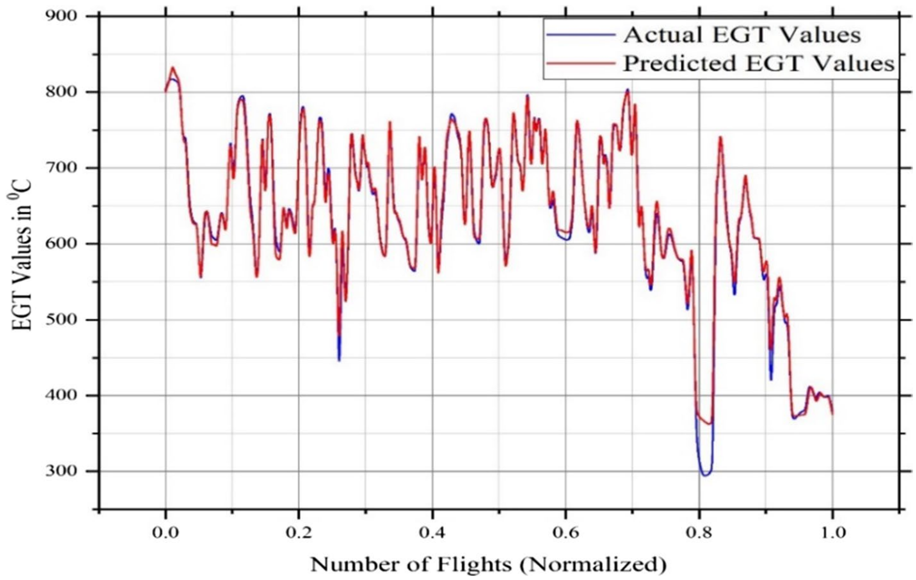


Fig. 11 Real versus estimated EGT

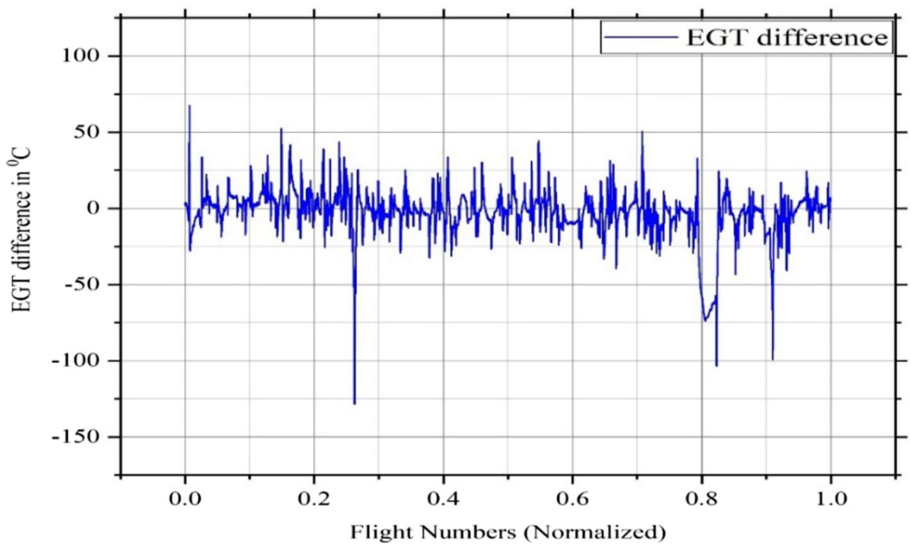


Fig. 12 Percentage error on the EGT

7 Conclusion

A review of state-of-the-art predictive maintenance techniques in use for aircraft's hydraulic system and engine has been explored in this work. A case study based on hydraulic system data from fighter aircraft has been included to illustrate fault diagnosis for an aircraft. The problem considered in the experimentation was to detect failure pattern when the fluid level reaches a critical value for creating an anomaly alert. Use of window-based pattern recognition has shown good results in detecting the failure well in advance. The paper presents the results of the window-based pattern detection for prognostics to obtain greater precision capable of prognosticating fault before occurrence. In addition, different machine learning algorithms, i.e., neural networks, logistic regression and deep learning, have been reviewed for developing prognostics models which can estimate the RUL with varying accuracy. Considering the time-series nature of the aircraft engine data the trend for predicting aircraft engine and hydraulic system failure is moving toward neural network, specifically LSTM. This paper also presents an LSTM based prognostics technique for aircraft fault prediction. The model is capable of correctly predicting engine behavior.

Acknowledgements The authors would like to thank and acknowledge the Higher Education Commission Pakistan for funding this work through the Grant TDF 03-054. This funding (TDF 03-054) was awarded to Dr. Tanvir Ahmad (PI) and Dr. Abdul Basit (Co-PI).

References

1. Ahmadzadeh F, Lundberg J (2013) Application of multi regressive linear model and neural network for wear prediction of grinding mill liners. IJACSA 4(5)
2. Albarbar A, Gu F, Ball A, Starr A (2010) Acoustic monitoring of engine fuel injection based on adaptive filtering techniques. Appl Acoust 71(12):1132–1141
3. Ali JB, Chebel-Morello B, Saidi L, Malinowski S, Fnaiech F (2015) Accurate bearing remaining useful life prediction based on Weibull distribution and artificial neural network. Mech Syst Signal Process 56:150–172
4. Analytics I (2017) Predictive maintenance market report 2017–22. Market Report. IoT Analytics, Hamburg, Germany
5. Anderson JD Jr (2010) Fundamentals of aerodynamics. Tata McGraw-Hill Education, New York
6. Atamuradov V, Medjaher K, Dersin P, Lamoureux B, Zerhouni N (2017) Prognostics and health management for maintenance practitioners-review, implementation and tools evaluation. Int J Prognos Health Manage 8(060):1–31
7. Babbar A, Syrmos VL, Ortiz EM, Arita MM (2009). Advanced diagnostics and prognostics for engine health monitoring. Paper presented at the 2009 IEEE aerospace conference
8. Babel AS, Strangas EG (2014) Condition-based monitoring and prognostic health management of electric machine stator winding insulation. Paper presented at the 2014 international conference on electrical machines (ICEM)
9. Badea VE, Zamfiroiu A, Boncea R (2018) Big data in the aerospace industry. Inform Econom 22(1):17–24
10. Banaee H, Ahmed MU, Loutfi A (2013) Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges. Sensors 13(12):17472–17500
11. Baptista M, de Medeiros IP, Malere JP, Prendinger H, Nascimento Jr CL, Henriques E (2016) A comparison of data-driven techniques for engine bleed valve prognostics using aircraft-derived fault messages. Paper presented at the third European conference of the prognostics and health management society
12. Baraldi P, Compare M, Sauco S, Zio E (2013) Ensemble neural network-based particle filtering for prognostics. Mech Syst Signal Process 41(1–2):288–300
13. Batzel TD, Swanson DC (2009) Prognostic health management of aircraft power generators. IEEE Trans Aerosp Electron Syst 45(2):473–482
14. Bazovsky I (2004) Reliability theory and practice. Courier Corporation, North Chelmsford
15. Bock JR, Brotherton T, Grabill P, Gass D, Keller JA (2006) On false alarm mitigation. Paper presented at the 2006 IEEE aerospace conference
16. Bonissone P, Hu X, Subbu R (2009) A systematic PHM approach for anomaly resolution: a hybrid neural fuzzy system for model construction. Paper presented at the annual conference of the PHM society
17. Bonissone PP, Xue F, Subbu R (2011) Fast meta-models for local fusion of multiple predictive models. Appl Soft Comput 11(2):1529–1539
18. Bousdekis A, Magoutas B, Apostolou D, Mentzas G (2018) Review, analysis and synthesis of prognostic-based decision support methods for condition based maintenance. J Intell Manuf 29(6):1303–1316
19. Byington CS, Watson M, Edwards D, Dunkin B (2003) In-line health monitoring system for hydraulic pumps and motors. Paper presented at the 2003 IEEE aerospace conference proceedings (Cat. No. 03TH8652)
20. Cadini F, Zio E, Avram D (2009) Model-based Monte Carlo state estimation for condition-based component replacement. Reliab Eng Syst Saf 94(3):752–758
21. Campolucci P, Uncini A, Piazza F, Rao BD (1999) On-line learning algorithms for locally recurrent neural networks. IEEE Trans Neural Netw 10(2):253–271
22. Carta S, Medda A, Pili A, Reforgiato Recupero D, Saia R (2019) Forecasting E-commerce products prices by combining an autoregressive integrated moving average (ARIMA) model and Google Trends data. Future Internet 11(1):5
23. Chehade A, Song C, Liu K, Saxena A, Zhang X (2018) A data-level fusion approach for degradation modeling and prognostic analysis under multiple failure modes. J Qual Technol 50(2):150–165
24. Chen J, Ma C, Song D, Xu B (2016) Failure prognosis of multiple uncertainty system based on Kalman filter and its application to aircraft fuel system. Adv Mech Eng 8(10):1687814016671445
25. Clifton D, Tarassenko L (2006) Condition monitoring of gas-turbine engines. Transfer report, Department of Engineering Science, University of Oxford
26. Coussement K, Lessmann S, Verstraeten G (2017) A comparative analysis of data preparation algorithms for customer churn prediction: a case study in the telecommunication industry. Decis Support Syst 95:27–36
27. Daigle MJ, Goebel K (2011) A model-based prognostics approach applied to pneumatic valves. Int J Prognos Health Manag 2(2):84–99
28. DePold HR, Gass FD (1998) The application of expert systems and neural networks to gas turbine prognostics and diagnostics. Paper presented at the turbo expo: power for land, sea, and air
29. Di Maio F, Zio E (2013) Failure prognostics by a data-driven similarity-based approach. Int J Reliab Qual Saf Eng 20(01):1350001
30. Dixon MC (2006) The maintenance costs of aging aircraft: insights from commercial aviation, vol 486. Rand Corporation, Santa Monica
31. Dole CE, Lewis JE, Badick JR, Johnson BA (2016) Flight theory and aerodynamics: a practical guide for operational safety. Wiley, Hoboken
32. Du J, Wang S, Zhang H (2013) Layered clustering multi-fault diagnosis for hydraulic piston pump. Mech Syst Signal Process 36(2):487–504
33. Duesterhoeft W, Schulz MW, Clarke E (1951) Determination of instantaneous currents and voltages by means of alpha, beta, and zero components. Trans Am Inst Electr Eng 70(2):1248–1255
34. Eker ÖF, Camci F, Jennions IK (2012) Major challenges in prognostics: study on benchmarking prognostic datasets
35. El-Betar A, Abdelhamed MM, El-Assal A, Abdelsatar R (2006) Fault diagnosis of a hydraulic power system using an artificial neural network. Eng Sci 17(1)
36. Elangovan K, Krishnasamy Tamilselvam Y, Mohan RE, Iwase M, Takuma N, Wood KL (2017) Fault diagnosis of a reconfigurable crawling–rolling robot based on support vector machines. Appl Sci 7(10):1025
37. Elattar HM, Elminir HK, Riad AM (2016) Prognostics: a literature review. Complex Intell Syst 2(2):125–154. https://doi.org/10.1007/s40747-016-0019-3
38. Eltoukhy AE, Chan FT, Chung SH (2017) Airline schedule planning: a review and future directions. Industrial Management & Data Systems
39. Ethington JM, Sturlaugson LE, Schimert J, Wilmering TJ (2019) Predictive aircraft maintenance systems and methods incorporating classifier ensembles. In: Google Patents
40. Faulstich S, Hahn B, Tavner PJ (2011) Wind turbine downtime and its importance for offshore deployment. Wind Energy 14(3):327–337

41. Ferreiro S, Arnaiz A, Sierra B, Irigoien I (2012) Application of Bayesian networks in prognostics for a new Integrated Vehicle Health Management concept. Expert Syst Appl 39(7):6402–6418
42. Fitch E (1979) An encyclopedia of fluid contamination control for hydraulic systems
43. Forecast GM (2017) Forecast 2017–2036, Airbus, Growing horizons. In
44. Frederick DK, DeCastro JA, Litt JS (2007) User's guide for the commercial modular aero-propulsion system simulation (C-MAPSS)
45. Gao Y, Zhang Q (2006) A wavelet packet and residual analysis based method for hydraulic pump health diagnosis. Proc Inst Mech Eng Part D J Autom Eng 220(6):735–745
46. Gao Y, Zhang Q, Kong X (2003) Wavelet-based pressure analysis for hydraulic pump health diagnosis. Trans ASAE 46(4):969
47. Gavrilovski A, Jimenez H, Mavris DN, Rao AH, Shin S, Hwang I, Marais K (2016) Challenges and opportunities in flight data mining: a review of the state of the art. AIAA Infotech@ Aerospace, 0923.
48. Gertsbakh I (2013) Reliability theory: with applications to preventive maintenance. Springer, Berlin
49. Gomes JPP, Leão BP, Vianna WO, Galvão RK, Yoneyama T (2012) Failure prognostics of a hydraulic pump using Kalman filter. Paper presented at the annual conference of the prognostics and health management society
50. Gomes JPP, Rodrigues LR, Leão BP, Galvão RKH, Yoneyama T (2016) Using degradation messages to predict hydraulic system failures in a commercial aircraft. IEEE Trans Autom Sci Eng 15(1):214–224
51. Goupil P (2010) Oscillatory failure case detection in the A380 electrical flight control system by analytical redundancy. Control Eng Pract 18(9):1110–1119
52. Gu J, Zhang G, Li KW (2015) Efficient aircraft spare parts inventory management under demand uncertainty. J Air Transp Manag 42:101–109
53. Hayton P, Utete S, King D, King S, Anuzis P, Tarassenko L (2007) Static and dynamic novelty detection methods for jet engine health monitoring. Philos Trans R Soc A Math Phys Eng Sci 365(1851):493–514
54. He W, Williard N, Chen C, Pecht M (2014) State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation. Int J Electr Power Energy Syst 62:783–791
55. Hinton GE, Osindero S, Teh Y-W (2006) A fast learning algorithm for deep belief nets. Neural Comput 18(7):1527–1554
56. Huang G, Huang G-B, Song S, You K (2015) Trends in extreme learning machines: a review. Neural Netw 61:32–48
57. Illman PE (1995) The pilot's handbook of aeronautical knowledge. TAB Books
58. Jardine AK, Lin D, Banjevic D (2006) A review on machinery diagnostics and prognostics implementing condition-based maintenance. Mech Syst Signal Process 20(7):1483–1510
59. Jaw LC (2005) Recent advancements in aircraft engine health management (EHM) technologies and recommendations for the next step. Paper presented at the turbo expo: power for land, sea, and air
60. Jegadeeshwaran R, Sugumaran V (2015) Fault diagnosis of automobile hydraulic brake system using statistical features and support vector machines. Mech Syst Signal Process 52:436–446
61. Jia F, Lei Y, Guo L, Lin J, Xing S (2018) A neural network constructed by deep learning technique and its application to intelligent fault diagnosis of machines. Neurocomputing 272:619–628
62. Jian X, Dong F, Xu J, Li Z, Jiao Y, Cui Y (2018) Frequency domain analysis of multiwavelength photoacoustic signals for differentiating tissue components. Int J Thermophys 39(5):58
63. Jianzhong S, Fangyuan W, Shungang NJCJoA (2020) Aircraft air conditioning system health state estimation and prediction for predictive maintenance. 33(3):947–955
64. Jun H-B, Kim D (2017) A Bayesian network-based approach for fault analysis. Expert Syst Appl 81:332–348
65. Korvesis P, Besseau S, Vazirgiannis M (2018) Predictive maintenance in aviation: Failure prediction from post-flight reports. Paper presented at the 2018 IEEE 34th international conference on data engineering (ICDE)
66. Lampis M, Andrews J (2009) Bayesian belief networks for system fault diagnostics. Qual Reliab Eng Int 25(4):409–426
67. Le Son K, Fouladirad M, Barros A, Levrat E, Iung B (2013) Remaining useful life estimation based on stochastic deterioration models: a comparative study. Reliab Eng Syst Saf 112:165–175
68. Lei Y, Lin J, He Z, Zuo MJ (2013) A review on empirical mode decomposition in fault diagnosis of rotating machinery. Mech Syst Signal Process 35(1–2):108–126
69. Létourneau S, Famili F, Matwin S (1999) Data mining to predict aircraft component replacement. IEEE Intell Syst Appl 14(6):59–66
70. Li S, Zhang G, Wang J (2017) Civil aircraft health management research based on big data and deep learning technologies. Paper presented at the 2017 IEEE international conference on prognostics and health management (ICPHM)
71. Li Y, Kurfess T, Liang S (2000) Stochastic prognostics for rolling element bearings. Mech Syst Signal Process 14(5):747–762
72. Lin XS, Li BW, Yang XY (2016) Engine components fault diagnosis using an improved method of deep belief networks. Paper presented at the 2016 7th international conference on mechanical and aerospace engineering (ICMAE)
73. Lin Z, Zheng G, Wang J, Shen Y, Chu B (2016) The method for identifying the health state of aircraft hydraulic pump based on grey prediction. Paper presented at the 2016 prognostics and system health management conference (PHM-Chengdu)
74. Litt JS, Simon DL, Garg S, Guo T-H, Mercer C, Millar R, Behbahani A, Bajwa A, Jensen DT (2004) A survey of intelligent control and health management technologies for aircraft propulsion systems. J Aerosp Comput Inf Commun 1(12):543–563
75. Liu K, Feng Y, Xue X (2017) Fault diagnosis and health assessment of landing gear hydraulic retraction system based on multisource information feature fusion. Paper presented at the 2017 international conference on sensing, diagnostics, prognostics, and control (SDPC)
76. Lowe D, Tipping M (1996) Feed-forward neural networks and topographic mappings for exploratory data analysis. Neural Comput Appl 4(2):83–95
77. Lu J, Huang J, Lu F (2017) Sensor fault diagnosis for aero engine based on online sequential extreme learning machine with memory principle. Energies 10(1):39
78. Lu P-J, Zhang M-C, Hsu T-C, Zhang J (2001) An evaluation of engine faults diagnostics using artificial neural networks. J Eng Gas Turbines Power 123(2):340–346
79. Lv Z, Wang J, Zhang G, Jiayang H (2015) Prognostics health management of condition-based maintenance for aircraft engine systems. Paper presented at the 2015 IEEE conference on prognostics and health management (PHM)
80. Ma J, Su H, Zhao W-l, Liu B (2018) Predicting the remaining useful life of an aircraft engine using a stacked sparse autoencoder with multilayer self-learning. Complexity 2018
81. Mahantesh N, Aditya P, Kumar U (2014) Integrated machine health monitoring: a knowledge based approach. Int J Syst Assur Eng Manag 5(3):371–382
82. Marinai L, Probert D, Singh R (2004) Prospects for aero gasturbine diagnostics: a review. Appl Energy 79(1):109–126

83. Marzat J, Piet-Lahanier H, Damongeot F, Walter E (2012) Model-based fault diagnosis for aerospace systems: a survey. Proc Inst Mech Eng Part G J Aerosp Eng 226(10):1329–1360
84. Mobley RK (2002) An introduction to predictive maintenance. Elsevier, Amterdam
85. Moir I, Seabridge A (2011) Aircraft systems: mechanical, electrical, and avionics subsystems integration, vol 52. Wiley, Hoboken
86. Montgomery DC (2007) Introduction to statistical quality control. Wiley, Hoboken
87. Mosallam A, Medjaher K, Zerhouni N (2016) Data-driven prognostic method based on Bayesian approaches for direct remaining useful life prediction. J Intell Manuf 27(5):1037–1048
88. Müller M, Falk E, Meira JA, Sassioui R, Sate R (2020) Predicting failures in 747–8 aircraft hydraulic pump systems. Paper presented at the 2020 IEEE aerospace conference
89. Nayyeri S (2013) Aircraft jet engine condition monitoring through system identification by using genetic programming. Concordia University
90. Nieto PG, García-Gonzalo E, Lasheras FS, de Cos Juez FJ (2015) Hybrid PSO–SVM-based method for forecasting of the remaining useful life for aircraft engines and evaluation of its reliability. Reliab Eng Syst Saf 138:219–231
91. Ning S, Sun J, Liu C, Yi YJPotIoME, Part O: Journal of Risk, & Reliability (2021) Applications of deep learning in big data analytics for aircraft complex system anomaly detection. 1748006X211001979
92. Niu G, Yang B-S (2009) Dempster-Shafer regression for multi-step-ahead time-series prediction towards data-driven machinery prognosis. Mech Syst Signal Process 23(3):740–751
93. Oddan H (2017) Multivariate statistical condition monitoring. NTNU
94. Oppenheimer CH, Loparo KA (2002) Physically based diagnosis and prognosis of cracked rotor shafts. Paper presented at the component and systems diagnostics, prognostics, and health management II
95. Orchard ME, Vachtsevanos GJ (2009) A particle-filtering approach for on-line fault diagnosis and failure prognosis. Trans Inst Meas Control 31(3–4):221–246
96. Pecht M, Kapur KC, Kang R, Zhang S (2011) Foundations of reliability engineering
97. Peel L (2008) Data driven prognostics using a Kalman filter ensemble of neural network models. Paper presented at the 2008 international conference on prognostics and health management
98. Perez PL, Boehman AL (2010) Performance of a single-cylinder diesel engine using oxygen-enriched intake air at simulated high-altitude conditions. Aerosp Sci Technol 14(2):83–94
99. Petit-Renaud S, Denœux T (2004) Nonparametric regression analysis of uncertain and imprecise data using belief functions. Int J Approx Reason 35(1):1–28
100. Pingchao LHWSO (2007) Fault diagnosis based on wavelet package and Elman neural network for a hydraulic pump. J Beijing Univ Aeronaut Astronaut 1
101. Pitta S, Rojas J, Crespo D (2017) Comparison of fatigue crack growth of riveted and bonded aircraft lap joints made of Aluminium alloy 2024-T3 substrates—a numerical study. Paper presented at the Journal of Physics: Conference Series, Volume 843, conference 1
102. Plakandaras V, Gogas P, Papadimitriou T (2019) The effects of geopolitical uncertainty in forecasting financial markets: a machine learning approach. Algorithms 12(1):1
103. Qin W-L, Zhang W-J, Lu C (2016) A method for aileron actuator fault diagnosis based on PCA and PGC-SVM. Shock Vib 2016
104. Rabenoro T, Lacaille J, Cottrell M, Rossi F (2015) Interpretable aircraft engine diagnostic via expert indicator aggregation. arXiv preprint 1503.05526
105. Ratner B (2017) Statistical and machine-learning data mining: techniques for better predictive modeling and analysis of big data. CRC Press, Boca Raton
106. Sadough Vanini Z, Meskin N, Khorasani K (2014) Multiple-model sensor and components fault diagnosis in gas turbine engines using autoassociative neural networks. J Eng Gas Turbines And ower 136(9)
107. Salfner F, Lenk M, Malek M (2010) A survey of online failure prediction methods. ACM Comput Surv (CSUR) 42(3):1–42
108. Saxena A, Goebel K, Simon D, Eklund N (2008) Damage propagation modeling for aircraft engine run-to-failure simulation. Paper presented at the 2008 international conference on prognostics and health management
109. Schneider T, Helwig N, Klein S, Schütze A (2018) Influence of sensor network sampling rate on multivariate statistical condition monitoring of industrial machines and processes. Paper presented at the multidisciplinary digital publishing institute proceedings
110. Schwabacher M, Goebel K (2007) A survey of artificial intelligence for prognostics. Paper presented at the AAAI fall symposium: artificial intelligence for prognostics
111. Selcuk S (2017) Predictive maintenance, its implementation and latest trends. Proc Inst Mech Eng Part B J Eng Manuf 231(9):1670–1679
112. Shao-ping W, Qian-xia M, Chuan-qi L (2015) State recognition based on wavelet packet norm entropy for aircraft hydraulic pump. Paper presented at the 2015 international conference on fluid power and mechatronics (FPM)
113. Shao Y, Nezu K (2000) Prognosis of remaining bearing life using neural networks. Proc Inst Mech Eng Part I J Syst Control Eng 214(3):217–230
114. Sikorska J, Hodkiewicz M, Ma L (2011) Prognostic modelling options for remaining useful life estimation by industry. Mech Syst Signal Process 25(5):1803–1836
115. Sotiris VA, Pecht MG (2007) Support vector prognostics analysis of electronic products and systems. Paper presented at the AAAI fall symposium: artificial intelligence for prognostics
116. Sridhar S, Rao KU, Umesh R, Harish K (2016) Condition monitoring of Induction Motor using statistical processing. Paper presented at the 2016 IEEE region 10 conference (TENCON)
117. Strączkiewicz M, Klepka A, Staszewski WJ, Aymerich F (2014) Triple correlation technique for damage detection in composite materials. Paper presented at the key engineering materials
118. Sun J, Li H, Xu B (2016) Prognostic for hydraulic pump based upon DCT-composite spectrum and the modified echo state network. Springerplus 5(1):1–17
119. Susto GA, Schirru A, Pampuri S, McLoone S, Beghi A (2014) Machine learning for predictive maintenance: a multiple classifier approach. IEEE Trans Industr Inf 11(3):812–820
120. Swędrowski L, Duzinkiewicz K, Grochowski M, Rutkowski T (2014) Use of neural networks in diagnostics of rolling-element bearing of the induction motor. Paper presented at the key engineering materials
121. Tayarani-Bathaie SS, Vanini ZS, Khorasani K (2014) Dynamic neural network-based fault diagnosis of gas turbine engines. Neurocomputing 125:153–165
122. Tobon-Mejia DA, Medjaher K, Zerhouni N, Tripot G (2011) Hidden Markov models for failure diagnostic and prognostic. Paper presented at the 2011 prognostics and system health managment confernece
123. Tongyang L, Shaoping W, Jian S, Zhonghai M (2018) An adaptive-order particle filter for remaining useful life prediction of aviation piston pumps. Chin J Aeronaut 31(5):941–948
124. Uday P, Ganguli R (2010) Jet engine health signal denoising using optimally weighted recursive median filters. J Eng Gas Turbines Power 132(4)

125. Vachtsevanos GZ (2006) Intelligent fault diagnosis and prognosis for engineering systems. Wiley, Hoboken
126. Vanini ZS, Khorasani K, Meskin N (2014) Fault detection and isolation of a dual spool gas turbine engine using dynamic neural networks and multiple model approach. Inf Sci 259:234–251
127. Vianna WO, Gomes JP, Galvão RK, Yoneyama T, Matsuura JP (2011) Health monitoring of an auxiliary power unit using a classification tree. Paper presented at the proceedings of annual conference of the prognostics and health management society
128. Vianna WOL, Yoneyama T (2017) Predictive maintenance optimization for aircraft redundant systems subjected to multiple wear profiles. IEEE Syst J 12(2):1170–1181
129. Volponi AJ, DePold H, Ganguli R, Daguang C (2003) The use of Kalman filter and neural network methodologies in gas turbine performance diagnostics: a comparative study. J Eng Gas Turbines Power 125(4):917–924
130. Walton P (2018) Artificial intelligence and the limitations of information. Information 9(12):332
131. Wang K-S, Sharma VS, Zhang Z-Y (2014) SCADA data based condition monitoring of wind turbines. Adv Manuf 2(1):61–69
132. Wang WQ, Golnaraghi MF, Ismail F (2004) Prognosis of machine health condition using neuro-fuzzy systems. Mech Syst Signal Process 18(4):813–831
133. Wang X, Lin S, Wang S (2016) Remaining useful life prediction model based on contaminant sensitivity for aviation hydraulic piston pump. Paper presented at the 2016 IEEE international conference on aircraft utility systems (AUS)
134. Wang Y, Deng C, Wu J, Wang Y, Xiong Y (2014) A corrective maintenance scheme for engineering equipment. Eng Fail Anal 36:269–283
135. Wang Y, Kung L, Wang WYC, Cegielski CG (2018) An integrated big data analytics-enabled transformation model: application to health care. Inf Manage 55(1):64–79
136. Wang Y, Ma Q, Zhu Q, Liu X, Zhao L (2014) An intelligent approach for engine fault diagnosis based on Hilbert-Huang transform and support vector machine. Appl Acoust 75:1–9
137. Wang Z, Lu C, Wang Z (2014) Chaotic information-geometric support vector machine and its application to fault diagnosis of hydraulic pumps. J Vibroeng 16(2):1033–1041
138. Wu S-D, Wu P-H, Wu C-W, Ding J-J, Wang C-C (2012) Bearing fault diagnosis based on multiscale permutation entropy and support vector machine. Entropy 14(8):1343–1356
139. Xu J, Wang Y, Xu L (2013) PHM-oriented integrated fusion prognostics for aircraft engines based on sensor data. IEEE Sens J 14(4):1124–1132
140. Yan H, Sun J, Zuo HJPotIoME., Part I: Journal of Systems, & Engineering, C (2020) Anomaly detection based on multivariate data for the aircraft hydraulic system. 0959651820954577
141. Yan H, Zuo H, Sun J, Gao N, Wang F (2019) Research on anomaly detection of civil aircraft hydraulic system based on multivariate monitoring data. Paper presented at the 2019 IEEE AUTOTESTCON
142. Yan X, Zheng L (2017) Fundamental analysis and the cross-section of stock returns: a data-mining approach. Rev Financ Stud 30(4):1382–1423
143. Yang J, Zhang Y, Zhu Y (2007) Intelligent fault diagnosis of rolling element bearing based on SVMs and fractal dimension. Mech Syst Signal Process 21(5):2012–2024
144. Yang S-B, Wang L-B, Xu D (2018) Computational analysis on actuator failures of flexible aircraft. Int J Comput Mat Sci Eng 7(01–02):1850014
145. Yang X, Pang S, Shen W, Lin X, Jiang K, Wang Y (2016) Aero engine fault diagnosis using an optimized extreme learning machine. Int J Aerosp Eng 2016
146. You C-X, Huang J-Q, Lu F (2016) Recursive reduced kernel based extreme learning machine for aero-engine fault pattern recognition. Neurocomputing 214:1038–1045
147. You M-Y, Liu F, Wang W, Meng G (2010) Statistically planned and individually improved predictive maintenance management for continuously monitored degrading systems. IEEE Trans Reliab 59(4):744–753
148. Yu X, Jiang J (2015) A survey of fault-tolerant controllers based on safety-related issues. Annu Rev Control 39:46–57
149. Zeldam S (2018) Automated failure diagnosis in aviation maintenance using explainable artificial intelligence (XAI). University of Twente
150. Zhang C, Wang N (2012) Aero-engine condition monitoring based on support vector machine. Phys Procedia 24:1546–1552
151. Zhang P, Huang J-Q (2008) SRUKF research on aeroengines for gas path component fault diagnostics. J Aerosp Power 23(1):169–173
152. Zhang S, Mathew J, Ma L, Sun Y, Mathew AD (2004) Statistical condition monitoring based on vibration signals
153. Zhanlin W (2000) Trends of future aircraft hydraulic system. Hydraul Pnenm Seals 1
154. Zhaomin H, Shaoping W (2014) Wear status recognition of piston pump based on side frequency relative energy summation. J Beijing Univ Aeronaut Astronaut 2:8
155. Zitzler E, Künzli S (2004) Indicator-based selection in multiobjective search. Paper presented at the international conference on parallel problem solving from nature

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.