Research on Fault Prognosis Methods Based on Data-driven: A Survey

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Abstract. Fault prognosis technology, as the key to realize autonomy support and carry out condition-based maintenance (CBM), has been fully developed and researched in recent years. In this paper, the existing fault prediction methods are briefly summarized and studied, and focused on the data-driven prediction method. In the light of the scale of data, all kinds of prediction methods are divided into small sample-based and large sample-based fault prediction methods. The basic principles, advantages and disadvantages of each type of typical analytical methods are summarized, and finally, we put forward the research prospect the development direction of future data-driven fault prediction.

1. Introduction
Regardless of whether it is in the civil field or the military field, aviation equipment has extremely high reliability requirements. In the process of using equipment, the maintenance support cost accounts for 24% of the entire life cycle cost of the equipment [1]. To effectively solve the problems of high maintenance cost and low supporting efficiency, the condition-based maintenance theory was proposed and fully developed. As the core of condition-based maintenance, fault prognosis technology has received the attention and research of scholars in recent years.

Fault prediction refers to the relevant maintenance personnel using the existing knowledge and experience, using appropriate prediction methods to analyze the operating state of existing equipment, predicting the operating state of equipment in a certain period of time in the future, and predicting possible failures when it occurs, in what way, and then taking effective and reasonable maintenance support measures to isolate the failure and ensure the normal operation of the equipment [2,3]. The content of fault prognosis includes: predicting the type of fault; predicting the time sequence of fault occurrence, involving the time of fault occurrence and equipment status monitoring; predicting the remaining service life of each component of equipment [4].

Notable results have been achieved in the study of fault prediction methods. Hou Xiaodong [5] proposed a condition-based method based on summarizing the original prediction methods by dividing the object of fault prediction into elementary level, component level, sub-system level and system level. Sun Qiang [6] summarized the problem of uncertain fault prediction and proposed four classification methods based on randomness, ambiguity, grayness and uncertainty. In general, failure prediction methods can be subdivided into the following three categories: knowledge-based fault prediction methods, failure physics-based fault prediction methods, and data-driven fault prediction methods [3, 7, 8].

Knowledge-based fault prediction does not require the establishment of complex models, but predicts the time of equipment failure according to the abundant knowledge experience, reliability theory and
related prediction algorithms of experts in related fields. This kind of method needs experts to accumulate a lot of knowledge information and establish knowledge base in daily work. Knowledge-based prediction methods include expert systems, Bayesian networks, et al. Although the knowledge-based forecasting method is relatively simple and the medium- and long-term forecasting effect is better, it also has some limitations, such as being easily limited to expert knowledge and experience.

The fault prediction method based on failure physics is based on the failure mode and mechanism of equipment components, and establishes a corresponding failure degradation model to predict its remaining life. The physical-based fault prediction method is founded on the fact that the process of equipment failure is a cumulative process, and the resulting failure is a gradual failure. The key systems of equipment, such as mechanical systems, power electronic systems, have different failure. Analysis and modeling usually use stress-strain method, corrosion and wear analysis method and accelerated life test method. Common physical models include stress-strength model, reaction model, weakest link model and fiber bundle model (rope model). Benmoussa [9] et al. established ordinary differential equations based on the kinetic principles of parameter degradation to predict the remaining service life of mechanical systems and achieved relatively accurate results. Fault prediction based on failure physics is often applied in the engineering field, especially for the cumulative damage process, using the degradation model to achieve a more accurate prediction of remaining service life.

The data-driven fault prediction method is to use the existing methods of data collection, processing, and analysis to maximize the internal knowledge and laws of various data during the use of equipment, to predict the upcoming faults of the system, and determine the location information and category of the fault. With the advent of the era of industrial big data, research on data-driven fault prediction methods has also become a research hotspot in related fields. Peng Yu [10] et al. divided data-driven fault prediction methods into direct data and indirect data-driven prediction methods, and analyzed the cycle life prediction examples of lithium batteries. Hu Changhua [11] summarized the three types of failure prediction techniques from failure data, degraded data and multi-source data fusion, such as the uncertainty in data-driven prediction. Djeziri [12] et al. realized the offline estimation and online prediction of RUL through the analysis methods of online data-driven and offline data-driven prediction and analysis of the data availability of the degradation process. Prajapati [13] et al. found that using existing subsystems to collect statistical data and build a software processing layer to achieve state-based maintenance, the process is simple and the cost is low. Through many literatures in the analysis set, the data-driven fault prediction method has become the best method for fault prediction for large complex equipment, high reliability elements and components that are difficult to analyze failure mechanisms. In this paper, the existing data-driven fault prediction methods are sorted and classified to provide a certain reference for the selection of data-driven fault prediction methods.

The core of data-driven fault prediction is to use equipment usage data and fault data, according to the correlation of the data, fully tap the internal connections and hidden information of the data, and use the data to analyze the potential faults of the equipment to achieve the purpose of fault prediction. There are numerous data-based fault prediction methods and algorithms. In this paper, according to the size of the data capacity, it is divided into fault prediction based on small sub-sample data and large sub-sample data, and the most basic ones are summarized for each method, the related algorithm theory is shown in Figure 1.
2. Fault prediction method based on small sample data
The use of high-reliability equipment and the new equipment just put into use, the amount of data collected is small, in this case, fault prediction based on small sample data is very necessary.

2.1. Time Series Prediction
Time series prediction is based on the randomness of the data distribution, treating the data as a random number sequence, and then arranging it in chronological order, analyzing the change trend of data variables with time, establishing a corresponding model, and fitting the time series to achieve the prediction purpose. Time series data essentially shows the following trend between random variables and time. Yang Haimin summarized the prediction methods of time series, introduced three prediction methods based on time series, and gave three characteristics: the current data is related to the data at the previous moment; the stability and non-stationarity of the time series; the size of the time series data gradually becomes larger [14]. The most basic models of time series models are Auto Regressive model (AR), Moving Average model (MA) and Auto Regressive Moving Average model (ARMA), of which ARMA is the most frequently used model. Hu Zewen [15] used the ARMA fault prediction model to simulate the voltage value of a piece of equipment, and obtained a confidence interval for the voltage value prediction with high reliability, which provided better data support for fault prediction.

The time series fault prediction method performs data analysis on small sample data, and the workload is relatively small, which can predict short-term faults well. With the deepening of research, time series analysis has also expanded more methods, such as based on multiple time Vector Auto Regressive model (VAR) for sequence analysis. Ni Yanyan [16] used multivariate data to fit VAR and compared it with the prediction effect of AR model fitting, and concluded that the prediction result of VAR was more accurate. Meng Yao [17] proposed a multi-scale chaotic time series fault prediction method. After the original temperature data was de-noised, the current carrying fault of the power equipment was predicted and the results showed that the prediction accuracy was high and the error was small. Sun Bo [18] researched and proposed a time series quadratic exponential smoothing prediction model based on the monitoring data of known characteristic parameters, which can simultaneously predict multiple failure modes.

The prediction method based on time series has good prediction accuracy for the prediction of small sample data, but it also has certain limitations. The prediction interval is short, and it is impossible to achieve high-precision fault prediction in the medium and long term. In addition, time series fault prediction methods are also integrated with other methods.

2.2. Grey model
Grey forecasting model [19] can realize forecasting under the condition of small data volume and lack of information. The gray theory was first proposed by Professor Deng Julong. The gray system theory is to use the gray sequence generated by the original data to reduce the randomness of the data, analyze...
its potential laws, and utilize the dynamic conversion between the difference equation and the differential equation to separate the gray sequence. The data establish a continuous differential equation, and then uses the solution of the dynamic differential equation to "whiten" the gray model to achieve an accurate prediction.

The most basic model of the gray model is the GM (1,1) model. Its establishment is to generate a generation sequence from an original data sequence through cumulative changes. The differential equation established for the generation sequence is the GM (1,1) model. For higher-order systems, the GM (1,1) model evolves into the MGM (1, n) model. The MGM (1, n) model is a first-order differential equation system, which is to establish an n-ary first-order differential equation system for the generated sequence. The gray model has obvious advantages in processing information and incomplete data for fault prediction. After years of development, the gray model has been widely used. Zhu Huayuan [20] et al used the GM (1,1) model to predict the failure of military aircraft flight control system sensors, and then optimized the GM (1,1) model using a homogeneous exponential function before realizing the prediction. The results showed that the optimized model has higher prediction accuracy. Zhang Guangyi [21] summarized and analyzed the gray theory and model, gave the steps of gray fault prediction, and took a certain type of airborne radio station as the research object, and predicted it based on the FM transmit power as the original data sequence. The results show that the prediction effect is better.

However, the gray model prediction method has low accuracy in the mid and long-term fault prediction, and high short-term fault prediction accuracy. This also pushes the gray model to combine with other prediction methods, and makes full use of the gray variable’s ability to integrate random data, and mine the implicit rules of the data.

2.3. Fuzzy Theory
The fuzzy theory is based on the ambiguity (uncertainty) of the object itself, and uses the uncertainty between the failure symptoms and the cause of the tested object to realize the failure prediction. Fuzzy theory is the earliest and widely used in the field of control. In fault prediction, it is mainly aimed at systems that cannot obtain a more accurate model and have less sample data, and the key to application is the representation of membership (Membership function, the value is between 0 and 1). Its mathematical basis is fuzzy sets and intuitionistic fuzzy sets [22]. The relationship between the fuzzy relationship matrix of fault prediction and the state set and fault set [23] can be expressed as

\[ Y = X \times R \]

Among them, \( X = \{x_1, x_2, \ldots, x_n\} \) is a state parameter set, \( Y = \{y_i\} \) is the fault set, \( R = \{Y_0\} \) is fuzzy relationship matrix.

Although the fault prediction method based on fuzzy theory is relatively mature, it still needs experience accumulation and expert knowledge to assist in decision-making. Liu Zhanjun [24] et al. used fuzzy theory and domain expert experience to establish an aircraft fault prediction system based on fuzzy prediction. Rough set theory and Vague set theory developed by fuzzy set theory is also used in fault prediction. Fuzzy sets study the uncertainty of each element within the set, and rough sets study the uncertainty between sets [25], Vague set theory generalizes the membership function, and believes that the membership function is not a single value, but a subinterval on [0,1], which can more accurately represent fuzzy information [26]. In addition, the fuzzy neural network formed by the combination of fuzzy theory and neural network has also become a research hotspot [8].

2.4. Support Vector Machines
Support Vector Machine (SVM) has obvious advantages in a small sample, nonlinear data classification and regression prediction analysis. Support vector machine belongs to a method of machine learning. The essence is to find the maximum margin hyperplane to realize data classification. The key to support vector machine is that only by finding a suitable kernel function can it fully reflects its strong generalization ability and high prediction accuracy, and the improved SVM has better results. Lin Xiangliang [27] analyzed the basic principles of support vector machines, summarized the basic
algorithms of support vector machine methods improved in recent years (FSVM, LSSVM, NN-SVM, BS-SVM), and pointed out its huge potential for application. Dai Linchao [28] used the principle of SVM regression algorithm to predict the airborne gyro from single SVM, multi-scale regression SVM, and multi-scale LS-SVM. The prediction results show that the optimized LS-SVM is better. Ju Jianbo [29] and other improved SVM regression algorithms, proposed weighting adaptive cropping SVM algorithm, which accelerates the speed and accuracy of the algorithm, and is verified based on a certain type of communication station as an example.

3. Fault prediction method based on large sample data
With the advent of the era of big data, various advanced sensor integration applications, equipment usage data, condition data, and fault data are large and the information is complex. This section summarizes the current research methods of large sample data for fault prediction.

3.1. Principal Component Analysis
Principal Component Analysis (PCA) is to convert high-dimensional data information into data with obvious low-dimensional features through feature extraction. These low-dimensional data contain a lot of information about the original data and the mapping is linear. Based on the principal component analysis, there are also Kernel Principal Component Analysis (KPCA) and Dynamic Principal Component Analysis (DPCA). Kernel Principal Component Analysis improves the mapping principle of principal component analysis and incorporates nonlinear mapping into principal component analysis; Dynamic Principal Component Analysis is proposed to solve the problem of dynamic multivariate function mapping. References [30, 31] performed detailed calculations on the above three principal component analysis steps. According to the improved KPCA, Zhang Ke [32] used the dichotomy method to optimize the nuclear parameters, and realized the fault detection of the electric spindle more accurately.

As a statistical method for processing complex data, PCA has become an important method for many scholars to refine the features of big data. Jiang Zhunan [33] et al conducted a principal component analysis and prediction on the flight data of nearly one thousand flights for the failure of the trailing edge flap sensor in the civil aircraft flight control system, and accurately analyzed that the sensor will fail after a specific flight. The advantages of principal component analysis of data preprocessing are not only used in fault prediction, but also in fault detection.

3.2. Machine learning
In recent years, artificial intelligence technology has been widely used in the field of fault prediction, and the core of artificial intelligence is machine learning. Under large sample data, machine learning can perform better data analysis and mining. Common machine learning algorithms used for fault prediction are deep learning [34], decision tree algorithm [35], random forest [36], and artificial neural networks. Artificial neural networks are relatively mature in their research. Neural network has obvious advantages for processing complex information and large amounts of data. It does not require too much prior knowledge. It has strong self-organization ability, strong nonlinear mapping ability of neural network structure, and outstanding generalization ability. The basic structure of the neural network is shown in Figure 2.
The neural network is composed of an input layer, a hidden layer and an output layer. In the data training process of using a neural network, the weights between neurons are usually changed to realize non-linear mapping, and then integrated by the activation function to achieve multi-parameters and multi-step prediction. From the most basic neural network types such as BP neural network, RBF neural network and Elman neural network, etc., to CNN (Convolutional Neural Networks), RNN (Recurrent Neural Network) etc. in deep learning, different neural network structures are not the same, but the basic structure is as shown in the figure 2. Although the neural network has its advantages, it also has some shortcomings, such as slow convergence and longtime consumption during network training, difficult to determine the network structure, and it is easier to fall into local optimum. In this regard, many experts and scholars have proposed different algorithms to solve the corresponding problems. Zeng Huijie et al. used the two-way LSTM neural network fault prediction method and verified it with the C-MAPSS data set. Compared with other network models, the error dropped by 33.58%, with higher prediction accuracy and better adaptability. A wavelet process neural network based on error correction is established to realize the fault prediction analysis of the turbo rocket pump of the liquid rocket engine. The experimental results show that the prediction accuracy and adaptability are better than other single neural networks. The biggest advantage of machine learning to achieve fault prediction is that it does not require too much prior knowledge. According to the collected data, it can realize supervised or unsupervised learning, and can achieve fault prediction with acceptable errors.

3.3. Hidden Markov Model
Hidden Markov Model (HMM) is a statistical analysis model, which belongs to Markov Chain (MC), and is used to study Markov processes with hidden unknown parameters. When processing a large amount of data information, HMM can analyze and mine the hidden information well, and express various conditions in the form of probability density distribution. It is often used in speech recognition, fault diagnosis, fault prediction and other fields. Zhuo Dongfeng et al. effectively collected fault data of hydraulic system and used wavelet transform and HMM model to effectively realize the fault prediction of the hydraulic system. The basic principle model of HMM is shown in Figure 3:

![Image of neural network](image_url)

**Figure 2.** Basic structure of neural network.

![Image of HMM](image_url)

**Figure 3.** Basic principles of HMM.

It can be seen from the model that an HMM process can be composed of a random process and a
Markov chain, \( B \) is the probability distribution of observations, \( A \) is the state transition probability matrix, and \( \pi \) is the probability distribution of the initial state space, which can be used to express concisely with \( \lambda = (A, B, \pi) \).

HMM evolves through development and research into HSMM (Hidden Semi-Markov Model). Compared with HMM, HSMM considers state resident, overcomes the limitations of HMM modeling, and can directly predict faults [40]. HSSM can be written as \( \lambda = (I, A, B, D) \), and \( I \) is the initial state probability distribution matrix. \( D \) is the maximum time the state resides. Zeng Qinghu [41] proposed a new method of fault prediction combining KPCA and HSMM, and realized degradation conditional recognition. The experimental results show that the conditional recognition accuracy and prediction accuracy are both ideal. Ji Yun [42] et al. conducted a review of the HMM-based mechanical equipment condition assessment and fault prediction, analyzed the domestic and foreign research status of HMM and HSMM to achieve fault prediction, and looked forward to two major problems to be solved based on HMM prediction in the future: determine the number of degradation states experienced by the equipment and improve accuracy. With the in-depth study of HMM, the fault prediction method based on HMM will have more obvious advantages in processing large sample data.

4. Conclusion
This article briefly summarizes the fault prediction technology and focuses on the research and analysis of the data-driven fault prediction method. According to the size of the sub-sample data, it is divided into the fault prediction method based on the small sample data and the large sample data. When solving practical problems, according to the fault characteristics of the research object, combined with the record of the available data, the corresponding best method is selected, which can not only save data processing time greatly, but also improve the accuracy of fault prediction. In the process of literature collation, it is found that a single fault prediction method has many defects. At present, all kinds of fault prediction methods are integrated, taking advantage of each other, extracting feature information from the data, mining hidden information, and seeking higher prediction accuracy. The development trend of data-driven fault prediction methods will move towards the fusion of multiple methods to achieve information fusion and seek to maximize the accuracy of prediction. After literature review, the methods and applicable objects shown in Table 1 are summarized.

| Classification | Method | Suitable Object |
|----------------|--------|-----------------|
| Fault prediction methods based on data-driven | Time Series Analysis | Small sample data, short-term prediction effect is obvious |
| Small sample data | Grey model | Less data and lack of information |
| Fuzzy Theory | Support Vector Machines | Less data and greater uncertainty |
| Principal Component Analysis | Large sample information volume and high data dimension | Small sample, nonlinear data, short-term prediction effect is good |
| Machine learning | Requires less prior knowledge, can realize multi-step prediction, and has good generalization ability |
| Hidden Markov Model | | Large sample data and implied information |

Fault prediction is to provide service for condition-based maintenance. How to implement the theory of failure prediction has become the key to PHM technology. Whether it is a new batch of products that have just been put in place or an old product that has already been put into use, in order to save maintenance efficiency and maintenance man-hours, it is necessary to collect the usage data, failure data, and detection data that can fully reflect the status of the equipment. The classification and storage of various data put forward higher requirements. Therefore, in the future, we must strengthen the management of equipment data and prevent the loss of a large amount of high-quality data, so as to
better carry out data-based fault prediction and health management, and achieve true state-based maintenance. At the same time, it is necessary to combine online prediction with offline prediction, and use offline prediction methods with specific problems to achieve online prediction so that we can truly reach the practical application of fault prediction.

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