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Fault Detection in Shipboard Integrated Electric Propulsion System with EEMD and XGBoost

Sheng Liu. Yue Sun*. Lanyong Zhang

College of Automation, Harbin Engineering University, Harbin 150001, China (e-mail: 576194000@hrbeu.edu.cn)*

Abstract: In this paper, a fault detection method of shipboard medium-voltage DC (MVDC) integrated electric propulsion system (IEPS) based on Ensemble Empirical Mode Decomposition (EEMD) and XGBoost is proposed. Particle swarm optimization (PSO) is used to optimize the parameters to solve the problem that the standard deviation of auxiliary white noise in EEMD needs to be artificially selected. Firstly, the voltage signal on the DC bus is preprocessed by PSO-EEMD, which is decomposed into a set of Intrinsic Mode Functions (IMFs) according to the local characteristic time scale of the signal, and then the energy entropy is calculated as the fault feature vector. The fault feature vector is used to train and test the fault classifier based on XGBoost, and finally, the fault detection is completed. The simplified model of shipboard MVDC IEPS is built in AppSIM Time Simulator. The faults on generator output and DC cable are used to verify the proposed fault detection method. Fault feature extraction method and fault classifier design are completed in Python. Verification by simulation platform and comparison with other intelligent detection methods illustrates that proposed detection method can detect different faults quickly and accurately, is enabled for future practical use.

Keywords: Fault detection and diagnosis; Statistical data analysis; Machine learning; Condition Monitoring; Modeling and simulation of power systems

1. INTRODUCTION

Shipboard integrated electric propulsion system (IEPS) is a mainstream trend of the development of high-tech ship power system in the world, which has gradually become the main development direction of the next generation of navy ships (Zohrabi, Shi, & Abdelwahed, 2019).

The range of shipboard MVDC IEPS is large. If the traditional fault detection method is adopted, the system needs to be divided in detail, and mang relays are installed to realize it, which consumes a lot of financial resources. And the damage of a relay will lead to the failure of detection. For MVDC system, a small negligence is likely to cause the whole system to be paralyzed. In recent years, many intelligent detection methods have emerged, such as Artificial Neural Networks, Support Vector Machines (SVM). However, the training process of the existing intelligent detection method model is slow, and it is faced with the problem of parameter selection, which will affect the accuracy of fault detection. These problems make the existing intelligent detection methods have limitations in engineering application.

Therefore, this paper proposes a fault detection method of shipboard MVDC IEPS based on Ensemble Empirical Mode Decomposition (EEMD) (Wu & Huang, 2009) and XGBoost (Chen, 2016). Particle swarm optimization (PSO) is proposed to optimize white noise parameters in EEMD, which can avoid unnecessary modal aliasing and end effect. Firstly, build the MVDC IEPS model in AppSIM real-time simulator and simulate various faults. The PAO-EEMD is used to preprocess the voltage signal of the DC bus and calculate the energy entropy of the decomposition result—Intrinsic Mode Function (IMFs). Then use the fault feature vector composed of energy entropy as the input of the XGBoost-based fault classifier to train it. Finally, the fault detection is realized.

This fault detection method does not need to rely on a large number of relays, and does not require complicated parameters selection and adjustment processes. Solved the problem that the standard deviation parameter of white noise in EEMD needs to be manually selected by PSO. It simplifies the complex MVDC IEPS fault detection problem and has strong generalization ability. The performance of this method is compared against to other intelligent detection methods, and results show its superiority.

2. SIMPLIFIED SHIPBOARD MVDC IEPS MODEL

This paper simplifies the shipboard MVDC power system concept model provided by electric ship research and Development Consortium (ESRDC) (Andrus M, December 2013). The simplified MVDC IEPS model used in this paper is shown in Figure 1. The main generator module uses a two-shaft gas turbine as the prime mover and drives the synchronous machine. IEEE AC8B exciter is used as excitation system. The AC is converted to DC through a six-pulse diode rectifier, which is delivered to the RL cable. The propulsion system is equivalent to a load resistor. A fault simulation is set at the output of the synchronous machine, and the single-phase ground fault F_1,two-phase ground fault F_2, three-phase short-circuit fault F_3, and two-phase short-circuit fault F_{11} are simulated respectively. Perform a short-circuit fault F_{DC} simulation on the DC cable.

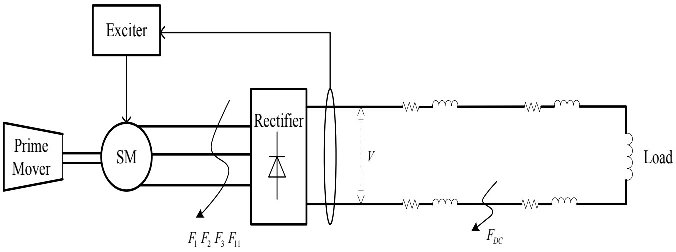

Fig. 1. simplified MVDC IEPS model

3. METHODOLOGY

3.1 Fault feature extraction

We need to pre-process the original fault data at first for a more efficient fault diagnosis model. First of all, we use EEMD to process and extract meaningful features from the original fault data in order to remove interference information. Then calculate the energy entropy of IMF (Yu, YuDejie, & Junsheng, 2006).

EEMD is a kind of signal processing method with strong adaptability and robustness. It does not need to set any basis function in advance. It can still maintain high resolution in the presence of background noise, so it is very suitable for fault signal pre-processing. The EEMD decomposes the signal into the sum of several orders of IMF components based on the local characteristic time scale of the signal. Different IMFs describe the frequency components of the signal. The EEMD method eliminates modal aliasing and end effect in the decomposition results by adding Gaussian white noise. The standard deviation of white noise should be selected according to the characteristics of the original signal. For signals with different frequency components, the sensitivity to white noise is different. Therefore, choosing appropriate standard deviation of white noise can avoid unnecessary mode aliasing and end effect. Too small noise power can not form a stable input data quasi binary filter structure, resulting in poor robustness of decomposition results. Although the increase of noise power will enhance the structure of the quasi binary filter group of the input data, the excessive noise power will cause the modal aliasing of the decomposition results.

This paper proposes a method to optimize the standard deviation parameter of white noise in EEMD by using PSO. It can quickly and accurately select the appropriate standard deviation according to different original signals, eliminating the trouble of selecting the standard deviation of white noise through multiple experiments. Whether the distribution of extreme points is uniform in each IMF is regarded as the goal of optimization.

The specific implementation process is as follows:

Step 1: Find the first three orders of IMF with the largest energy entropy.

Step 2: The maximum max points and minimum point min in each IMF are used for following calculation. The difference between the horizontal and vertical coordinates of two adjacent large (small) points are calculated respectively as

$$\begin{cases} Dv\_xp(k) = xmax(k+1) - xmax(k) \\ Dv\_yp(k) = ymax(k+1) - ymax(k) \end{cases} \tag{1}$$

$$\begin{cases} Dv\_xm(k) = xmin(k+1) - xmin(k) \\ Dv\_ym(k) = ymin(k+1) - ymin(k) \end{cases} \tag{2}$$

Where, the horizontal and vertical coordinate sequences of the maximum value are expressed as $xmax$ and $ymax$ respectively, and the minimum value 's are expressed as $xmin$ and $ymin$.

Step 3: The standard deviation of $Dv\_xp(k)$, $Dv\_yp(k)$, $Dv\_xm(k)$, and $Dv\_ym(k)$ are calculated. They are denoted as std_xp_n, std_yp_n, std_xm_n, and std_ym_n, respectively. Then do the following:

$$std\_p_n = std\_xp_n \times std\_yp_n \tag{3}$$

$$std\_m_n = std\_xm_n \times std\_ym_n \tag{4}$$

where std_p_n (std_m_n) is the standard deviations of the horizontal and vertical coordinates of all the maximum (minimum) values in the n th IMF component.

Step 4: The optimization objective is:

$$G = \frac{\sum_{n=1}^{N} (std\_p_n + std\_m_n)}{2 \times N} \tag{5}$$

Where $N = 3$ in this condition.

It can be seen from the equation that the smaller the G is, the more balanced the distribution of extreme points in the IMF, indicating the better the result of EEMD decomposition.

3.2 Fault identification

XGBoost is an efficient implementation of the Gradient boosting (GB) algorithm. It usually uses Classification and Regression Tree (CART) as the base classifier, which is a very important and widely used decision tree learning method. The main idea of XGBoost algorithm is to continuously split features to grow a tree. The essence of adding a tree each time is to learn a new function to fit the residual of the last prediction. Finally, the prediction value is calculated by the sum of the leaf node scores of each tree corresponding to the test sample characteristics.

4. EXPERIMENT

Numerical simulation based on AppSIM real-time simulator is conducted to evaluate the performance of the proposed fault diagnosis method of ship MVDC IEPS. The simplified MVDC system model mentioned in Section 2 is implemented on AppSIM real-time simulator and the switching details of the power electronic converter can be simulated in real time. The configuration of the AppSIM real-time simulator is shown in Figure 2. Three-phase short-circuit fault F_3, two-phase short-circuit fault F_2, single-phase short-circuit fault F_1 and two-phase ground fault F_{11} are simulated on a synchronous generator and a ground fault F_{DC} on DC bus is simulated on RL cable with simplified MVDC system model.

The voltage of the DC bus after the fault occurs is taken as the fault detection sample. PSO-EEMD was used to pre-process it, and then the energy entropy of IMF was calculated. The fault feature vector composed of energy entropy is used as the input of XGBoost to get the fault detection model of MVDC IEPS. The above methods are implemented in Python. 5400 samples were randomly selected as training data, and the remaining 600 samples were used as test data. Comparing the performance of the fault classifier with other intelligent methods, the comparison results presented in Table 2. It can be seen that the XGBoost-based fault classifier used in this paper is superior to other methods in training speed and diagnostic accuracy. BP, RBF and fuzzy neural network-based method needs longer training time because they use gradient descent method as training method. An approximate algorithm is proposed in XGBoost, which can greatly improve the learning speed when the data set is large. Therefore, the fault detection method proposed in this paper has faster training speed and can ensure accurate fault detection. EEMD method for fault feature extraction solves the problem of parameter selection in WT. This fault detection method effectively solves the problem that the traditional method relies too much on the relay and slow training speed.

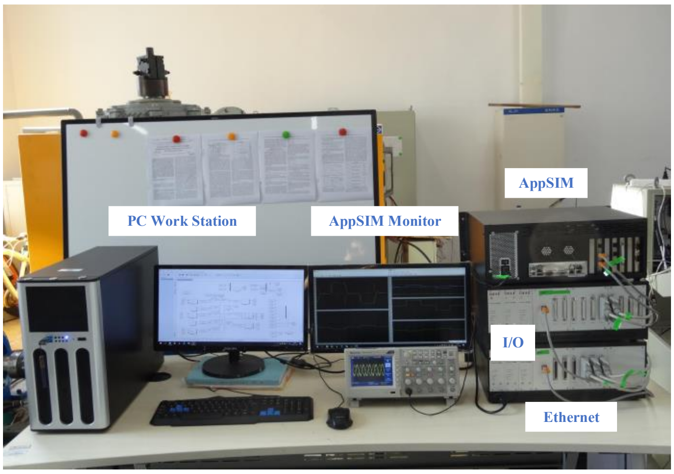

Fig. 2. The AppSIM real-time simulator

Table 2. Comparing the performance of the fault classifier with other intelligent methods

Method	*Training time*	*Testing time*	*Average accuracy(%)*
BP neural network	several minutes	0.03274s	97.56
RBF neural network	several minutes	0.04687s	97.83
Fuzzy neural network	several minutes	0.05195s	98.67%
XGBoost	12.0181s	0.0253s	99.50%

5. CONCLUSIONS

This paper proposes a fault detection method for shipboard MVDC ISPE based on PSO-EEMD and XGBoost. Firstly, PSO-EEMD is used to preprocess the voltage signal on DC bus and calculate the energy entropy of IMF. Then the energy entropy is input into the fault classifier based on XGBoost as the fault feature vector for training. Finally, the fault detection of the ship MVDC IEPS is realized. The ship MVDC IEPS model is built in AppSIM Real Time Simulator, and the fault feature extraction and fault classifier design are realized by Python. The experimental results are compared with other intelligent fault detection methods. The method proposed in this paper has high training speed and diagnosis accuracy.

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