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Fault Diagnosis of Wind Power Converters Based on Compressed Sensing Theory and Weight Constrained AdaBoost-SVM

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Abstract

As the core component of transmission systems, converters are very prone to failure. To improve the accuracy of fault diagnosis for wind power converters, a fault feature extraction method combined with a wavelet transform and compressed sensing theory is proposed. In addition, an improved AdaBoost-SVM is used to diagnose wind power converters. The three-phase output current signal is selected as the research object and is processed by the wavelet transform to reduce the signal noise. The wavelet approximation coefficients are dimensionality reduced to obtain measurement signals based on the theory of compressive sensing. A sparse vector is obtained by the orthogonal matching pursuit algorithm, and then the fault feature vector is extracted. The fault feature vectors are input to the improved AdaBoost-SVM classifier to realize fault diagnosis. Simulation results show that this method can effectively realize the fault diagnosis of the power transistors in converters and improve the precision of fault diagnosis.

Key words: AdaBoost, Compressive sensing, Fault diagnosis, Support vector machine, Wavelet power converter

I. INTRODUCTION

These days, wind power is playing an extremely important role in the field of electric energy. Power converters need to be used in the process of grid connection and serve as the transfer station between power generation systems and the power grid [1]. It ensures that power can be stable at random wind speeds and can meet grid requirements. Power converters are usually placed in bad working environments for a long period of time and are extremely prone to failure [2], [3]. During the working process of a wind power converter, if faults are not diagnosed, they can affect the power quality and paralyze the entire power grid [4]. Therefore, the fault diagnosis of power converters has a high research value and is the basis for the subsequent fault tolerance of converters.

Short-circuits and open-circuits of power switch components (Insulated Gate Bipolar Transistor, IGBT) are the two most common types of faults in wind power converters [5]. When an IGBT is short-circuited, it experiences a very large current in a very short time and burns out its series-connected protection device. Finally, it behaves as an open-circuit fault of the IGBT. Therefore, this paper mainly discusses the open-circuit fault diagnosis of IGBTs.

In current power converter fault diagnosis techniques, a great deal of research has focused on analytical models and data-driven methods [6], [7]. In [8], a method using a bilinear current observer was proposed, where the bilinear current observer was constructed to obtain current information from the converter to realize fault detection and diagnosis based on the model characteristics of a doubly-fed generator and power converter. The method in [9] was based on a switching function voltage model and operating mode analysis, which can diagnose faults quickly and reliably. Although the above diagnostic methods achieved good effects in the fault diagnosis of power converters, it is necessary to establish an accurate mathematical model and modeling processes are complicated. In recent years, data driven methods have been widely used in the field of fault diagnosis due to their high flexibility and easy implementation. The authors of [10] put forward a fault diagnosis method based on a self-organizing map (SOM) neural

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network. This method was able to meet the requirements for the intelligent fault diagnosis of the existing wind power converter fault library, and easily diagnose new types of faults. In [11], an adaptive neuro-fuzzy inference system (ANFIS) network was proposed, where the measured voltage and current were input to the established ANFIS network to identify faults in power converters. Moreover, a method using a discrete wavelet transform (DWT) and two support vector machine (SVM) classifiers was proposed in [12]. In this method the DWT was used to detect discontinuity of the normalized current signal. The count of the zero current samples near the detection point was selected as the characteristic of the input data of SVM1 to classify the fault phase. The sum of the samples in the previous half cycle and the sample changes in the next quarter cycle were selected as inputs to SVM2 to implement fault diagnosis of the switching device. In addition, a technique using a wavelet packet transform (WPT) was put forward in [13], where the DC voltage was analyzed and processed by the WPT to obtain the detail signal with the largest energy value. Then the detail signal was subjected to spectrum analysis. The power spectrum value in the frequency band was extracted as a fault feature vector. Then a wind power generator was diagnosed by establishing an SVM classifier. The authors of [14] proposed the use of wavelet decomposition to extract fault features from circuit output signals and established a fault diagnosis model by integrating neural networks. However, in the iterative process of the AdaBoost algorithm, the authors did not consider the degradation of the performance of the classifier or the differences between weak classifiers. The above data driven methods were based on the Nyquist sampling theorem. Since the sampling frequency needs more than two times its signal frequency, a large amount of data was collected, which increased the complexity of the signal analysis and recognition. In the last few years, compressive sensing theory [15] has attracted a great deal of attention in the field of signal detection and analysis. This method used data sampling and compression far below the Nyquist sampling frequency to obtain a small amount of data. In [16], the characteristics of a disturbance signal were extracted by a two-dimensional tree complex wavelet, and the classification recognition of four kinds of instantaneous disturbance signals were realized by using the sparse representation method in the compressed sensing theory. The authors of [17] proposed a fault diagnosis method based on two stage matching pursuit. A similarity pursuit was performed on the compressed data to construct a dictionary matrix. Then the target data was classified by a matching pursuit algorithm in the compressed sensing theory.

This paper proposes a fault feature extraction method based on a wavelet and compressed sensing theory, and realizes fault diagnosis by an improved AdaBoost-SVM classifier. This method uses the wavelet to reduce the noise of the output current signal and compresses the signal after the noise reduction. Then it uses an orthogonal matching pursuit algorithm to obtain the sparse feature vector. The fault diagnosis is implemented by the AdaBoost-SVM algorithm which limits the weight of the sample and increases the difference between the weak classifiers. When compared with the traditional AdaBoost-SVM model, the classification accuracy and generalization ability are improved.

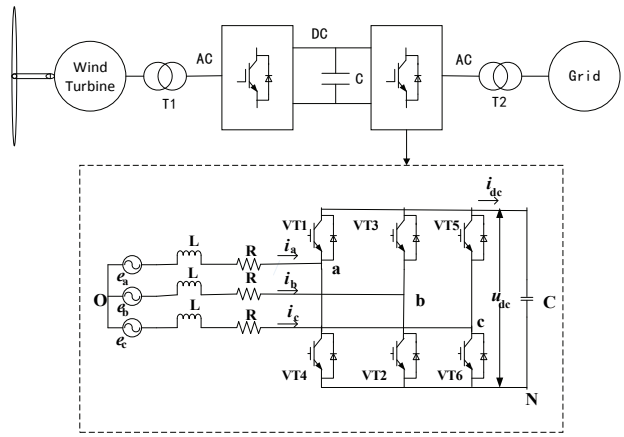

Fig. 1. Topology structure of a wind power generation system.

TABLE I
FAULTY COMPONENTS AND THEIR CORRESPONDING FAULT LABELS

Fault Label	Faulty Components	Fault Label	Faulty Components
1	VT1	12	VT3,VT5
2	VT4	13	VT4,VT6
3	VT3	14	VT4,VT2
4	VT6	15	VT2,VT6
5	VT5	16	VT1,VT6
6	VT2	17	VT1,VT2
7	VT1,VT4	18	VT3,VT4
8	VT3,VT6	19	VT3,VT2
9	VT5,VT2	20	VT5,VT4
10	VT1,VT3	21	VT5,VT6
11	VT1,VT5	22	No faults

II. RESEARCH ON THE POWER DEVICE FAULTS OF CONVERTERS

In a wind power generation system, converters are the core component of the whole system. The topology structure of a wind turbine side converter is the same as that of a grid side converter. Therefore, the grid side converter is only studied in this paper. The Topology structure of a wind power generation system is shown in Fig. 1.

In view of the large number of power switches in the converter main circuit, it is possible for there to be many failures at the same time. Thus, it is necessary to classify various types of faults. In actual operation, an open-circuit fault of the single power switch and the two power switches of power converters are the most common. Thus, this paper mainly considers the open-circuit faults of the two kinds of power switches. As shown in Fig. 1, there are 6 IGBTs in the grid side converter. Therefore, there can be 22 cases during

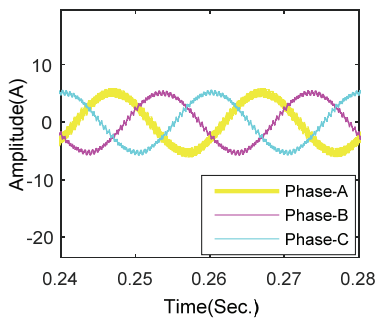

Fig. 2. Three-phase current waveform without faults.

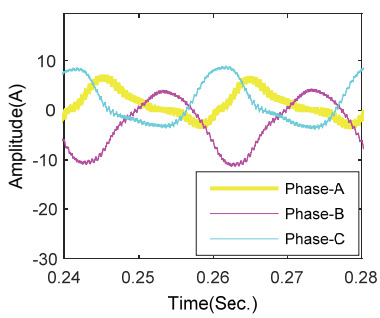

Fig. 3. Three-phase current waveform for a VT1 open-circuit fault.

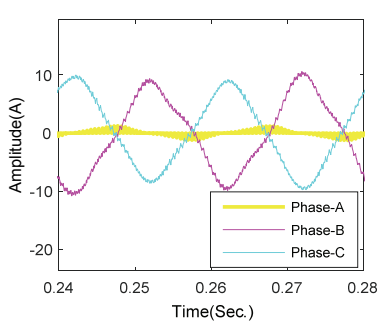

Fig. 4. Three-phase current waveform for a VT1 and VT4 open-circuit fault.

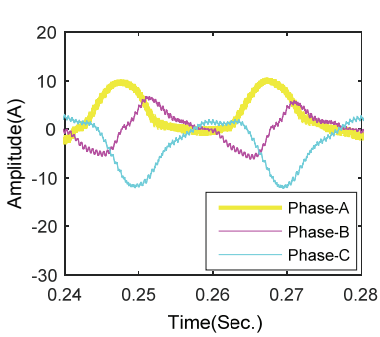

Fig. 5. Three-phase current waveform for a VT1 and VT3 open-circuit fault.

operation. A table showing the faulty components and the corresponding fault labels is illustrated in Table I. The three-phase output currents of a grid side converter under several typical faults are shown in Figs. 2-6. When an open-circuit fault occurs in different IGBTs, the three-phase current of the power converter has different degrees of distortion when compared with the normal operation state.

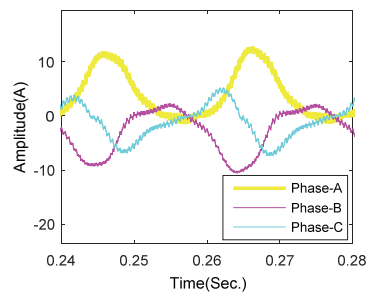

Fig. 6. Three-phase current waveform for a VT1 and VT2 open-circuit fault.

III. Feature Extraction Combining Wavelet and Compressed Sensing

A. Wavelet Analysis

The key to wavelet analysis is the choice of the wavelet basis function and decomposition level. Based on characteristic information of the output voltage signal and relevant literature, this paper selects a db10 wavelet base function. The wavelet basis function can provide a more practical and specific digital filter with a finite length. Thus, each frequency has a better division effect. The selection of the number of layers in wavelet decomposition affects the effect of noise reduction. In this paper, 3 layers of decomposition are selected according to a number of experimental results.

B. Compressed Sensing Theory

Compressed sensing [18] is a completely new theory for information acquisition and processing based on sparse representation and approximation theory. The theory shows that if signal $X_{N\times 1}$ is sparse or if the signal is sparse after a certain transformation Ψ, a measurement matrix $\Phi_{M\times N}$ that is independent of the transformation matrix can be used to reduce the dimension of the signal. This can ensure that all of the information of the high-dimensional signal is contained in the low dimensional signal.

$$Y=\Phi X=\Phi\Psi\Theta \tag{1}$$

Where A=$\Phi\Psi$ is the sensing matrix, and Y is an observational vector after dimensionality reduction. By solving the following l0-norm optimization problem, the original signal can be reconstructed with a high probability.

$$\begin{cases}\hat{\Theta}=\arg\min\|\Theta\|_0\\ s.t.Y=\Phi\Psi\Theta\end{cases} \tag{2}$$

Where $\|\Theta\|_0$ is l_0- norm, Φ is the sensing matrix, Ψ is the measurement matrix, and $\hat{\Theta}$ is the required sparse vector.

In order to effectively preserve the useful information in the original signal X after reducing the dimension of the vector Y, the measurement matrix must satisfy the restricted isometry property (RIP) [20].

$$(1-\delta_k)\|X\|_2^2\le\|\Phi X\|_2^2\le(1+\delta_k)\|X\|_2^2 \tag{3}$$

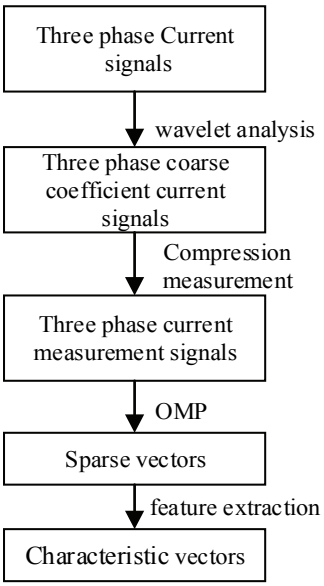

Fig. 7. Flow chart of feature extraction.

Where δ_k is the RIP constant and $\delta_k \in (0,1)$.

The process of solving sparse vectors is equivalent to the l_0-norm of Equ. (2). When the measurement matrix satisfies the RIP, the l_0-norm solution can be transformed into a l_1-norm solution.

$$\begin{cases} \hat{\Theta} = \arg\min \|\Theta\|_1 \\ s.t. Y = \Phi\Psi\Theta \end{cases} \tag{4}$$

In this paper, the orthogonal matching pursuit (OMP) method is used to solve the problem of Equ. (4). This is done to realize an accurate reconstruction of the dimensionality reduction signal.

C. Feature Extraction

When the power converter works in different states, the frequency components of the output current also change. The change in the components of the current indirectly reflects the operation mode. In addition, it is possible to judge whether there is any fault. Therefore, combining wavelet and compressed sensing theory can be used to extract the characteristics of the collected current data. Fig. 7 is a feature extraction flow chart and the specific steps are as follows.

(1) Use the wavelet transform to decompose the three-phase output current of a wind power converter at each scale. Then reconstruct the decomposition coefficients and extract the coarse coefficients.

(2) Use the compressed sensing theory to reduce the dimension of the coarse coefficients. Then obtain sparse vectors by an orthogonal matching pursuit algorithm.

(3) Construct the characteristic vectors using the root mean square and standard deviation for each phase sparse vector. This is shown in the following equations:

$$T_{STD} = \sqrt{\sum_{i=1}^{K} (\Theta(i) - \overline{\Theta})^2 \Big/ K} \tag{5}$$

$$T_{RMS} = \sqrt{\sum_{i=1}^{K} \Theta(i)^2 \Big/ K} \tag{6}$$

Where K is the number of elements in the sparse vector, $\Theta(i)$ is the element of the sparse vector, and $\overline{\Theta}$ is the mean value of the sparse vector.

IV. Fault Diagnosis of Power Converters Based on an Improved AdaBoost – SVM Model

A. Support Vector Machine Principle

A support vector machine (SVM) is a machine learning method based on statistical learning theory, which was proposed by Vapnik et.al. for small sample classification and prediction [19]. It is based on the principle of structural risk minimization to ensure that the global optimal solution is obtained and that it is good at solving small sample classification problems.

SVM uses a kernel function to map the original sample to the high-dimensional feature space to obtain the optimal linear classification plane. The radial basis function (RBF) has fewer parameters and better results than other kernel functions. Therefore, this paper uses the RBF kernel function. The equation is as follows:

$$k(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{\sigma^2}\right) \tag{7}$$

Where σ is the width of a kernel function. In RBF-SVM training, the penalty factor C and the parameter σ of the kernel function have a great influence on classifier performance. Therefore, it is necessary to choose the best C and σ. The bird swarm algorithm (BSA) in [20] is better than grid search, genetic algorithm and particle swarm optimization in terms of the ability to deal with optimization problems. Therefore, this paper uses the BSA to optimize the optimal value of the two parameters.

B. AdaBoost Algorithm and its Improvement

The AdaBoost algorithm [21] was introduced by Freund and Schapire in 1997 through an improvement of the boosting algorithm. This algorithm is widely used in applications such as pattern recognition and regression prediction [22], [23]. The essence is to use the same training sample set to train weak classifier, and then combine the trained weak classifiers to make up a strong classifier. The iterative process of the AdaBoost algorithm is a process to enhance a weak classification algorithm. The weights of each training sample are given, and the weight of each sample is updated according to the classification error rate of the previous round. In the process of

algorithm training, the weight of wrongly classified samples is increased and the weight of correctly classified samples is reduced. Through multiple iterations, a strong classifier is obtained by combining multiple weighted weak classifiers to improve classification accuracy.

In this paper, SVM based on the RBF kernel function is used as a weak classifier, and BSA is used to optimize the parameters. An AdaBoost algorithm is used to enhance the training. Finally, a strong classifier is constructed by a linear weighted combination. The AdaBoost-SVM model structure is shown in Fig. 8.

By analyzing and studying the derivation of the AdaBoost algorithm, it can be seen that some samples that are easy to be misclassified for many times in the iterative process of the algorithm, which leads to an increase in the training error of the sample. Due to the degradation of classifier performance, the training error bounds of the AdaBoost algorithm are analyzed and deduced. The training error is as follows:

$$\begin{aligned} R\left(H_{final}\right) &= \frac{1}{N}\sum_{i=1}^{N}\left|\left\{i : y_i \neq H_{final}(x_i)\right\}\right| \\ &= \frac{1}{N}\sum_{i=1}^{N}\begin{cases}1, y_i \neq H_{final}(x_i) \\ 0, else\end{cases} \\ &= \frac{1}{N}\sum_{i=1}^{N}\begin{cases}1, y_i f(x_i) \leq 0 \\ 0, else\end{cases} \leq \frac{1}{N}\sum_{i=1}^{N}\exp(-y_i f(x_i)) \end{aligned} \tag{8}$$

The weight distribution equation of the updated training sample is as follows:

$$D_{t+1}(i) = D_t(i)\frac{\exp\left(-\alpha_t y_i h_t(x_i)\right)}{Z_t} \tag{9}$$

The adjustment of Equ. (9) is as follows:

$$Z_T D_{T+1}(i) = D_T(i)\exp(-\alpha_T y_i h_T(x_i)) \tag{10}$$

The right side of the inequality sign in Equ. (8) is deduced as follows:

$$\begin{aligned} &\frac{1}{N}\sum_{i=1}^{N}\exp(-y_i f(x_i)) \\ &= \frac{1}{N}\sum_{i=1}^{N}\exp(-\sum_{t=1}^{T}\alpha_t y_i h_t(x_i)) \\ &= \sum_{i=1}^{N} D_{1,i}\prod_{t=1}^{T}\exp(-\alpha_t y_i h_t(x_i)) \\ &\overset{(10)}{=} \sum_{i=1}^{N} Z_1 D_{2,i}\prod_{t=2}^{T}\exp(-\alpha_t y_i h_t(x_i)) \\ &\overset{(10)}{=} Z_1\sum_{i=1}^{N} Z_2 D_{3,i}\prod_{t=3}^{T}\exp(-\alpha_t y_i h_t(x_i)) \\ &\overset{(10)}{=} Z_1 Z_2\sum_{i=1}^{N} Z_3 D_{4,i}\prod_{t=4}^{T}\exp(-\alpha_t y_i h_t(x_i)) \\ &= Z_1 Z_2 Z_3 \cdots Z_{T-1} Z_T = \prod_{t=1}^{T} Z_t \end{aligned} \tag{11}$$

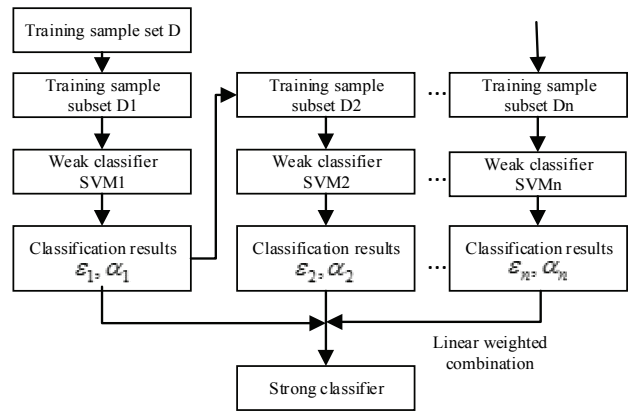

Fig. 8. Structure of an AdaBoost-SVM model.

It can be seen from the derivation of the above equation that the upper bound of the error of the AdaBoost equation is the product of the normalized factor Z_t of each round.

$$R\left(H_{final}\right) \leq \prod_{t=1}^{T} Z_t \tag{12}$$

From the above equation, it can be seen that with an increase of iterations, the upper bound of error should be gradually reduced. However, there are some samples which are easy to be misclassified in practical problems. With an increase of iteration times, the normalization factor of the sample weights may also increase. As a result, the classification performance of a strong classifier is degraded. To avoid this problem, the normalized factor Z_t should be made as small as possible when generating a weak classifier $h_t(x)$ in each round. The decomposition equation of the normalization factor Z_t is shown as follows:

$$\begin{aligned} Z_t &= \sum_{i=1}^{N} D_t(i)\exp\left(-\alpha_t y_i h_t(x_i)\right) \\ &= \sum_{x_i \in A} D_t(i)\exp\left(-\alpha_t\right) + \sum_{x_i \notin A} D_t(i)\exp\left(\alpha_t\right) \\ &= -\left(1-\varepsilon_t\right)\sqrt{\frac{\varepsilon_t}{1-\varepsilon_t}} + \varepsilon_t\sqrt{\frac{1-\varepsilon_t}{\varepsilon_t}} \\ &= 2\sqrt{\frac{\varepsilon_t}{1-\varepsilon_t}} \end{aligned} \tag{13}$$

In this equation: $\varepsilon_t = \sum_{x_i \notin A} D_t(i)$. Through an analysis of Equ. (13), it is found that if the samples are easily misplaced during an iteration, their weights increase with the increase of the number of iterations. This makes the sum of the weights of the misclassified samples get closer to the weights of the correctly classified samples, which increases the normalization factor Z_t of each round. As a result, the performance of the classifier is degraded. In order to avoid the above problems, the sample weight updating strategy, which was wrongly divided into the

original algorithm, was improved. The updating equation for improving the weights of the misclassified samples is:

$$D_{t+1}(i)=\begin{cases} D_t(i)\bullet\dfrac{e^{\alpha t}}{Z_t}, k=1 \\ D_t(i)\bullet\dfrac{k+e^{\alpha t}}{Z_t(k+1)}, k=2,3\cdots T \end{cases} \tag{14}$$

Where k is the number of erroneous classifications, α_t is the weight of a weak classifier, and $\alpha_t > 0$. In addition, $e^{\alpha t} > 1 \Rightarrow e^{\alpha t} + \frac{1}{k}e^{\alpha t} > 1 + \frac{1}{k}e^{\alpha t} \Rightarrow e^{\alpha t} > \frac{k+e^{\alpha t}}{k+1}$. It can be seen from the derivation that the method of updating the weight value of Equ. (14) inhibits excessive accumulation of the weight of the error samples, and is sensitive to the number of errors in the previous training. In addition, $f(k)=\left(\frac{k+e^{\alpha t}}{k+1}\right) \Rightarrow f'(k)=\frac{1-e^{\alpha t}}{(k+1)^2}<0$. It can be concluded from the derivation that the larger the number of erroneous classifications, the smaller the extent of the weight expansion. This updating algorithm can limit the weight growth and make it easier to allocate weights.

To better integrate the support vector machine, the difference between the weak classifiers is expanded. The BSA algorithm is used to change the kernel function parameters of each weak support vector machine model according to the sample distribution of each iteration. Then strong classifier is generated. The specific algorithm is described as follows:

Input: Training set $D=\{(x_1,y_1),(x_2,y_2)\cdots(x_n,y_n)\}$, weak classifier RBF-SVM, and number of iterations T.

Step1: Initializing the weight of each sample $D_t(i)=1/N, i=1,2\cdots N$.

Step2: For $t=1,2,\cdots T$

(1) According to the distribution of sample weights in D, a training sample set d_t for training a weak learner is obtained.

(2) d_t is used as the training sample set. Then the BSA algorithm is used to perform a 10-fold cross validation on d_t to get the best parameters (C, σ) of SVM and to get a weak classifier h_t.

(3) The training error ε_t of the weak classifier h_t is calculated according to Equ. (15):

$$\varepsilon_t=\sum_{i=1}^{N} D_t(i)\left(h_t(x_i)\neq y_i\right) \tag{15}$$

(4) If $0<\varepsilon_t<0.5$, calculate the weight value α_t according to Equ. (16), and update the sample weight according to Equ. (17).

$$\alpha_t=0.5*\ln\frac{1-\varepsilon_t}{\varepsilon_t} \tag{16}$$

$$D_{t+1}(i)=\begin{cases} D_t(i), h_t(x_i)=y_i \\ formula(14), h_t(x_i)\neq y_i \end{cases} \tag{17}$$

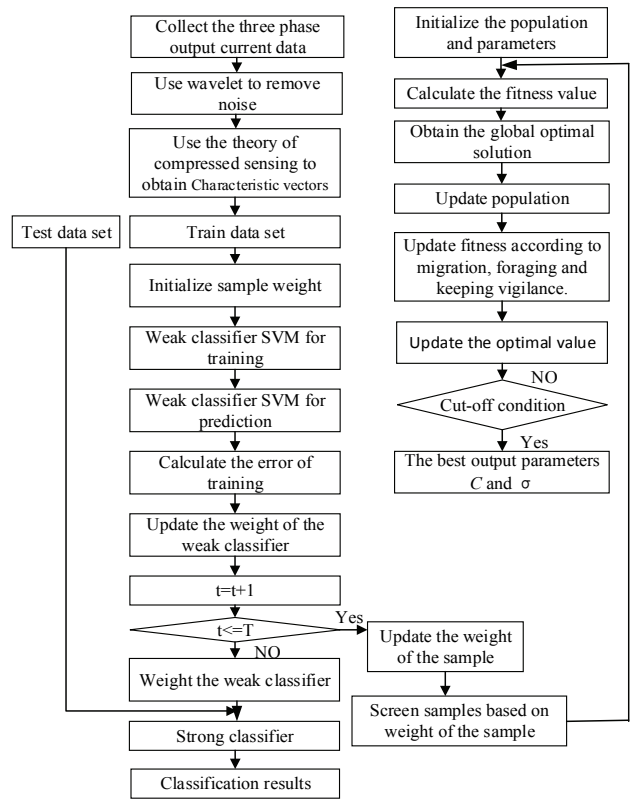

Fig. 9. Flow chart of the fault diagnosis method.

$$\text{Output: } H_{final}(x)=\arg\max\left(\sum_{t=1}^{T}\alpha_t h_t(x_i)\right) \tag{18}$$

C. Fault Location of a Power Converter Based on an Improved AdaBoost-SVM Algorithm

The specific steps of a fault diagnosis method based on an improved AdaBoost-SVM algorithm are shown as follows and a flow chart of the fault diagnosis is shown in Fig. 9. The specific steps are as follows.

(1) Collect the three-phase output current signal of a converter under different faults condition.

(2) Use the proposed method in the third section to get the feature extraction of the three-phase current signal and construct the characteristic vector.

(3) Use the obtained characteristic vectors to train the weak classifier SVM and obtain the model parameters.

(4) Use the test data set to test the classification accuracy of the improved AdaBoost-SVM model.

V. Simulation and Experimental Analysis

A. Data Acquisition and Preprocessing

According to the different open circuit faults of a power switch device IGBT of a converter, the corresponding

simulation model is established in MATLAB. The output current data of a converter under an open circuit fault are collected and presented in Table I. There are 20 sets of data in each fault mode. In order to improve the speed of fault diagnosis, the sample data set is normalized. The maximum and minimum normalization method is used to set all of the attributes to [0, 1] in this paper. Define the Normalization equation as follows:

$$x_{nor} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{19}$$

B. Simulation and Results

A D-MPSG system model is built in the Simulink environment to simulate an open circuit fault of a converter. The main parameters of the simulation are as follows.

The parameters of the permanent magnet synchronous generator (PMSG): rated power P=2.2kW, rated speed N=1500r/min, rated voltage V=380V, stator resistance R = 0.86Ω, and moment of inertia J=0.0032kg.m^2. Converter parameters: the rated line voltage is 380V, and the switching frequency is 8KHz. System parameters: the DC-link capacitance is 1000μF, the DC bus voltage is 630V, and the grid frequency is 50Hz. Each of the faults in Table I is simulated. The converter output three-phase current signals under each fault are collected and processed. Then the fault feature set is constructed.

To verify the effectiveness of the proposed feature extraction method, the traditional AdaBoost-SVM method is used to diagnose fault characteristics. The above 220 data was randomly selected as the training set of the AdaBoost-SVM model, and the rest was selected as the test set. The results are shown in Fig. 10. It can be seen from the Fig. 10 that 18 samples were classified as errors in 220 test samples. The correct rate of classification is 91.8181%. Under actual working conditions, the signal is mixed with a lot of noises. This paper simulates the noise effect under actual working conditions by adding random noise to the three-phase current signals. Although the fault recognition rate has dropped, it is still 85.45%.

The same data set is used as input for improving the AdaBoost - SVM model. When training the weak classifier RBF-SVM, the BSA is used to find the parameters C and σ of each weak classifier according to the samples screened in each iteration. The maximum iteration number of the algorithm is T=15, and the parameters of the SVM in each iteration are shown in Table II. It can be seen from table II that the different weak classifier SVM has different kernel parameters. When compared with the traditional AdaBoost-SVM model, each weak classifier SVM has the same kernel parameters. This shows that the algorithm increases the difference between weak classifiers. The corresponding experimental error results are shown in Fig. 11.

TABLE II
PARAMETER PAIRS SELECTED FOR WEAK CLASSIFIER SVM IN EACH ITERATION

Weak SVM	(C, σ)	Weak SVM	(C, σ)
1	(81.5,0.51)	2	(99.26,0.45)
3	(45.97,8.41)	4	(27.88,0.92)
5	(82.38.0.62)	6	(55.41,1.88)
7	(45.30,3.13)	8	(18.59,9.53)
9	(15.89,7.26)	10	(26.25,1.62)
11	(77.56,0.96)	12	(54.98,3.14)
13	(62.21,12.10)	14	(100,0.26)
15	(57.26,3.69)		

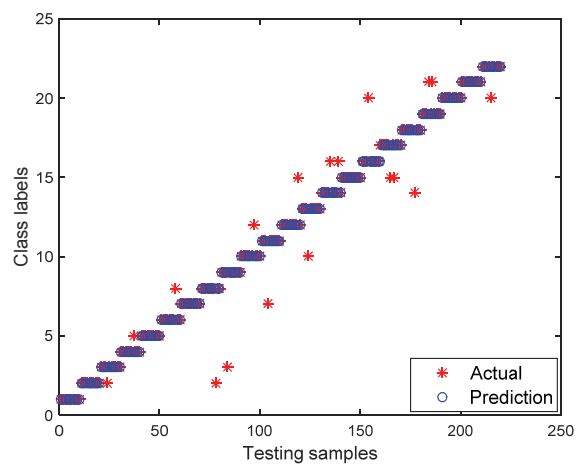

Fig. 10. Classification results of the traditional AdaBoost-SVM.

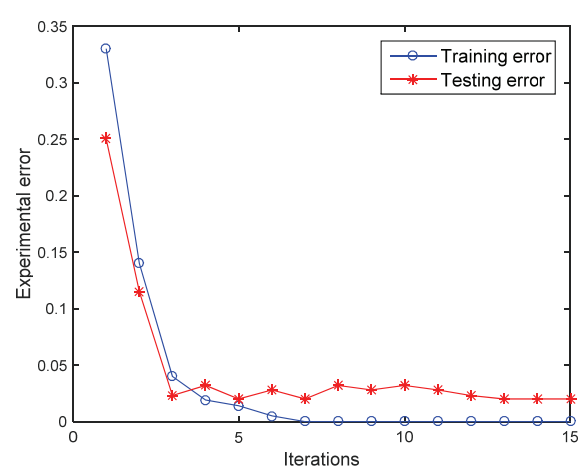

Fig. 11. Training and testing error curves.

It can be seen from Fig. 11 that the training error and test error of fault diagnosis samples show a decreasing trend with an increase of the iterations. The training error and the corresponding test error tend to zero with an increase of the iterations. Although there are some upward trends in the test error curve, the overall trend is still decreasing. When the training error is reduced to zero, the overall trend of the test error continues to decline.

For the sake of verifying the advantages of the improved

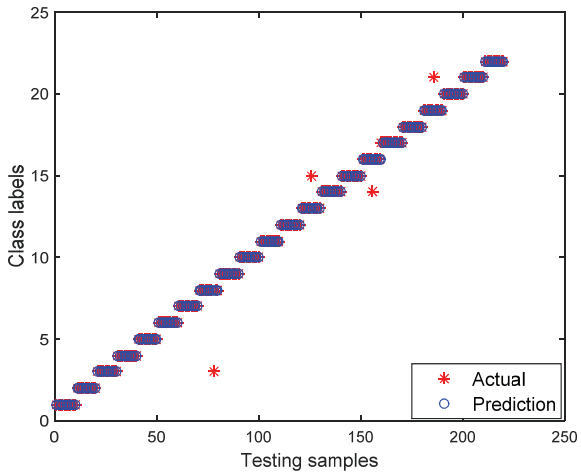

Fig. 12. Classification results of the improved AdaBoost-SVM.

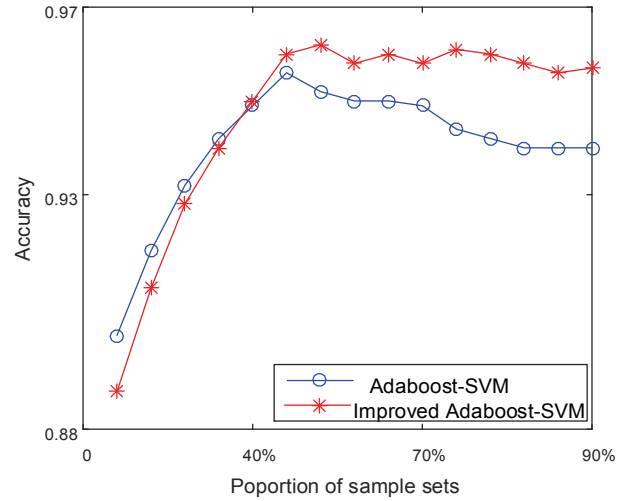

Fig. 13. Fault diagnosis results under different proportions of sample sets.

AdaBoost-SVM fault diagnosis model, the method proposed in this paper is compared with a traditional fault diagnosis model based on AdaBoost-SVM. The comparability of the experiment is guaranteed by using the sample set mentioned above. Experimental results are shown in Fig. 10 and Fig. 12.

In Fig. 10, the asterisks represent the actual classification results of the traditional AdaBoost-SVM fault diagnosis mode on the test set, and the circles represent the correct target output. The circles in Fig. 12 represent the classification results of the improved AdaBoost-SVM fault diagnosis model on the test set. It can be seen from Fig. 10 that 10 samples are classified errors in the 220 test samples. The correct rate of classification is 91.8181%. In Figure. 12, only 4 samples are misclassified and the correct rate of classification is 98.1818%. When compared with the traditional AdaBoost-SVM classification algorithm, results based on the improved AdaBoost-SVM algorithm are more reliable. The overall classification effect of the algorithm is improved and its generalization ability is better.

For the purpose of studying the classification performance of the improved AdaBoost-SVM model under different proportional sample sets, 20%~90% data samples were randomly selected from the total samples. In each case, the data set was divided randomly (70% for the training set and 30% for the test set). To avoid errors caused by the random selection of samples, fifty simulations were carried out in each case, and the average accuracy is taken as the classification performance.

Comparing the classification performance of the two models for the sake of convenience, the classification results are combined into a graph. Fig. 13 shows that as the number of samples increases, the performance of the improved AdaBoost-SVM classifier is gradually improved. Although the performance curve fluctuates a little, the overall performance gets better and the final performance tends to be stable. When the number of sample sets is small, the performance of the improved classifier is almost the same as that of the traditional classifier. Even the classification performance of the latter is slightly better than that of the former. Although the performance of the traditional AdaBoost-SVM classifier gradually improves with an increase of the sample size, the performance of the classifier is degraded from about 50% of the sample set. This is far from the highest precision of its performance, and the improved AdaBoost-SVM classification performance is relatively stable and good. By comparison, it is known that the improved AdaBoost-SVM model has a higher overall classification performance and a more stable classification performance.

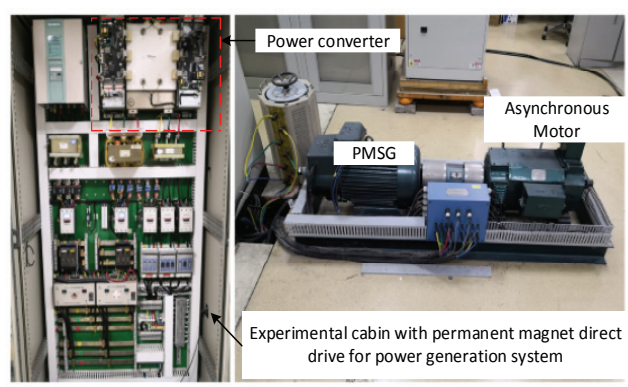

Fig. 14. Experiment platform.

C. Experiment and Result

The validity of the fault diagnosis method is further validated by constructing an experimental platform for a permanent magnet direct drive wind power system. The experimental system is shown in Fig. 14.

In this experiment, a VT1 open circuit fault is taken as an example, and the three-phase current output of the power converter is shown in Fig. 15. The system parameters used in the experiment are the same as those used in the simulation. Twenty samples were collected for each fault mode in Table I, and fault feature vectors were constructed according to the feature extraction method in this paper. Using the same method mentioned above, the classification performance of the

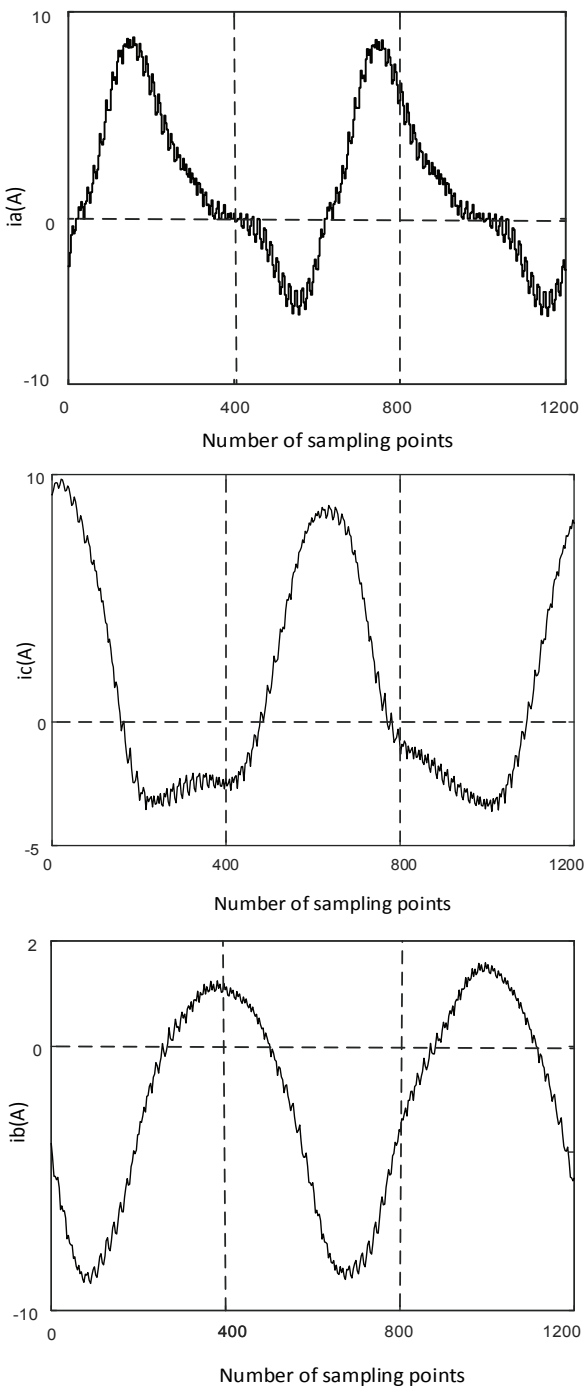

Fig. 15. Three-phase current waveform for a VT1 open-circuit fault.

TABLE III
FAULT DIAGNOSIS RESULTS UNDER DIFFERENT PROPORTIONS OF SAMPLES

Proportion / Accuracy	50%	60%	70%	80%
AdaBoost-SVM	92.23%	91.19%	90.93%	88%
Reference [16]	94.09%	92.2323%	93%	91.2%
Improved AdaBoost-SVM	96%	95.23%	95.36%	94%

improved AdaBoost-SVM model was compared with that of the traditional AdaBoost-SVM model and the methods discussed in [16]. In Table III, it can be sees that with the increase of the sample proportion, the fault diagnosis accuracy of the three methods decreases in varying degrees. However, the performance of the improved AdaBoost-SVM model is better and more stable, which is consistent with the simulation results.

VI. CONCLUSION

This paper proposes a combination of a wavelet transform and a compressive sensing method for the fault feature extraction of converter power switches. The effectiveness of the method is verified. A fault diagnosis model of the improved AdaBoost-SVM is also proposed in this paper, which adjusts the weight of the sample according to the number of errors in the previous iterations after each iteration. By deducing and analyzing the upper bound of the error of the AdaBoost algorithm, the weights of easily misclassified samples are restricted. Thus, degradation of the ensemble strong classifier performance is reduced. For making a weak SVM different in the process of integration, the best model parameters of each SVM are found through an iterative optimization of the BSA in this paper. Simulation and experiment results show that the performance of the improved AdaBoost-SVM fault diagnosis model is better than that of the traditional fault diagnosis model, which improves the accuracy of fault diagnosis and the generalization ability of the integrated strong classifier.

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