A Review of Fault Detection and Diagnosis of Satellite Power Subsystem

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Abstract. This paper reviews the state of the art in fault detection and diagnosis in satellite power subsystem. Different algorithms are compared, and some examples are given. Finally, the existing problems and the future development trend are given.

Keywords: Fault detection · Diagnosis · Model-base · LSTM · FTA

1 Introduction

With the rapid development of industrial technology and new generation information technology, intelligent manufacturing has become the main focus of competition in the world. In 2010, the German cabinet passed the 2020 high tech strategy formulated under the auspices of the German Federal Ministry of education and research and put forward "Industry 4.0". General Electric of the United States put forward the concept of "Industrial Internet" in 2012. In 2015, Keqiang Li put forward the grand plan of "Made in China 2025" for the first time when he made the "government work report" at the national two sessions [1], it can be seen that the major manufacturing countries in the world are strategically deploying a new round of industrial revolution at the national level.

In recent years, there has been a climax of satellite launch in the world. In 2019 alone, 103 launches have been carried out worldwide, with a total of 505 payloads on board. Among them, China carried out 34 space launches in 2019, becoming the country with the largest number of space launches in the world for two consecutive years. So far, China is operating more than 300 satellites. Satellite power system plays an extremely important role in all subsystems of satellite. The failure of power system often leads to disastrous consequences of the whole satellite. According to historical data statistics, the ratio of on orbit failure of power system is the highest (35%) of all subsystems. The satellite power supply system is responsible for the generation, storage, transformation, regulation and distribution of satellite electric energy. It is an important symbol of the life knot of the satellite and the development level of space technology, and the basic guarantee for the safe and reliable operation of the satellite. According to NASA's Golan

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Research Center, from 1990 to 2006, there were 64 power system failures only reported by commercial and scientific scientists. In addition, the power system is global and typical in all satellite sub-systems. The state of power system will also affect or constrain the functional behavior of other sub-systems, thus directly affect the mission capability of the satellite. For example, in order to detect a specific area, a satellite needs to lock the area by means of a sudden orbit, side sway, etc. the energy supply in the process of side sway maneuver directly affects the attitude adjustment of the satellite. At the same time, the normal operation of the visible light, multispectral, SAR and other high-power earth observation loads depends on the normal and stable operation of the power system.

In conclusion, the research on fault detection and diagnosis methods of satellite power system can improve the operation and maintenance support ability of the satellite. Not only that, because of the typicality of the power system, the technical route and research method adopted by the Research Institute of power system fault diagnosis and prediction can be extended to other subsystems, so as to comprehensively improve the health assurance and safety operation and maintenance capacity of China's satellites, which has important social, economic and military value.

2 Fault Detection of Satellite Power Subsystem

A large number of telemetry data are generated by satellites in orbit every day. These data are large-scale, multivariate time series data. Most of these data are in normal state, while the number of abnormal samples is very limited. Therefore, the challenge of fault detection is to model normal patterns and detect patterns that have not been found before, which may prompt machine failure. In the past, this was usually done by engineers with sufficient domain knowledge. However, in terms of time, this is usually expensive. Therefore, the fault detection method of satellite power system must have the ability to effectively complete this unsupervised task [2]. In recent years, the unsupervised fault detection method has achieved fruitful results. As shown in Fig. 1, the existing achievements can be divided into statistical based method, nearest neighbor rule-based method, clustering based method and deep-learning based method. From this point of view, the paper analyzes the research status of unsupervised fault detection methods.

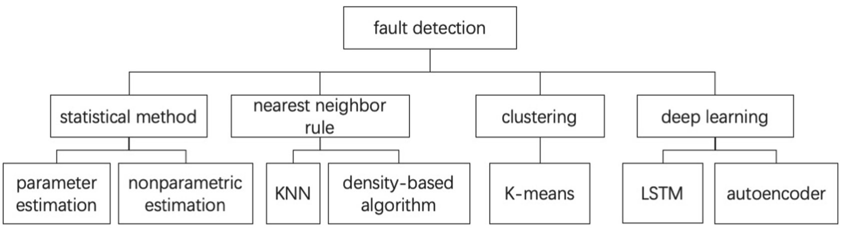

Fig. 1. Classification diagram of fault detection methods

2.1 Fault Detection Technology Based on Statistical Method

The principle of fault detection technology based on statistics is that the normal data appears in the high probability region of the random model, while the fault occurs in the low probability region of the random model [3]. This method uses normal data to train a statistical model, and then uses this statistical model to test data instances. When the probability value of the detected data instance belonging to this statistical model is relatively low, the data can be judged as abnormal. Both parametric and nonparametric estimation methods can estimate the parameters of stochastic models, which are described in detail below.

Parameter Estimation. As mentioned above, the parameter estimation assumes that the normal data is generated by a parameter distribution, which includes parameter 0 and probability density function f (x, 0). When the abnormal evaluation score of a test instance does not meet the probability density function, it can be determined that the instance is an abnormal value. In addition, statistical hypothesis test can also be used for outlier detection [4]. The original hypothesis of this test is that the sample is generated by the estimated distribution with parameters. If the statistical test does not meet the original hypothesis, it can be said that the sample of this test is an abnormal sample. Commonly used parameter estimation methods are based on Gaussian model [5], regression model [6] and mixed parameter distribution [7]. Yuhao Sun et al. [8] used the distance correlation coefficient to select the prediction variables and estimated the generalization error of the model to set a more reasonable prediction interval to detect the continuous fault of the data flow. Finally, the experiment verified that it can be used to detect the early fault of the satellite.

Nonparametric Estimation. In nonparametric estimation, the basic distribution is not assumed, and the information of random sampling itself is mainly used to judge the quality of estimators. The maximum score estimator method is a nonparametric estimation method. Using nonparametric statistical model for fault detection, the model structure is not defined by prior knowledge, but determined by the given data. Compared with parametric technology, this technology usually assumes less data, such as density smoothness [3]. The common nonparametric estimation methods are histogram-based methods [9] and kernel-based methods [10].

2.2 Fault Detection Technology Based on Nearest Neighbor Rule

The principle of fault monitoring technology based on the nearest neighbor rule is that the normal data is distributed in the dense neighborhood, while the abnormal data is far away from the nearest place. The nearest neighbor rule needs a reasonable distance or similarity to calculate the distance between different samples. Euclidean distance is the most commonly used method. Other methods include Mahalanobis distance and simple matching coefficient. Based on the nearest neighbor rule, fault monitoring technology can be roughly divided into two categories according to the calculation method of fault score: one is to take the distance from the sample to the K-th adjacent center as the fault score. The other is to calculate the relative density of each sample as the abnormal score.

KNN. K-nearest neighbor (KNN) algorithm is a relatively mature algorithm in theory. This method assumes that in the feature space, if most of the k-nearest samples near a sample belong to a certain category, then the sample also belongs to this category. Using this principle, we can distinguish the abnormal point from the normal point. This basic technology has been applied in fault detection. Byers et al. [11] have been used to detect mines from Landsat ground images since 1998. Guttomsson et al. [12] detected short circuit in large synchronous turbo generators. It is usually determined whether the test instance is abnormal by judging whether the abnormal score exceeds the threshold value.

Density-Based Algorithm. Density based fault detection technology estimates the density of each data sample neighborhood. A sample in a low-density cluster may be an exception if the sample in a high-density cluster is normal. Different from the distance-based clustering algorithm, the clustering result of the distance-based clustering algorithm is a spherical cluster, while the density-based clustering algorithm can find clusters of any shape. DBSCAN (density based spatial clustering of applications with noise) is a representative density-based clustering algorithm. It defines a cluster as the largest set of points connected by density, which can divide the area with enough high density into clusters and can find clusters of any shape in the samples with "noise".

2.3 Fault Detection Technology Based on Clustering

There are many similarities between fault detection based on clustering and nearest neighbor rule. For example, they all need distance measurement, and the choice of distance measurement method has a great impact on the results. The most difference between these two types of technologies is that the distance considered by clustering technology is the distance between each sample and its cluster center, while the distance from each sample point to its nearest neighbor is considered by the technology based on the nearest neighbor rule [3]. The fault detection technology based on clustering can determine whether a sample is abnormal in three cases: (1) normal samples are located in a cluster center, while abnormal samples are far away from any cluster center. (2) Normal samples are located in large and dense clusters, while abnormal samples are located in small and sparse clusters. (3) Normal samples are close to the nearest cluster center, while abnormal samples are far away from the nearest cluster center. The common clustering algorithm is K-means clustering.

K-means. The main principle of K-means clustering is to divide each sample into clusters represented by the nearest cluster center point given K initial cluster centers. After all samples are allocated, the center points of the cluster center are recalculated according to all samples in a cluster center (take the average value), and then the steps of allocating samples and updating the cluster center points are iterated Suddenly, until the change of clustering center is very small, or reach the specified number of iterations. The similarity evaluation index of K-means clustering algorithm is distance. The sum of error squares from sample points to clustering center is used as the evaluation index of clustering quality, and the sum of error squares function of overall classification is minimized by iteration.

2.4 Fault Detection Technology Based on Deep Learning

Artificial intelligence sprouted in the 1950s. After several peaks and troughs, it finally ushered in explosive development in the second decade of the 20th century. Artificial intelligence simulates the neurons of human brain based on artificial neural network. It is a kind of information processing method similar to human brain that can be realized by computer [13], and produces some intelligent behaviors, such as learning, reasoning, thinking, planning, etc. Deep learning is the only way to realize artificial intelligence. The concept of deep learning was put forward by Hinton et al. in 2006. By combining low-level features, it can form more abstract high-level representation of attribute categories or features to discover the distributed feature representation of data. This practical advantage of deep learning algorithm provides a high potential in practical application. In some cases, due to the lack of domain knowledge, the relevant input characteristics cannot be defined manually, and the extracted features may be too complex for engineers to code them. At this time, deep learning can be competent for this work. For example, in the task of object recognition, human beings can recognize objects intuitively, but they cannot easily derive a complete set of rules for the algorithm to recognize specific objects, which have invariance to the scale, direction or position in the image. However, the current object recognition model based on deep learning has surpassed the human eye in efficiency and accuracy. Because deep learning can abstract the high-level features of data, using this feature, normal data distribution can be obtained by training normal data first, when the sample does not belong to this distribution, it can be judged as abnormal. The commonly used deep learning models for fault monitoring are LSTM (long short term memory) and autoencoder.

LSTM. Sepp Hochreiter [14] found the problem of long-term dependence when studying the cyclic neural network, that is, when learning the sequence data, it can't learn the long-term information, and there will be the phenomenon of gradient disappearance and gradient explosion. In order to solve this problem, Sepp Hochreiter et al. Proposed a long-term and short-term memory network [15] in 1997. The long-term and short-term neural network is a special type of cyclic neural network, in which "gate" is added to each cyclic body to control the flow of information. The three gates are forgetting gate, input gate and output gate. The forgetting gate determines what information we will discard from the LSTM unit, the input determines how much new information we will add to the state of the LSTM unit, and the output determines what information we will output. This makes LSTM not only have the advantages of dynamic memory of cyclic neural network, but also have stronger adaptability in time series data analysis and can extract features of non-stationary parameters [16]. This characteristic makes LSTM outstanding in recognition and prediction. NASA uses the powerful non-linear modeling ability and automatic feature extraction ability of LSTM, takes remote control command and telemetry data as input at the same time, constructs LSTM model, and detects spacecraft anomalies with nonparametric dynamic threshold [17]. Li Hui et al. [16] used the LSTM model to train the parameters of satellite power system, taking the absolute value of the difference between the predicted parameter data and the actual parameter data as the model training target, using the parameter time series predicted by the model and the dynamic detection threshold generated by the model training error to detect the parameters, so as to realize the fault detection of satellite power system. Jingyi Dong et al. [18] used the strong nonlinear modeling ability of LSTM, combined with matrix norm to realize the multi-mode mining of remote control instructions, and through the construction and effective integration of multi LSTM prediction model, improved the adaptability of the model to the complex working conditions of spacecraft, and then effectively marked the anomalies in the telemetry data.

Autoencoder. Autoencoder is a neural network with the same input and learning objectives. It can learn the efficient representation of input data through unsupervised learning. Generally, autoencoder consists of encoder and decoder. The encoder transforms the input data into a fixed length high-order feature, which is generally much smaller than the input dimension. The high-order feature is used as the input of decoder to reconstruct the input sequence. Therefore, autoencoder can learn meaningful information to fully explain the characteristics of data. From encoder input sequence to sequence (sequence to sequence) model, this kind of model can monitor the fault by reconstructing the original sequence and compare the reconstruction results with the original input to find out the abnormal information.

Dechang PI et al. [19] break through the limitation of the traditional experience model, adopts the pure data drive model, on the basis of the variational automatic encoder, introduces the countermeasure network idea, uses the error of the reconstructed data and the original data to judge whether the satellite telemetry data is abnormal, and combines the week of the satellite orbit operation According to periodicity, a dynamic threshold determination method based on periodic time window is proposed to reduce the rate of misjudgment. Weihua Jin et al. [2] proposed a new stage training de-noising autoencoder (ST-DAE), which can train data characteristics in stages. Compared with the common autoencoder sparse autoencoder and de-noising autoencoder, this method has better reconstruction ability and outstanding performance in satellite power system abnormal monitoring.

3 Fault Diagnosis of Satellite Power Subsystem

Fault diagnosis methods can be divided into knowledge-based method, model-based method and data-driven method. The classification of fault diagnosis methods is shown in Fig. 2. For knowledge-based and model-based method, a priori knowledge is needed. The basic priori information in diagnosis is fault set and the relationship between symptom and fault. For data-driven methods, only a large amount of historical data is needed. There are many methods to convert these data into prior information in diagnosis, which can be used as a qualitative extraction process from historical data.

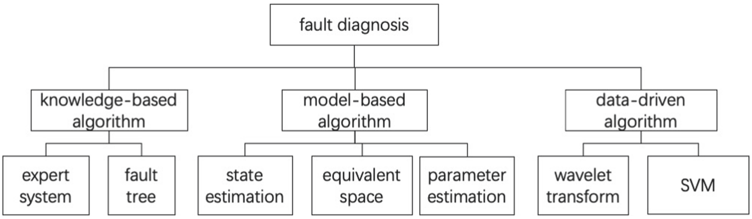

Fig. 2. Classification diagram of fault diagnosis methods

3.1 Fault Diagnosis Technology Based on Knowledge

Fault Diagnosis Technology Based on Expert System. The fault diagnosis method based on expert system constructs a knowledge base about the target object by inheriting the knowledge and experience of the experts in the field. The knowledge base is composed of abstract if-then rules [13]. In addition to the knowledge base, each expert system has an important part of "inference engine". According to some abnormal phenomena or fault field data, the inference engine calls the knowledge in the knowledge base and determines the fault step by step according to the inference steps [20]. Based on the expert system, Zheng Wei et al. [21] used neural network to expand the knowledge base, solved the "bottleneck" problem of knowledge acquisition in the expert system, and finally used the system to diagnose the satellite fault. Lian-xiang Jiang et al. [22] proposed the knowledge acquisition model of satellite fault diagnosis expert system to solve the bottleneck problem of establishing expert system. Firstly, a data discretization algorithm based on fuzzy set is proposed to discretize the decision table. Secondly, a rule extraction algorithm is proposed to extract production rules from decision table. Taking the satellite fault diagnosis expert system as an example, this paper illustrates how to extract effective rules. The operation parameters of the satellite power system are collected and discretized, which proves the correctness and validity of the knowledge acquisition model and the accuracy of fault diagnosis. Genqing Yang [23] proposed a design of knowledge base for Satellite Autonomous Fault Diagnosis Expert system. The resource knowledge base uses fault Petri net to describe the knowledge of satellite in detail, the position represents the state of component or system, and the transformation represents the evolution fault of component or system. In order to keep the consistency and correctness of knowledge base, the author proposes a verification algorithm of redundant rules.

Fault Diagnosis Technology Based on Fault Tree. Fault tree analysis (FTA) forms a complete fault analysis tree by building the logical relationship among the system, subsystems and components. Fault analysis tree is a deductive failure analysis method from top to bottom. According to the fault tree, we can infer from top to bottom, infer the components, causes, influence degree and failure probability of the failure [19, 24]. Jianing Wu et al. [25] analyzed the reliability of spacecraft solar array and determined the most critical subsystem of solar array. According to the working process of the satellite mechanical system, the FTA model is established, the logic expression of the top event is obtained by Boolean algebra, and the reliability of the solar array is calculated. Yi Yang et al. [26] analyzed the reliability of the solar array deployment mechanism by using the impact and hazard analysis (FMECA) and FTA. The main failure modes and their effects and hazards are described. A fault tree is established. The qualitative and quantitative analysis of fault tree is carried out. The probability of top event, structural importance and critical importance coefficient of different basic events are calculated. The suggestions for improving the reliability of the solar array are put forward, which provide the basis for the reliability design and structural improvement of the deployment mechanism of the satellite solar array.

3.2 Model Based Fault Diagnosis Technology

Fault Diagnosis Method Based on Quantitative Model. Quantitative model-based method, also known as analytical model-based method, is the earliest, most in-depth and most mature method of fault diagnosis. This kind of method makes full use of the knowledge synthesis of system structure, behavior and function to carry out reasoning diagnosis for the system. According to the different ways of generating residuals, analytical model method is divided into state estimation method, equivalent space method and parameter estimation method [27]. These three kinds of methods are developed independently. Generally, the parameter estimation method is more suitable for nonlinear systems than the state estimation method, while the equivalent space method is generally only suitable for linear systems [28].

State Estimation. The principle of state estimation is to evaluate the state of the system by constructing an observer or a filter to obtain the output of the system, and then compare the output value obtained with the output value of the real system to get the residual. In general, the residual signal of the system is usually very small or close to zero. On the contrary, if there is a fault in the system, the residual signal of the system should have obvious changes. The common state estimation methods are observer method and Kalman filter method. Wen Chen et al. [29] designed an iterative learning observer (ILO) to realize time-varying fault estimation and proposed a fault identification strategy based on ILO using learning mechanism to estimate fault instead of using the integrator commonly used in the classical adaptive observer. The stability of estimation error dynamics is established and proved. The experimental results show that the time-varying thruster fault can be diagnosed accurately. P. V. Sunil nag et al. [30] proposed a model-based nonlinear fault detection and diagnosis method. The global unscented Kalman filter (UKF) is applied to the fault diagnosis of LEO satellite. The results show that the spherical UKF can achieve better results without sacrificing the accuracy and saving the calculation amount. So, it is more suitable for real-time fault diagnosis.

Equivalent Space Method. The equivalent space method is to use the analytical mathematical model established by the system to construct the equivalent mathematical relationship between the input and output variables of the system. Through the mathematical relationship, it reflects the static direct redundancy between the input and output variables and the dynamic analytical redundancy between the input and output variables, to detect and separate faults. The main methods are equivalent equation method based on constraint optimization.

Parameter Estimation Method. The basic idea of parameter estimation method is to combine theoretical modeling with parameter identification. When using the significant change of parameters to describe the fault, the existing parameter estimation method can be used to detect the fault information, and then the system fault can be evaluated according to the deviation between the estimated value of parameters and the normal value. The fault diagnosis method based on the parameter estimation thinks that the fault will cause the change of the system process parameters, and the change of the process parameters will further cause a series of changes of the model parameters, Therefore, the fault diagnosis can be carried out by detecting the parameter changes in the model. With the development of the research, the fault diagnosis method based on parameter estimation has some new results. For example, the parameter estimation method based on fuzzy reasoning, the parameter estimation method based on neural network and the parameter estimation method based on image signal generator, etc., all of these methods improve the performance of fault detection and separation in varying degrees.

3.3 Data Driven Fault Diagnosis Technology

Wavelet Transform. Wavelet transform was first put forward by J. Morlet [31], an engineer who was engaged in oil signal processing in France in 1974. After gradual development, it can solve many problems that are difficult to be solved by using Fourier transform, so it is considered as a breakthrough development of Fourier analysis method. Compared with Fourier transform and window Fourier transform (Gabor transform), it is a local transform of time and frequency, so it can extract information from the signal effectively, and perform multi-scale analysis on the function or signal through the operation functions of scaling and translation.

According to the characteristics of multi-resolution analysis of wavelet transform, Wengao Lu [32] decomposed the telemetry data into four layers of wavelet. Through the analysis of the signal reconstructed by high frequency wavelet coefficients, the online real-time interpretation of telemetry data is realized, and the correctness and fault diagnosis efficiency of the method are verified. Wen Xin et al. [33] Based on the theory of wavelet neural network, combined with the problem of spacecraft fault detection and system reconstruction of the leader of spacecraft cluster, a fault diagnosis framework is constructed by combining wavelet neural network and neural network, and the feasibility is verified by simulation experiments.

Support Vector Machine (SVM). Support vector machine was first proposed by Cortes and Vapnik in 1995. It has many unique advantages in solving small sample, nonlinear and high-dimensional pattern recognition, and can be extended to other machine learning problems such as function fitting. The support vector machine method is based on the VC dimension theory of statistical learning theory and the principle of structural risk minimization. According to the limited sample information, it seeks the best compromise between the complexity of the model (i.e. the learning accuracy of specific training samples, accuracy) and the learning ability (i.e. the ability to identify arbitrary samples without error), in order to obtain the best generalization ability.

Hong Yin et al. [34] proposed an improved support vector machine (SVM) based on hybrid voting mechanism (HVM-SVM) to solve the problem of large parameters, multiple faults and small samples in satellite fault diagnosis. A large number of experimental results show that the accuracy of fault diagnosis using HVM-SVM is improved. Mingliang Suo et al. [35] proposed a feature selection method based on Fuzzy Bayesian risk (FBR), which can automatically generate the optimal feature subset without preset feature number. A heuristic forward greedy feature selection algorithm based on Fuzzy Bayesian risk theory is designed. Then, a data-driven fault diagnosis strategy is designed by using FBR and SVM. Finally, numerical experiments on UCI data and satellite power system fault diagnosis are carried out to verify the superiority and applicability of this method.

4 Discussion

In the past decade, fault detection and diagnosis technology has developed rapidly, especially the model-based fault diagnosis technology has made great progress, which has a wide range of applications in spacecraft fault detection and diagnosis, but there are still many problems to be further studied and solved. With the rapid development of artificial intelligence, how to apply this new technology to fault detection and diagnosis, many people have made different attempts, but there are few applications in practice, which need further research and application.

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