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Diagnosis of Vienna Rectifier Faults Based on EMD Feature Extraction and Optimized RF Classification#

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ABSTRACT

The front-end part of the DC charging module for electric vehicles commonly utilizes the Vienna rectifier, whose stable operation directly impacts the overall status of the charging module. Therefore, focusing on the characteristics of open-circuit faults in core components such as power switches and electrolytic capacitors of the Vienna rectifier, this paper proposes a diagnostic method based on Empirical Mode Decomposition (EMD) and Whale Optimization Algorithm (WOA) optimized Random Forest (RF) algorithm. Firstly, by constructing a simulation model of the Vienna rectifier, the waveform characteristics of the input current during open-circuit faults are summarized. The fault current signal is decomposed, and feature vectors are constructed using the EMD method. These feature vectors are then input into the classification model with optimized parameters using the WOA-optimized Random Forest. Simulation results demonstrate that this method achieves a high fault diagnosis rate and reduces diagnosis time, providing practical guidance for fault diagnosis in DC charging piles for automobiles.

Keywords: Vienna rectifier, Empirical Mode Decomposition, Whale Optimization Algorithm, Random Forest, Fault diagnosis.

1. INTRODUCTION

Nowadays, under the context of carbon emission targets and new infrastructure construction, the country vigorously promotes the popularization of new energy vehicles. Correspondingly, the development of charging facilities has also rapidly expanded[1]. Currently, DC charging piles have stood out in charging facilities due to their advantages, such as efficient and rapid charging, leading to a significant amount of research focused on DC charging piles[2].

The Vienna rectifier, as the front-end part of the current DC charging module, directly affects the operational efficiency of the entire charging module[3]. Industrial application data statistics show that power capacitors and power switch failures account for the highest proportion, with failure rates reaching 30 % and 26 % respectively[4]. Power switch failures are primarily categorized as open circuit faults and short circuit faults. Ultimately, short circuit issues will be transformed into open circuit problems[5]. Open circuit faults can lead to distortion of the input current and increased stress on device components. Therefore, it is crucial to diagnose open circuit faults in power converters to improve their reliability[6, 7].

Currently, there are two main approaches for diagnosing open circuit faults in Vienna rectifiers. The first approach is based on analytical models[8]. However, this method is not suitable for situations with complex nonlinear characteristics where accurate mathematical models cannot be established. The second approach is based on signal processing. Power switch failures can be further divided into two categories: popular deep learning methods[9] and machine learning methods[10]. When converting one-dimensional signals into two-dimensional or even multi-dimensional representations, this process may introduce data redundancy and easily lead to feature loss issues. Traditional machine learning typically involves two steps: feature extraction[11] followed by classification or regression[12]. However, this process requires manual selection of fault features, which may have a certain impact on the final diagnostic results.

This paper proposes a diagnostic method based on Empirical Mode Decomposition (EMD) and Whale Optimization Algorithm (WOA) optimized Random Forest (RF) algorithm. The method takes the three-phase input current as the raw signal, undergoes EMD

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decomposition, and creates feature vectors inputted into the WOA-RF classification. Through simulation verification, it is evident that this method can improve the accuracy of model diagnosis and shorten diagnosis time.

2. TOPOLOGY AND FAULT ANALYSIS OF VIENNA RECTIFIER

This paper selects the three-phase six-switch Vienna rectifier circuit for research. The topology of the three-phase three-wire Vienna rectifier is illustrated in Fig. 1.

In the Vienna rectifier, faults in power switches and electrolytic capacitors are inevitable. However, investigations have shown that the likelihood of simultaneous failure of multiple components is minimal. Therefore, this study focuses on the analysis of individual component open circuit faults, including power switches S_1 to S_6, the DC side capacitors labeled as C_1 and C_2, as well as the fault-free state. The corresponding fault types are denoted as Y_1 to Y_9.

Utilizing the topology structure shown in Fig. 1, a Vienna rectifier simulation model is constructed in Simulink. The input phase voltage is set to 220 V, and the rated output voltage is 750 V. Open circuit fault simulations are conducted for the aforementioned 8 key components, and based on the simulation results, the characteristics of the three-phase input currents in the Vienna rectifier are summarized.

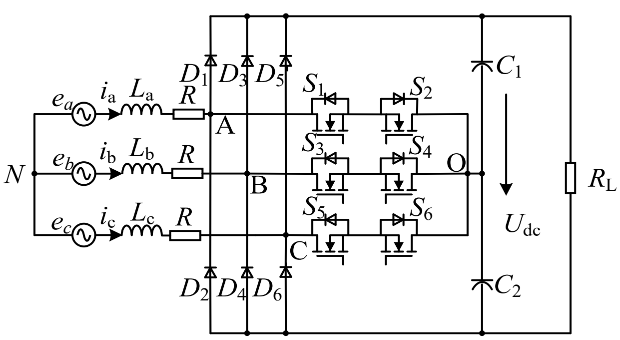

Fig.1 Topology Diagram of Three-Phase Vienna Rectifier

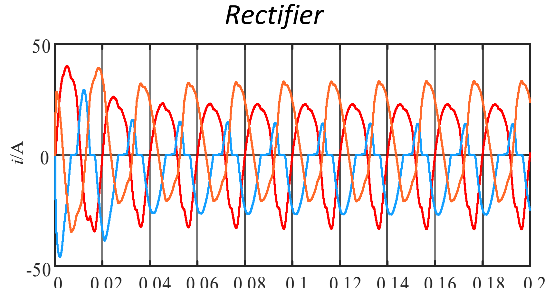

Fig.2 Input Current Distortion After Power Switch S_3 Experiences an Open-Circuit Fault

Taking phase B as an example, the variation trend of the input current in the rectifier when switch S_3 experiences an open circuit fault is analyzed. As depicted in Fig. 2, significant fluctuations occur in the waveforms of phases A and C, with the distortion in the input current of phase B being the most severe.

3. FAULT FEATURE EXTRACTION

EMD decomposes complex signals into a finite number of Intrinsic Mode Functions (IMFs) and a residual component. Each IMF component captures local feature signals of various time scales from the original signal.

The basic decomposition process of EMD is illustrated in Fig.3. Thus, through EMD decomposition, the original signal $x(t)$ is decomposed into a linear combination of IMF components ranging from high frequency to low frequency, along with a residual term $r(t)$.

$$x(t) = \sum_{i=1}^{M} c_i(t) + r(t) \tag{1}$$

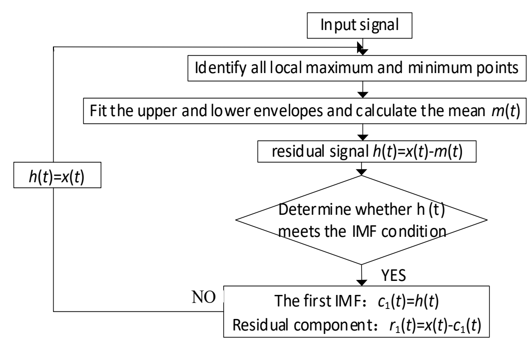

Fig.3 EMD Decomposition Process Diagram

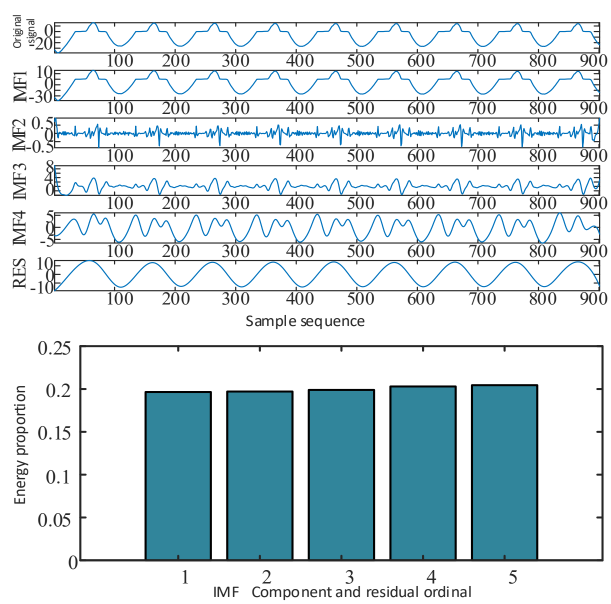

Fig.4 EMD decomposition results and energy distribution ratio

In the equation: $c_i(t)$ represents the i^{th} IMF component; $r(t)$ is the residue term, which does not include oscillatory modes of the signal but reflects the overall trend of the signal. The first few high-frequency IMF components contain significant and important feature information from the original signal. Taking the example of an open-circuit fault occurring in power switch S_3, this paper decomposes the faulty input current of phase B using EMD, as shown in Fig.4.

it can be observed that the energy ratio of IMF components contains significant and important feature information from the original signal. Decomposing the residue partially characterizes the degree and direction of deviation from the origin of the original signal, as well as the sum of energies of all components, denoted as E_{total}. Thus, a 6-dimensional feature vector is constructed for the faulty current of phase B, combined with currents of phases A and C, to form a comprehensive feature vector.

4. WHALE OPTIMIZATION ALGORITHM OPTIMIZED RANDOM FOREST

4.1 Principles of WOA and RF algorithm

Random Forest (RF) is a parallel ensemble learning algorithm based on decision trees, proposed by Breiman in 2001. It improves the prediction and generalization capabilities of the model by constructing multiple independent decision trees and combining them together. The algorithmic process is illustrated in Fig.5.

The WOA simulates two hunting behaviors of whale groups: “surrounding prey” and “bubble-net hunting”. During the iterative process, it continuously adjusts the movement direction and step size of the current whales to achieve a balance between global exploration and local exploitation. The principle is as follows:

(1) The position of an individual whale in n-dimensional space is: $X = (x_1, x_2, ... x_n)$. The model assumes that whales choose two hunting behaviors with equal probability, $P_1 = P_2 = 0.5$.

(2) During surrounding prey behavior, whales will swim towards the optimal or random position.

At that $|A| \geq 1$ time, whales will swim towards the optimal position whale, and its position update formula is:

$$X_i^{t+1} = X_{best}^t - A\left|CX_{best}^t - X_i^t\right|, (p < 0.5) \tag{2}$$

where, t represents the current iteration number, X^t_{best} and X^t_i are the position vectors of the optimal whale and the i^{th} whale, respectively, at the current iteration. X^t_{best} will be updated when a better whale position is found during the iteration. p is a random number within the range [0, 1].

When $|A| \leq 1$, the whale will swim towards a random position whale, and its position update formula is:

$$X_i^{t+1} = X_r^t - A\left|CX_r^t - X_i^t\right| \tag{3}$$

where X^t_r represents the position vector of the random whale, and A and C are coefficient vectors, calculated as follows:

$$A = 2ar - a \tag{4}$$

$$C = 2r \tag{5}$$

where the initial value of a is 2 and linearly decreases to 0 with the iteration count, and r is a random vector in the range [0, 1].

(3) Bubble-net feeding. When whales engage in bubble-net feeding, they swim in a spiral shape, and the position update formula is:

$$X_i^{t+1} = \left|X_{best}^t - X_i^t\right| \cdot e^{bl} \cdot \cos(2\pi l) + X_b^t (p \geq 0.5) \tag{6}$$

where b is a constant (default value is 1), which determining the shape of the spiral; l is a random number within the range [-1, 1].

4.2 WOA-RF model

The parameters N_{tree} and M_{tree} affect the recognition accuracy and efficiency of the random forest classification process. Therefore, we use particle swarm optimization algorithm to optimize these two parameters. The process of optimizing RFD with WOA algorithm is illustrated in Fig.6, and the specific optimization steps are as follows:

1)Descriptive statistical analysis and normalization processing of the slope dataset, followed by a random split into training and testing sets with a ratio of 7:3. Initialize the parameters of RF, setting the upper and lower bounds for the parameters to be optimized.

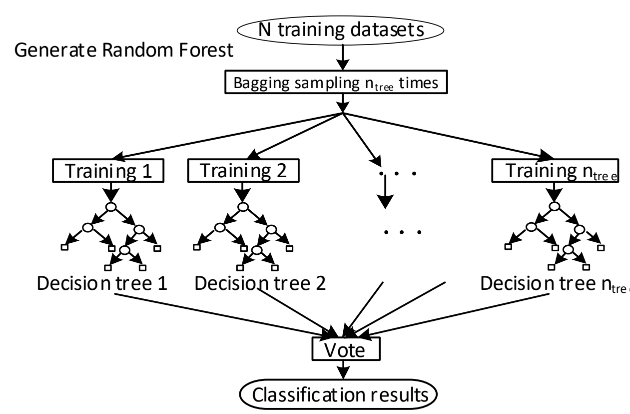

Fig.5 Random Forest Algorithm Workflow

2)Initialize the parameters of WOA, setting the population size of whales.

3)Identify the best search agent and update its position with each iteration according to formulas (2) - (6).

4)When the termination iteration condition is met, output the optimal hyperparameter combination and construct the optimal WOA-RF model based on this.

5. SIMULATION RESULTS AND ANALYSIS

Considering the energy storage and filtering effect of the input filter inductor, aimed at tracking the ability of input voltage and current ripple, the inductance and capacitance are chosen as 2.5 mH and 2000 μF, respectively. In Simulink, the critical parameter design is as follows: Input phase voltage is 220 V, output voltage is 800 V, fundamental frequency of input voltage is 50Hz, output power is 18.4kW and power factor is 0.995.

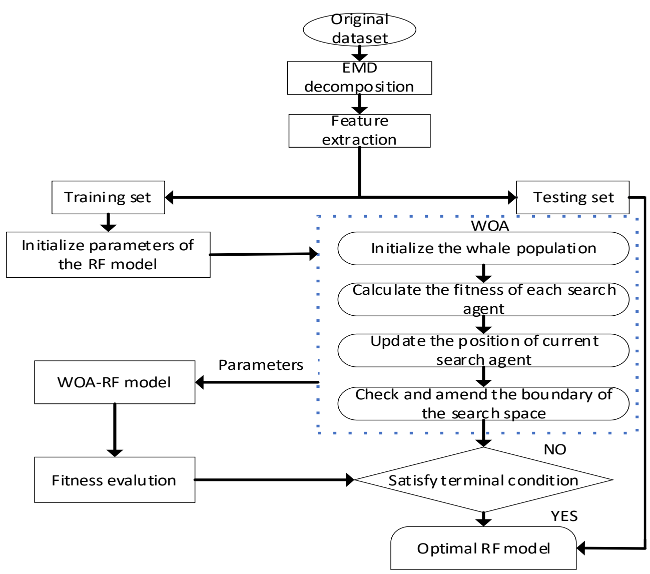

Fig.6 WOA-RF Diagnostic Model

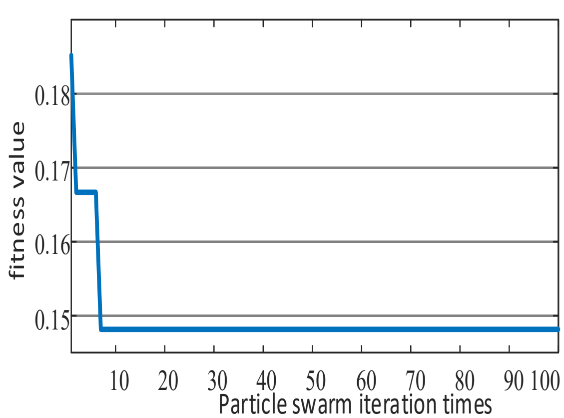

Fig.7 Algorithm Fitness Curve

In this study, to obtain comprehensive fault data, 30 samples were collected for each fault type, the dataset was divided into training and test sets with a ratio of 7 : 3. Each sample data was analyzed and processed using the EMD method to obtain fault feature vectors. These data were then input into the WOA-RF diagnostic model,

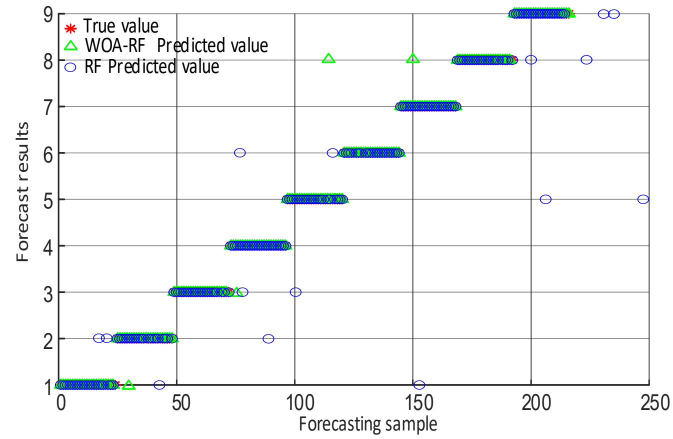

Fig.8 Comparison of Prediction Results between Two Algorithms

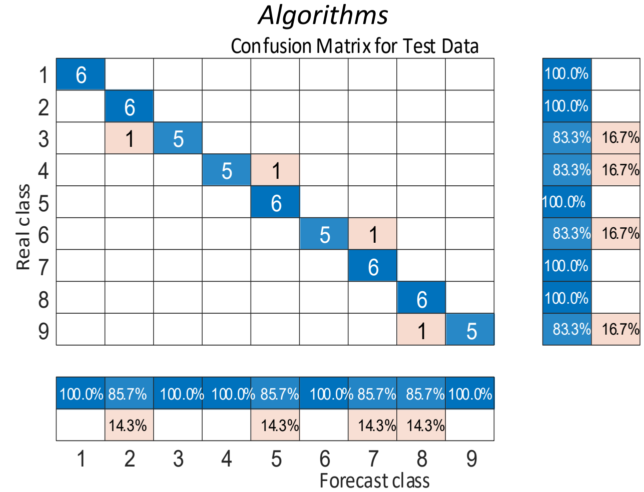

Fig.9 Confusion Matrix of the Test Set in the WOA-RF Model

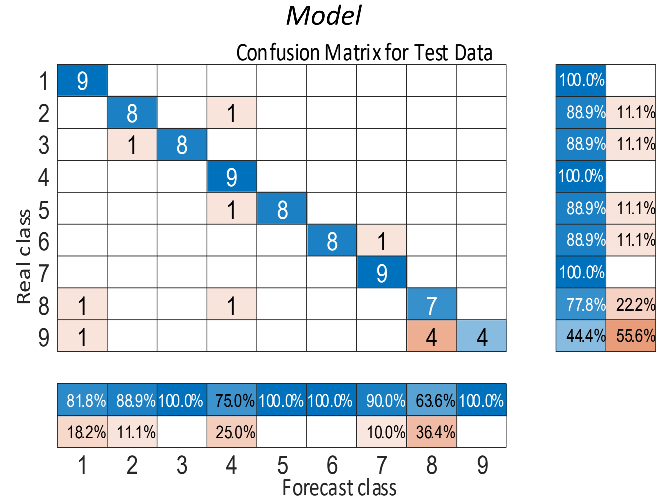

Fig.10 Confusion Matrix of the Test Set in the RF Model

where the Whale Optimization Algorithm was used to optimize the number of trees and layers in the random forest. The iteration error change of the model is shown in Fig.7. From the change in iteration error of the model, it can be observed that the overall error is decreasing, ultimately leading to the optimal solution for the number of decision trees and layers.

As shown in Fig.8 below, the prediction performance of traditional RF and WOA-RF algorithms on test samples is compared. It is evident that the optimization capability of the Whale Optimization Algorithm is apparent.

Although both WOA-RF and RF algorithms are under the decomposition of the EMD algorithm, their performance in terms of accuracy, training time, and mean square error are significantly different. A comparison of algorithm results reveals that the WOA-RF algorithm improves diagnostic accuracy by 6.2 % compared to the RF algorithm, reduces training time by 2.8 seconds, and decreases mean square error by 0.005. Fig. 9 and 10 respectively show the confusion matrices of the test set in the WOA-RF model and the RF model.

6. CONCLUSIONS

The three-phase Vienna rectifier, as a prominently performing AC-DC rectifier, is widely used. Addressing the issue of single-component open circuit faults, this study proposes the use of the EMD algorithm to decompose complex time-domain signals, thereby obtaining signals containing crucial fault information. Energy is utilized as a feature. The WOA is utilized to optimize two key parameters of the random forest. Compared to traditional RF, this method improves diagnostic accuracy and shortens diagnostic time. These findings provide practical guidance for future research on fault diagnosis in power electronic converters.

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