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Fault Diagnosis for Power Converters based on Random Forests and Feature Transformation

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Abstract—Power converters have been key enablers of many energy conversion fields, and it is a trend to apply artificial intelligent (AI) technology to power converters to improve stability. A novel fault diagnosis method based on the combination of random forests (RFs) and feature transformation is proposed in this paper. Firstly, the three-phase AC fault currents of three-phase PWM rectifier are analyzed as examples. Secondly, the feature transformation, a novel current trajectories slopes based method, is adopted to transform the fault currents data. With the help of feature transformation, the fault diagnosis classifier can obtain a good load adaptability. And then the RFs based method, a data-driven method, is employed to train the fault diagnosis classifier with the fault current trajectories slopes data. Finally, the proposed method is carried out on an three-phase PWM rectifier system, which can detect and locate the open-circuit faults of IGBTs.

Index Terms—fault diagnosis, power converters, data-driven, random forests, feature transformation, current trajectories slopes

I. INTRODUCTION

Power converters have been widely utilized in various energy conversion applications, such as AC-DC grid, electric aircrafts, smart grids, utility interfaces with renewable energy resources and so forth [1] [2] [3]. And meanwhile AI technology has also been rapid development, therefore, it has been a trend to apply AI technology to the control design and fault diagnosis of power converters, which is conducive to greatly improving the stability of power converters [4] [5] [6].

Generally, AI technology is used in the open-circuit fault diagnosis of power converters, because the open-circuit fault is less harmful but it is a hidden danger to other equipment [7]. On the contrary, since short-circuit fault is generally more

destructive, short-circuit fault is usually directly detected by standard hardware protection system, such as fuse and breaker, and then the short-circuit fault becomes open-circuit fault [8]. Therefore, open-circuit faults diagnosis is of great significance to improve the stability of power converters.

At present, there are some researches about the open-circuit faults diagnosis of power converter based on AI techniques have been reported. A fault detection method based on artificial neural network(ANN) was proposed in [4] for the switch devices of three-parallel power converters, in which the surface of current vector, vector angle, distributed angle were used to train the neural network fault diagnosis classifier. A Bayesian network based fault diagnosis methodology was proposed in [9] for three-phase inverters, in which the fast Fourier transform was adopted to extract fault features of two output line-to-line voltages. [10] proposed an intelligent fault protection algorithm based on ANN for MMC-based(Modular multilevel converter) DC grids, in which the discrete wavelet transform(DWT) algorithm was adopted to preprocess the input signals. Based on the grid current processing, [11] proposed an ANN-based method for the grid current prediction in the active rectifier to deal the transistors open-circuit faults. Based on the model-based and data processing perspective, [12] proposed a fault detection and isolation method for open-circuit faults of IGBTs in grid-connected neutral-point-clamped (NPC) inverters. Based on the relationship of the operation state and binaried output of voltage sensors, [13] proposed a Boolean logic operation fault indicator, which could detect and locate the open-circuit faults and improve the reliability of the MMC. In addition, some example applications of AI techniques in smart grid and renewable energy systems have been introduced in [14], especially the applications of expert systems, fuzzy logic and artificial neural networks in

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Fig. 1. Fault diagnosis schematic for power converters

power electronics and power engineering. But few scholars consider the influence of loads, input voltages and other external conditions. Three-phase PWM rectifiers play a critical role in many energy conversion fields, and meanwhile RFs can overcome the problems of over-fitting and low training speed in comparison with other AI algorithms [15]. Therefore, the three-phase PWM rectifier system is selected as an example for research, a novel current trajectories slopes based method is proposed to transform the fault currents, which can adapt to the influence of different loads. And the RFs is adopted to train the fault diagnosis classifier with the transformed fault data, which can obtain a good load adaptability.

The fault diagnosis schematic for power converters is shown in Fig.1. And the rest of the paper is organized as follows. Section II describes fault AC currents of three-phase PWM rectifiers. Section III presents the RFs and feature transformation based method, and the performance of RFs fault diagnosis classifier is evaluated. The proposed method is carried out on an three-phase PWM rectifier system in section IV. Conclusions are drawn in the last section.

II. THREE-PHASE AC FAULT CURRENTS OF THREE-PHASE PWM RECTIFIER

The experimental platform of the three-phase PWM rectifier system is shown in Fig.2, and the input phase voltage is 40V, output voltage is 100V. As shown in Fig.1, the open-circuit faults happened in IGBT S_{a1} . Fig.3 and Fig.4 show the three-phase fault current waveforms with the 16 Ω load and 32 Ω load, respectively. According to Fig.3 and Fig.4, there is a relationship between fault waveforms and fault modes, the negative half cycle of phase-current waveform will be affected when the upper IGBTs suffer open-circuit faults, and the positive half cycle of phase-current waveform will be affected when the lower IGBTs suffer open-circuit faults. It's obvious that the fault currents values are not the same under different loads. Therefore, it is necessary to study a method to reduce the influence of current amplitudes.

Fig. 2. Experimental platform

(a) S_{a1} open-circuit fault

(b) S_{a2} open-circuit fault

Fig. 3. Fault current waveforms with 16 Ω load

(a) S_{a1} open-circuit fault

(b) S_{a2} open-circuit fault

Fig. 4. Fault current waveforms with 32 Ω load

III. FAULT DIAGNOSIS METHOD BASED ON RFs AND FEATURE TRANSFORMATION

In this section, it has been certified that the novel current trajectories slopes are not affected by the loads. And the

performance of RFs fault diagnosis classifier is evaluated, which has the adaptive ability to different loads.

A. Feature transformation

The expressions of three-phase sinusoidal AC currents can be described as

$$\begin{cases} i_a = A \sin(\omega t) \\ i_b = A \sin(\omega t - \frac{2}{3}\pi) \\ i_c = A \sin(\omega t + \frac{2}{3}\pi) \end{cases} \quad (1)$$

where A represents the amplitude of three-phase AC currents, and the frequency $\omega = 100\pi$.

The current trajectories about (i_a, i_b) , (i_a, i_c) and (i_b, i_c) are oblique ellipses (as shown in Fig.5), whose shape is not affected by the amplitude A , but the minor axis semidiameter and major axis semidiameter are affected by the amplitude A . However, the novel current trajectories slopes are not affected by the loads (as shown in Fig.6 and Fig.7).

Fig. 5. Novel current trajectories

After a series of analysis and formula, the expressions of oblique ellipse can be described as follows

$$(x+y)^2 + \frac{(x-y)^2}{3} = A^2 \quad (2)$$

The slopes of ψ_1 , ψ_2 and ψ_3 are expressed as

Fig. 6. Fault current trajectories with 16 Ω load

$$\begin{cases} \psi_1 = \frac{i_a(t)}{i_b(t)} = \frac{\sin(\omega t)}{\sin(\omega t - \frac{2}{3}\pi)} \\ \psi_2 = \frac{i_a(t)}{i_c(t)} = \frac{\sin(\omega t)}{\sin(\omega t + \frac{2}{3}\pi)} \\ \psi_3 = \frac{i_b(t)}{i_c(t)} = \frac{\sin(\omega t - \frac{2}{3}\pi)}{\sin(\omega t + \frac{2}{3}\pi)} \end{cases} \quad (3)$$

Take i_a, i_b , and i_c as the first phase current, respectively. The original fault data are transformed to $(\psi_{A1}, \psi_{A2}, \psi_{A3})$, $(\psi_{B1}, \psi_{B2}, \psi_{B3})$ and $(\psi_{C1}, \psi_{C2}, \psi_{C3})$, representing 9 features (as shown in Fig.6 and Fig.7), meanwhile the current trajectories slopes have the adaptive ability to different loads.

B. Training and evaluation of RFs fault diagnosis classifier

The training process of RFs and the proposed method are shown in Fig. 8 and Fig.9. Table I shows the fault location and fault labels. Table II and Table III show the accuracies of single RFs method and the proposed method, respectively.

Compared with the single data-driven method, the proposed method introduces feature transformation. After inputting fault samples, the fault samples can be transformed to

Fig. 7. Fault current trajectories with $32\ \Omega$ load

TABLE I
FAULT LOCATION AND FAULT LABELS

Fault location	Fault codes					
	d1	d2	d3	d4	d5	d6
Normal state	0	0	0	0	0	0
S_{a1}	1	0	0	0	0	0
S_{a2}	0	1	0	0	0	0
S_{b1}	0	0	1	0	0	0
S_{b2}	0	0	0	1	0	0
S_{c1}	0	0	0	0	1	0
S_{c2}	0	0	0	0	0	1
...						

$(\psi_{A1}, \psi_{A2}, \psi_{A3})$, $(\psi_{B1}, \psi_{B2}, \psi_{B3})$ and $(\psi_{C1}, \psi_{C2}, \psi_{C3})$. And then the RFs method is adopted to train the fault diagnosis classifier. By this way, the influence of loads can be reduced. As shown in Table II and Table III, the fault diagnosis classifiers are trained by the fault samples under $16\ \Omega$ load, and the fault data of other loads are adopted to validate the robustness of the proposed method.

Fig. 8. Training process of single RFs

Fig. 9. Training process of the proposed method

TABLE II
ACCURACIES OF SINGLE RFs METHOD

Fault location	$16\ \Omega$	$32\ \Omega$
	diagnostic accuracy	diagnostic accuracy
Normal state	0.9752	0.7824
S_{a1}	0.9694	0.8231
S_{a2}	0.9702	0.7342
S_{b1}	0.9762	0.7452
S_{b2}	0.9762	0.7625
...		

IV. FAULT DIAGNOSIS EXPERIMENTS

In section III, the adaptive ability of the proposed method to the load has been proved. Therefore, the mature fault diagnosis

TABLE III
ACCURACIES OF PROPOSED METHOD

Fault location	16Ω diagnostic accuracy	32Ω diagnostic accuracy
Normal state	0.9765	0.9758
S _{a1}	0.9682	0.9662
S _{a2}	0.9742	0.9683
S _{b1}	0.9783	0.9764
S _{b2}	0.9805	0.9803
...	...	...

classifier is tested with the open-circuit faults data under 16 Ω load. Of course, other situations also tell the similar story. The open-circuit faults diagnosis process is shown in Fig. 1, the bottom hardware controller sends 200 fault samples to the mature fault diagnosis classifier every 20ms, and the fault diagnosis classifier can obtain 200 results every 20ms. Fig.10 shows the S_{a1} fault diagnosis experiment, and Fig.11 shows the S_{a1} fault diagnosis result. According to Fig.10 and Fig.11, 200 groups of samples can be obtained in one cycle, and then the fault samples were transformed by the proposed method, finally the 200 groups results were given by the mature fault diagnosis classifier during fault diagnosis. The first 100 samples were diagnosed as normal, and the last 100 samples were diagnosed as S_{a1} fault, thus it is considered that the fault location is S_{a1}.

Fig. 10. S_{a1} fault diagnosis experiment

V. CONCLUSIONS

A novel fault diagnosis method based on RFs and feature transformation is proposed in this paper. It has been certified that the novel current trajectories slopes are not affected by the loads, and the slopes are adopted to train the fault diagnosis classifier based on RFs, which has the adaptive ability to different loads. The proposed method dose not only reduce the dependence on fault model, but also reduce the dependence

Fig. 11. S_{a1} fault diagnosis result

on training data. Finally, the proposed method is carried out on an three-phase PWM rectifier system, which can detect and locate the open-circuit faults of IGBTs. Furthermore, the proposed method is suitable for most of three-phase energy conversion systems.

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