



## Review Article

# Prediction of Failure Time and Remaining Useful Life in Aviation Systems: Predictors, models, and challenges

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**Abstract**

In many important industries, such as aerial transportation, offshore wind turbine (OWT) structures, and nuclear power plants that reached or are near the end of their useful life, the structural conditions for continued usage are acceptable. Thus, safe continued operation with required modifications and assessment is more cost-effective than replacing them with a new system. To achieve this goal, many studies have been performed on predicting failure time and remaining useful life, especially in systems that require a very high level of reliability. The present review investigates the articles that predict the remaining useful life or failure time in aviation systems, from three perspectives: 1. Methods and algorithms, especially Machine Learning algorithms, which are growing in recent years in the field of Prognosis and Health Management. 2. Historical predictors such as working life history, environmental conditions, mechanical loads, failure records, asset age, maintenance information, or sensor variables and indicators that can be continuously controlled in each system, such as noise, temperature, vibration, and pressure. 3. Challenges of researches on prediction of the failure time of flying systems. The literature assessment in this field shows that using diagnostic and prognostic outputs to identify possible defects and their origin, checking the system's health, and predicting the remaining useful life (RUL) is increasing due to market needs.

**Keyword:** Aviation accidents; Failure time; Machine learning; Prognosis and health management; Remaining useful life.

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## 1. Introduction

Prognosis is one of the frequently repeated words in the medical world, which provides a prediction of the future state of the patient according to the clinical conditions of the patient and available medical facilities because the prognosis of various diseases plays an important role in clinical decision making for the physician [1]. The same interpretation and attitude are present in the industrial world, and a patient can be an industrial system, a device, or a component. Then, the prediction of the health status of the system using monitoring data will affect the diagnoses and maintenance decisions for the system. Due to long usage and customers' needs, many assets in different industries, such as aviation and military structures, offshore wind turbine structures (OWT), and nuclear power plants, have reached or are near the end of their useful life. However, they still have acceptable structural conditions for further use. These assets are valuable and expensive; thus, it is interesting and desirable for the owners to continue operations with them for economic aspects and replacement burden. The

prediction of remaining useful life is technically possible and economically beneficial because the cost of required maintenance activities is much lower than the cost of substitution with a new system [2]. This goal can be achieved by monitoring the system's health and maintaining reliability within the acceptable level. The condition-based maintenance calculates the probable failure time for the system or part and assures safe operation during this time. Prognosis and Health Management (PHM) predict the remaining useful life (RUL) using diagnostic outputs and prognostic and follows optimal maintenance policies for the systems and equipment. PHM identifies the potential faults and their origin and checks the system conditions to balance the highest level of availability and the lowest cost [3]. The time before a system fails and loses acceptable performance is called the remaining useful life [4, 5].

The purpose of the remaining useful life prediction is to anticipate the time of failure before it happens, according to the conditions that the system experienced in the past and the present condition [6]. The purpose of PHM is to prevent risks and financial losses that usually

are not compensable by predicting the air vehicles' remaining useful life or other health condition indicators. Aviation industries are now seeking prognostic and condition-based predictive maintenance rather than preventive maintenance and periodic inspections. Aviation health monitoring systems development requires advanced data acquisition systems and tedious, expensive, and time-consuming flight tests. However, the existence of such systems leads to a significant reduction in maintenance costs, man-hours, and financial losses. The models that can identify system defects using key characteristics and warn the system failures before occurrence are very useful and necessary for safe flight [7]. To establish predictive maintenance systems instead of preventive maintenance, it is necessary to define models that can predict the remaining useful life and the time of failure. Machine learning tools have grown in recent years and have shown acceptable performance in this field. The published articles on machine learning (ML) in the field of PHM from 2013 to 2019, based on the model type, are shown in Figure 1, which shows the growing trend of these tools in this field [8]. Convolution Neural Networks (CNN), Auto Encoder (AE), Long-Short Term Memory (LSTM), Deep Belief Networks (DBN), Deep Boltzmann Machine (DBM), Hybrid models, and Generative Adversarial Networks (GAN) are complete phrases related to the types of machine learning methods mentioned in the Figure 1.

The purpose of this study is to review the articles that predict the failure time and remaining useful life in the field of aviation accidents from three perspectives: 1. Predictors and variables 2. Methods and algorithms, especially ML algorithms, have been growing in recent years in PHM 3. challenges.

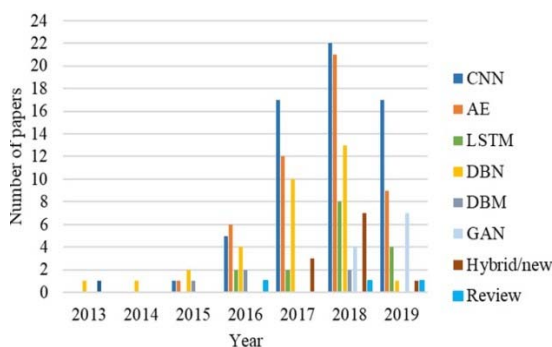


Figure 1. ML articles growth in the field of PHM in recent years [8]

## 2. Predictors and Variables

ML models predict the output variable by selecting system characteristics or input variables. ML models will have higher prediction capability if: firstly, the number of data is much enough, and secondly, the input variables are correctly selected and reflect the health status of the system. Model inputs play a key role in

reducing the prediction error and reaching a reliable failure time prediction. Some articles consider three categories to define the inputs of the prediction model technical health, design records, and environmental conditions [9,10]. The technical status of a system is measured with information such as working life history, environmental conditions, mechanical loads, failure records, asset age, maintenance information, and indicators that can be continuously controlled in each system, such as noise, temperature, vibration, and pressure. Shafiee presents a structured framework for RUL estimation to decide on life extension. It is suggested that first of all, the health of vital parts should be checked. Since the number of these parts is high, especially in complex systems, and checking all of them is difficult, these important and key parts can be identified with the techniques such as failure mode effect analysis (FMEA), fault tree analysis (FTA), and event tree analysis (ETA). This method is rational because the evaluation and control of the components that are in unfavorable conditions and have a destructive effect on the life and reliability of the system minimize the risk for the whole complex and increase the remaining useful life. Then, all data, including supervisory, operational, environmental, and breakdown data, would be collected and checked [11]. In real systems, more than one failure mode can be counted for the critical components and parts of a system, therefore, in such studies, the dominant failure mechanism is identified, and it is determinant in the prediction of failure time [9]. Using normalizing, statistical indicators, signal processing approaches, and reducing data dimensions, and raw data can be prepared to enter learning algorithms. In this way, ML algorithms work better, and the final model has higher validity and accuracy; this is called feature engineering [12]. The purpose of feature selection is to specify a subset of variables from the entire raw data, determine the optimal effective input data, and minimize the adverse effects of noise and irrelevant information errors as much as possible [13]. Figure 2 shows the place of feature engineering in ML models.

If these variables are too many or not enough, the answers of the model will be associated with false alarms. In a valid model, the rate of false alarms should be low and the correct detection rate is high as possible [3]. The defined feature engineering for each system is specific for it and is not generalized for others. In addition, it depends on the knowledge and experience of the system experts. Therefore, its correct implementation is difficult; in the meantime, Deep learning (DL) networks help to find features by structural matching between the model and data. DL models do not need feature engineering [14]. DL will be discussed in more detail in the next section.

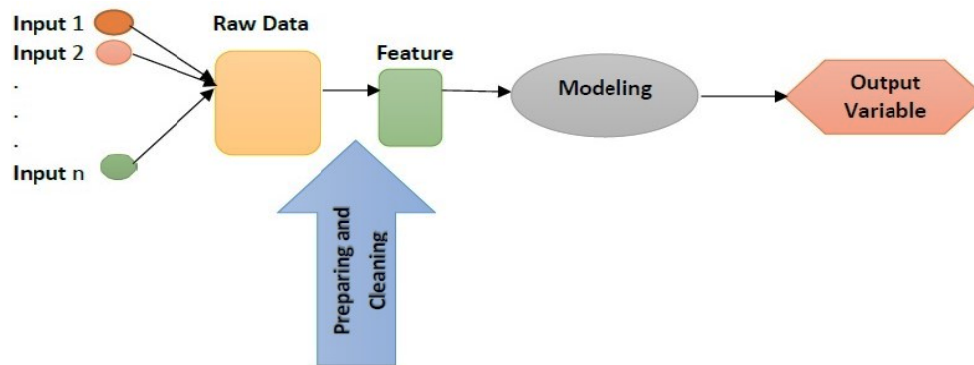


Figure 2. Feature engineering in the structure of the ML

The life of aircraft systems, their performance, and the health of components significantly depend on the environmental conditions in which the aircraft is operated. The humidity, temperature, vibration, loading, corrosive environment, environmental pollutants, and ultraviolet rays affect the performance of the components and parts. The safety of aircraft structures is affected by corrosion and fatigue, which are important factors in damage tolerance analysis on the performance and integrity [15]. According to the mentioned items, the calculation and prediction of the failure time of the structure after passing the determined life heavily correlate with the current health status and the history of the structure's failures. In addition, it is possible to use the investigation of environmental factors' effects, records of failures, and technical examination and inspection for the health monitoring of aerial structures, as the input variables for a failure time prediction model.

Human errors in repairs and maintenance are considered a cause of aviation accidents because articles present that for some the flight systems like helicopters probability of an accident is more in the early hours after repairs and maintenance [16]; so, the variable "Duration since the last inspection" can be proposed as a predictor variable for anticipating of an accident.

Control metrics, time since the inspection, adverse weather metrics, max elevation, and cabin temperature are characteristics that were propounded for the occurrence of aviation accidents [17]. Some variables that are considered to enter the model for predicting of helicopter accidents are: (a) the maximum takeoff weight (MTOW) [18]; (b) the diameter of main rotor [18]; (c) the number of main rotor blades [18,19]; (d) the type of engine [18,19] and (e) the number of engines [18,19].

Some researchers consider ways to increase the reliability and make the failure time far as possible. The redundancy allocation problem is revisited for reliability optimization, which results in a GA-based redundancy strategy called K-mixed to improve system reliability as a combination of active and standby redundancy strategies [20]. An appropriate model is

developed to take dependent failures, which are a common cause and load share, into consideration for evaluating redundant systems' reliability and MTTF. Based on the Markov chain, three models are used to evaluate the MTTF of a 2-out-of-3 redundant system by considering dependent failures [21].

### 3. Methods and Algorithms

In general, four approaches to PHM can be perceived from the literature [22,23]:

- a) Model-based or physics-based approaches that seek explicit and clear mathematical models to predict RUL [24]
- b) Data-based approaches or Data-driven, where predictive knowledge is extracted from a large volume of data
- c) Approaches based on the judgment of experts
- d) Combined approaches that are a combination of the aforementioned items. This combination can be any of the three states mainly seen in the model-based and data-based approaches [25]. There are few studies on hybrid approaches and limited articles in this field [24,26]. Due to the difficulty of building accurate models for complex systems, the application of model-based approaches is limited, but in contrast to data-driven approaches, they are models that learn the performance of systems directly from data and do not have the limitations and disadvantages of model-based methods. Therefore, in recent years, they have received wide attention and are divided into two categories: ML approaches and statistical learning approaches [27]. In the research related to failure prognosis, most articles are devoted to ML/DL-based data [28]. ML refers to tools that can extract patterns from data, predict future data using undiscovered patterns, and make decisions under uncertainty [29]. On the other hand, the process of collecting data from the equipment to check and predict the accuracy of the system state

for the data-driven approaches is the most important part of the problem. Data unavailability can be a key challenge in these approaches [30]. The data can be from sensors or event data [31]. Sensor data refers to the parameter values obtained from the system measurement, such as voltage, current, temperature, vibration, and pressure. The mechanical, magnetic, electrical, and event data includes the appropriate procedures for repair and maintenance that the operators and employees have performed and recorded according to the different conditions of the systems and equipment [28]. DL is a subset of ML and ML is a very useful subset of artificial intelligence. Deep neural networks (DNN) have more neurons and hidden layers than normal neural networks, and subsequently, the number of weights in these networks is much higher, so it has higher learning ability. CNN, Recurrent Neural Networks (RNN), AE, and GAN are among DNNs. The application of ML tools has recently made extensive progress in the field of reliability, failure time prediction, and PHM. The wide application of ML in reliability engineering can be studied in [32].

Figure3 shows the categories of ML and the subcategories, which include a) Supervised learning, b) Unsupervised learning, c) Semi-supervised learning, and d) Reinforcement learning .Table 1 introduces and shows some of the most important types of ML models for the four mentioned categories along with their advantages and disadvantages [32], in the meantime, as a few examples of the use of machine learning models in the field of reliability, the following item scan be mentioned:

basic linear regression (LR) [33], polynomial response surface (PRS) [34], random forest regression (RFR) [35], decision tree regression (DTR) [36-39], Bayesian network [40, 41], can be mentioned. In addition, deep learning networks have emerged as a very effective tool for pattern recognition, which has the potential to improve the performance in current intelligent prognostication. Newer tools such as DNN models [42-44], LSTM [45,46], RNN [47], CNN [48,49], AE networks [50], Support Vector Regression (SVR) [51,52], have been used in the field of reliability in the recent years and result in good and significant results.

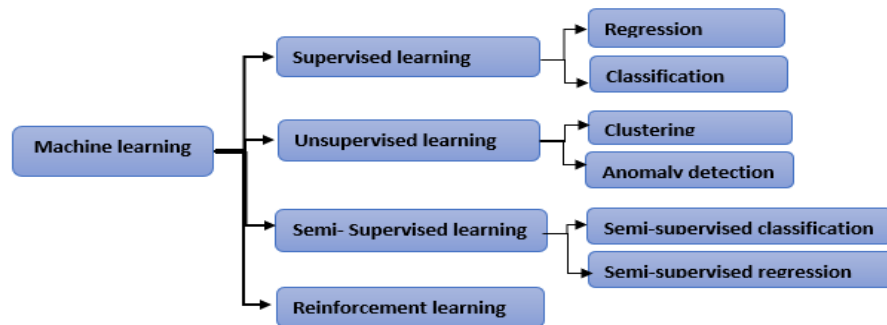


Figure 3. Tree diagram of ML categories [32]

Table 1. Introduction of the most important types of ML models [32]

ML model	Advantage	Disadvantage
Support vector regression (SVR)	1. High prediction precision and efficiency in comparison with the traditional models 2. Potent to data noise	1. It is not appropriate for data with high dimensions and sparse 2. Need previous knowledge to determine kernel
Relevance vector machine (RVM)	1. High prognostic precision in comparison with the traditional models	1. It is not appropriate for data with high dimensions and sparse
Deep neural network (DNN)	1. Supreme long- and mid-term prediction precision and high training power	1. It is expensive computationally 2. Interpretation of the ‘black box is difficult
Convolutional neural network (CNN)	1. It has high prediction precision for multidimensional and nonlinear data	1. It needs a lot of data for training 2.. It is expensive computationally
Recurrent neural network (RNN)	1. It does not need previous knowledge and investigation of data	1. Problem of vanishing gradient

ML model	Advantage	Disadvantage
	2. High prediction precision in comparison with the traditional models	
Deep bidirectional long short-term memory (LSTM)	1. It does not need previous knowledge 2. High precision and efficiency 3. It can analyze time-varying systems well	1. Over fitting problem 2. It is expensive computationally
Gaussian process regression (GPR)	1. Great learning and Model parameter update power 2. High prediction precision and efficiency in comparison with the traditional models 3. It is appropriate for complex, multidimensional, and nonlinear system	1. Need previous knowledge to determine kernel
Decision tree (DT)	1. High precision with great learning	1. Not potent to data with noise
Random Forest (RF)	1. High prediction precision and appropriate for discrete classification	1. Interpretation of the 'black box is difficult 2. More complexity compared to DT
K-nearest neighborhood (KNN)	1. High prediction precision and efficiency	1. It is not appropriate for data with high dimension 2. Not potent to data noise
Support vector classification (SVC)	1. Faster than in comparison with the traditional models 2. Better prediction precision 3. Potent to data with noise	1. It is not appropriate for data with high dimension 2. Need previous knowledge to determine kernel
Gaussian process classification (GPC)	1. Great computational power for complex system	1. Requires prior knowledge for kernel selection
Support vector machine (SVM)	1. Powerful models for feature extraction 2. High detection power for system anomalies	1. It is not appropriate for data with high dimensions and sparse 2. Need previous knowledge to determine kernel
Radial basis network (RBN)	1. High precision and robustness.	1. Interpretation of the black box is difficult
Bayesian networks	1. High precision and efficiency for complicated systems and discrete classification	1. Need previous knowledge
Self-organizing map (SOM)	1. High accuracy for detection of the fault	1. Interpretation of the 'black box is difficult
Graph-based model (GBM)	1. Supreme self-learning power and visualization of data 2. High precision and efficiency	1. Need previous knowledge
One class support vector machine (OCSVM)	1. Accurate prediction	1. It is not appropriate for data with high dimension
Semi-supervised Support vector machine(S3VM)	1. Appropriate precision for high-dimensional system	1. Not potent to noisy data

Li et al., using simulated data, designed several deep convolutional neural networks for the NASA turbofan engine degradation problem to estimate the remaining useful life of each engine. The results of this study indicate a promising approach for prognosis based on data [53]. Khalif et al., conducted on the turbofan engine degradation data set available at NASA, tried to estimate the RUL of the equipment directly from the sensor values. In the mentioned method, estimation of degradation modes or failure threshold is not required, a support vector regression model was used to determine the relationship between health indicators and sensor values [54]. Jun et al. proposed a PHM technique to

increase the useful life of tactical missiles and by examining the application of classical techniques, engineering approaches to data acquisition architecture, life destruction factor analysis, and life prediction process [55]. Another study predicted helicopter accidents in the United States with the help of ML tools; among different ML techniques, DNN showed the best performance [18]. Ma et al. designed a PHM system to predict the remaining useful life of the aircraft engine with the approach of life prediction and fault diagnosis, as well as checking the health status of the system. For this purpose, performance reduction characteristics were

measured with the help of several sensors on the engine, and AE and logistic regression models were used [56]. Liu et al. predicted the remaining useful life of the aircraft engine using a data-based model, with the help of CNN, and detecting the risk of equipment failure and consequently reducing losses demonstrated the effectiveness of this proposed structure [57]. Farsi developed a convolutional neural network based on the raw data recorded by the vibration sensor and transformed to the frequency domain. This algorithm can detect a defective bearing from a healthy and perfect bearing and then determine the location and size of the damage[58].De Potter et al. designed a predictive repair and maintenance model for the remaining useful life of the aircraft fleet. The structure of the model is such that these forecasts are updated periodically, and based on the evaluation of these forecasts over time, alarms are created, and by activation of alarms, the maintenance program is planned. The mentioned model, with the help of a convolution network was designed for a fleet of 20 planes with 2 types of turbofan engines [59]. Lee and Mitty Kay (2022) proposed a plan for repairs and maintenance with high reliability and reasonable cost. For this purpose, they evaluated various traditional and predictive maintenance strategies. This study investigated Gaussian process learning models and adaptive sampling for all maintenance plans. Finally, they concluded that predictive maintenance and repairs based on remaining useful life prognosis were superior to other plans [60]. Subagia et al. investigated the relationship between helicopter accidents and their configuration and examined 825 accidents from 2005 to 2015.They only considered characteristics such as the number of main rotor blades, the number of engines, rotor diameter, and take-off weight, in the mentioned study, the logistic regression model with the response variable of the probability of accidents was used [61]. Sampaio et al. proposed a method that simulates the collected data from a vibration system for an engine. These collected values enter the test and training dataset into a neural network and predict the failure time. A model was built to simulate normal engine vibrations and measurements instead of real accelerometers, and ML tools were used to make predictions [62]. Zhao et al. focused on the remaining useful life prediction of an

aircraft engine in a progressive degradation mode. In their paper, they pointed out that there is a certain relationship between the degradation process and the remaining useful life, and they tried to learn this destruction pattern by a neural network that reflects this relationship [63]. Celikmih et al., for the prediction of aircraft system failures, offered Multilayer Perceptron (MLP) model as an artificial neural network (ANN), support vector regression (SVR), and linear regression (LR) as ML. The aircraft equipment maintenance and failure data were collected in two years, and nine input variables were determined; a hybrid data preparation model is proposed to improve the success of failure number prediction in two steps. In the first step, a feature selection method is used for feature evaluation to find the most effective and ineffective parameters. In the second step, a K-means algorithm is modified to remove noisy or inconsistent data [64]. Liu et al. predicted the remaining useful life of aircraft engines with the help of 7 input variables and using LSTM networks [65]. Another study that was conducted on the NTSB aviation accident data by Zhang, investigated aviation accidents and the probability of death on the NTSB accident database using (LSTM) [66]. In addition, Zhang et al. constructed a formulated Bayesian network to show causal relationships in the sequence of NTSB incidents [67].

#### 4. Current Challenge

To examine the challenges in the mentioned field more closely and to reveal the research opportunities and gaps in this research field, 7 leading articles are compared with details in Table 2. One of the existing challenges in the studies investigating the failure time (especially in aerial accidents) is the lack of availability of run-to-failure sensor data in real conditions. Most of the studies in the field of calculating the failure time of aerial accidents have used the simulation data, e.g., the NASA data bank, CMAPSS, which has simulated the sensor data related to the failure of the aircraft engine until the moment of the failure, or other data that are mostly simulations.

**Table 2.** Articles in the field of calculation of failure time in aviation systems with simulation data

Author	Output Variable	Number and type of data	Case study	Prediction model
Xu et al. 2020 [17]	the occurrence or non-occurrence of an accident	13055 real data from NTSB helicopter accident	-	K-nearest- neighbor (KNN) Decision tree (DT) AdaBoost DT (ADT) Random forest (RF) Naïve Bayes (NB) and(DNN)
De pater et al. 2022 [57]	Estimate of remaining useful life	C-MAPSS simulation data - 4 databanks of 100 or 250 - NASA data	Airplane turbofan engine	CNN

Author	Output Variable	Number and type of data	Case study	Prediction model
Liu et al. 2021 [64]	Estimate of remaining useful life	C-MAPSS simulation data - 4 databanks of 100 or 250 - NASA data	Aircraft engine failure data	(LSTM)/ Clustering (RNN) / Linear Programming (LP)
Zhanget al. 2021 [65]	Is the plane damaged or not? Is there a possibility of death or not?	1675 Data - NTSB Actual Data Bank	Airplane accident	(LSTM)
Zhang et al. 2021 [66]	Showing causal relationships in the sequence of events	NTSB Actual Data Bank		Bayesian networks
Zhao et al. 2017 [62]	Estimate of remaining useful life	Simulation data	Engine airplane	Neural network
Jiao et al. 2020 [5]	Estimate of remaining useful life	C-MAPSS simulation data - 4 databanks of 100 or 250 - NASA data	Aircraft engine failure data	Gap-DBN SVDD Particle filter
Sampaio et al 2019 [61]	Prediction of failure time	9180 simulated data	Cooling fan vibrations	Artificial Neural Network (ANN), Regression Tree (RT), Random Forest (RF), Support Vector Machine (SVM)

Table 2 shows that the proposed methods heavily depend on the training data. But, failure data in the aviation system is not available enough to reach the required level of confidence now. The unavailability of run-to-failure sensor data is a major limitation in calculating the failure time and accidents, which can be considered in future research. The clustering methods and PCA (principle component analysis) can be augmented to them to minimize the required data and optimize the test conditions.

The second challenge is that the failure time prediction is usually made as a static calculation based on historical data. Then, the degrading condition of the system is not considered. The proposed method output can be updated using data fusion with monitoring signals. In this way, the maintenance credit for the air vehicles can be shown to the standard authority organizations and limitations of the training dataset can be compensated with monitoring data to some extent.

The third challenge is related to the balance of model-based and data-driven prediction algorithms. Both of them lack some things to fulfill the required precision and validity domain. Thus, a fair combination of two methods augmented with the ML techniques can be used to cope with the dynamic behavior of the air vehicles' health. The innovative idea is to use non-physical models to determine the residuals for failure time prediction and fault distinguishing. This method can eliminate the model-based problem and help use the available data on direct training instead of physical model parameter estimation. In addition, the non-physical models can be valid for larger flight conditions and aircraft configurations.

## 5. Discussion and Conclusion

ML algorithms are widely used in many engineering fields and show satisfactory performance in real applications. In the present work, the prediction of failure time in the field of aviation accidents was investigated. The tools, models, predictors, variables, and challenges in this field were discussed. Investigations showed that ML models in the field of the aviation industry provide increasing performance and are considered powerful tools for predicting failure time and RUL. The variables and factors of accidents predictor were mentioned mainly for airplanes and helicopters in different studies. In the case of helicopter accidents, the maximum take-off weight, the diameter of the main rotor blades or the diameter of the rotor, the number of main rotor blades, the type of engine, and the number of engines were among the variables used in some studies. The C-MAPSS dataset with 21 variables was used in several studies to analyze airplane engine accidents.

Due to the complications of the model-based or physics-based approaches, researchers have widely used data-driven approaches. On the other hand, having a database with accurate and sufficient data is considered the first step and challenge of using data-driven approaches.

Sometimes the run-to-failure sensor data is unavailable, making it hard to analyze and predict failure based on data. According to the use of simulation data in aviation industry articles and the high cost and risk of flight testing, this issue seems to be one of the most important challenges for future studies in this field.

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