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An Intelligent Fault Diagnosis Method for Open-Circuit Faults in Power-Electronics Energy Conversion System

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ABSTRACT Applying the fault diagnosis techniques to power electronic equipments is beneficial to improve the stability and reliability of renewable energy system, because power electronic equipments are a key component of renewable energy system that largely defines their performance. This paper presents a novel intelligent fault diagnosis method for a three-phase power-electronics energy conversion system based on knowledge-based and data-driven methods. Firstly, the three-phase AC currents of the power-electronics energy conversion system are collected and used to analyze. Secondly, the feature transformation, a knowledge-based method, is utilized to preprocess the fault data. After feature transformation, the slopes of current trajectories (transformed features) are not affected by different loads. And then random forests algorithms (RFs), a data-driven method, are adopted to train the fault diagnosis classifier with the processed fault data. Finally, the proposed method is implemented online on an actual three-phase PWM rectifier platform. The results show that the proposed fault diagnosis method can successfully detect and locate the open-circuit faults in IGBTs of the three-phase PWM rectifier. In addition, the proposed method is suitable for most of three-phase power-electronics energy conversion systems.

INDEX TERMS Open-circuit faults, power-electronics energy conversion system, slopes of current trajectories, data-driven, intelligent fault diagnosis, knowledge-based.

I. INTRODUCTION

With the development of energy systems, the high proportion of renewable energy is accessed by the energy systems, which bring more challenges and unsteadiness [1]–[3]. Recently, more power electronic converters have also been interconnected with the power grid because the clean energy has been more and more concerned [4]. Among them, three-phase PWM rectifiers, one kind of the most widely used energy conversion equipment, play a significant role in the fields of AC-DC grid, drives of electrical motors, and other energy conversion fields [5], [6]. Three-phase PWM rectifier is similar to other power-electronics energy conversion systems, the reliability of which is vital to the whole energy system.

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Therefore, fault diagnosis and state monitoring for power-electronics energy conversion systems are necessary [7].

The typical fault diagnosis methods can be classified as knowledge-based and data-driven methods, meanwhile more and more intelligent methods are widely used in power-electronics energy conversion systems [8]–[13]. A fault diagnosis method based on knowledge models was presented in [14] to detect and isolate faults in a PWM inverter which was applied in a synchronous motor drive, and the method was based on the analysis of the fault current-vector trajectory and the instantaneous frequency. A model-based open-circuit fault diagnosis method was presented in [15] for single-phase three-level neutral-point-clamped converters in electric railway application, in which the changing rate of the grid current residual was adopted for diagnosis, and the mixed logical dynamic (MLD) model of the converter was built to estimate the grid current. A model-based diagnosis method

was presented in [16] to improve fault isolability in Solid Oxide Fuel Cell (SOFC) energy conversion systems, these models provide a set of redundant residuals, which react only when the faults occur in the related components. A data mining based method was presented in [17] to identify and interpret the power consumption patterns and associations, which was able to identify energy consumption patterns and extract energy consumption rules in variable refrigerant flow systems. A novel fault diagnosis method was presented in [18] for battery systems in electric vehicles based on big data statistical methods, in which the neural network algorithm with big data statistical regulation was used to construct a more complete battery system fault diagnosis model. A data-driven diagnosis approach was presented in [19] for polymer electrolyte membrane fuel cell (PEMFC) systems, in which the fisher discriminant analysis (FDA) algorithm was used to extract more effective features from raw individual cell voltages data, and the directed acyclic graph support vector machine (DAGSVM) algorithm was used to classify the extracted features into various classes related to health states. A data-driven method for online monitoring the variation of a wind turbine power curve was presented in [20] to identify impaired power generation performance. A data-driven fault diagnosis method was presented in [21] for proton exchange membrane fuel cell systems, in which shapelet transform was adopted to extract the discriminative features, and sphere shaped multiclass support vector machine was carried out in the feature space to realize fault detection and fault isolation. A data-driven approach was presented in [22] to build an equivalent steady state model of a wind farm under normal operating conditions, which can detect anomalous functioning conditions of the wind farm as a whole. The knowledge-based methods often require sufficient domain knowledge, although it is difficult to establish fault model of power-electronics energy conversion system and difficult to apply it directly to fault diagnosis, the knowledge-based methods can be applied to feature transformation and feature extraction. Most data-driven technologies are highly dependent on data, although it can extract the mapping relationship knowledge from the historical fault data, it ignores many available knowledge in the system, which can be used to reduce its over-reliance on fault data [23]. To overcome the individual shortcomings of the knowledge-based and data-driven methods, a hybrid method has been proposed by combining both the knowledge-based and data-driven methods in this study.

Considering that power-electronics energy conversion systems are essential for modern power systems, and the high fault rate of power converters which is associated to power semiconductor [24], [25]. Therefore, fault diagnosis in power converters is becoming more and more important. Since short-circuit faults in IGBTs, are considered as the most destructive, and usually protected by standard hardware circuits [26], [27]. However, the open-circuit faults, which may not be detected immediately during the early stage of fault and easy lead secondary fault to other equipment, have attracted much attention [28]. Thus, open-circuit faults of IGBTs in

three-phase PWM rectifiers are considered as examples for study. The AC currents, the signals applied in the control system, are employed as the measured signal. And then the feature transformation based knowledge is used to calculate the slopes of the current trajectories, the transformed features are not affected by different loads. Meanwhile the random forest algorithm has good performance against overfitting [29]. Knowledge-based method has strong knowledge performance and feature transformation capabilities, and data-driven method is good at nonlinear fitting. Therefore, the random forest algorithm and the slopes of current trajectories are combined to train the fault diagnosis classifier, which has the ability to adapt to different loads.

Different methods have different advantages and backgrounds. References [10], [15] and [31] rely on the specific thresholds, the performance of fault diagnosis is easily affected by thresholds, and the set methods are all different. A novel intelligent fault diagnosis method is proposed for three-phase power-electronics energy conversion systems, which can reduce dependence of the fault data under different loads, and does not need to set complex thresholds. The detailed contributions of this study are summarized as follows:

- (1) Develops a knowledge-based feature transform method in which the slopes of the current trajectories are not affected by the loads.
- (2) Presents a unique combination of knowledge-based and data-driven method for three-phase power-electronics energy conversion systems.
- (3) Proposes a multiple timescale fault diagnosis process, which can successfully online detect and locate the open-circuit faults in IGBTs.

Fig.1 illustrates the fault diagnosis schematic of power-electronics energy conversion system. The paper is organized as follows. Section 2 describes fault waveform of AC currents of the power-electronics energy conversion system, and the actual fault data are collected. In section 3, it has been certified that the slopes of two current trajectories are not affected by the loads, and presents the design of the proposed method, and the ability of fault diagnosis classifier is quantified. The proposed method is implemented online on an actual power electronic platform in Section 4. Conclusions are drawn in the last section.

II. THREE-PHASE AC FAULT CURRENTS DATA ACQUISITION AND ANALYSIS

The experimental platform of power-electronics energy conversion system is shown in Fig.2 consists of a three-phase PWM rectifier equipment, a computer, oscilloscope and so forth. The control strategy of proportional resonance (PR) was used to control the three-phase PWM rectifier in this study, which can be referred to [32]. The main parameters of the experimental platform are given in Table 1. In order to obtain actual fault data of the three-phase PWM rectifier system, the open-circuit faults of IGBTs can be simulated by closing the driving signal.

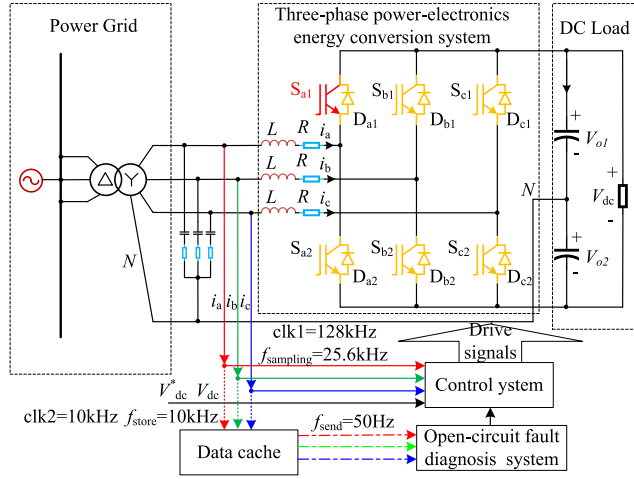


FIGURE 1. Fault diagnosis schematic of power-electronics energy conversion system.

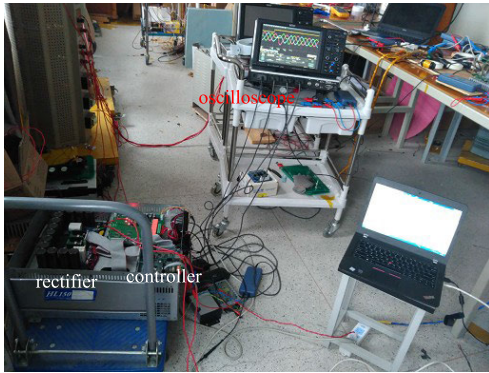


FIGURE 2. Experimental platform of power-electronics energy conversion system.

TABLE 1. Experimental platform parameters.

Parameters	Value
Input voltage	40V, 50Hz
Output voltage	100V
DC-link capacitances	7000uF
Filter inductance	500uH
IGBT	FS1501212ET4
Switching frequency(kHz)	12.8kHz

Fig.1 illustrates a typical three-phase PWM rectifier for the power-electronics energy conversion system, which is composed by three independent single-phase half-bridge rectifiers [33]. Therefore, taking open-circuit faults of IGBTs S_{a1} and S_{a2} as examples, and the phase current is conducted by both of IGBTs and the equipped diodes. The operations of A-phase IGBTs and diodes are listed in Table 2, and the A-phase current paths under different directions of i_a are presented in Fig.3. When the gate signal is equal to 1, the IGBT conducts, and when the gate signal is equal to 0, the IGBT does not conduct. For a normal operation state, the phase current i_a flows through the IGBT S_{a1} and the diode D_{a2} if $i_a < 0$, whereas it flows through the IGBT S_{a2} and the diode D_{a1} if $i_a \geq 0$.

TABLE 2. Operations of A-phase IGBTs and diodes.

Gate signal	$i_a \geq 0$	$i_a < 0$
$S_{a1}=1, S_{a2}=0$	D_{a1} ON	S_{a1} ON
$S_{a1}=0, S_{a2}=1$	S_{a2} ON	D_{a2} ON

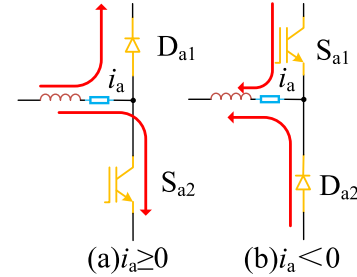


FIGURE 3. A-phase current paths under different directions.

Under the normal operation mode, the three-phase AC currents of three-phase PWM rectifier are sinusoidal waves, while the open-circuit faults occur in IGBTs of the rectifier, the phase current waveforms will be distorted. For example, three-phase fault current waveforms with 16Ω load and 32Ω load are shown in Fig.4 and Fig.5, respectively. The *Signal* is adopted to determine the fault occurrence and the instantaneous measurements of three-phase AC current are employed to locate the fault IGBTs. It can be seen that the positive half-cycle phase current disappears for the open-circuit fault occurred in the lower IGBT S_{a2} , while the phase current is negative, the rectifier is slightly affected. And meanwhile the negative half-cycle phase current disappears for the open-circuit fault occurred in the upper IGBT S_{a1} , while the phase current is positive, the rectifier is slightly affected. For this case, the waveform of phase current depends entirely on whether the fault occur in an upper IGBT or a lower IGBT.

According to Fig. 4 and Fig. 5, it can be seen that that different faults locations have different influences on the three-phase AC current waveforms. Under the fault condition, the current will increase, but it does not reach the current limitation. However, long term operation with fault will bring secondary damage to other equipment. And meanwhile the fault currents are not the same under different loads. Therefore, it is necessary to transform or extract fault features to obtain more effective fault features, so as to reduce the over-reliance on fault data under different loads.

III. INTELLIGENT FAULT DIAGNOSIS METHOD BASED ON KNOWLEDGE-BASED AND DATA-DRIVEN APPROACH

In this section, it has been certified that the slopes of two current trajectories are only related to sampling interval T and time t , are not affected by the load. And the slopes are used to train the fault diagnosis classifier, which has the adaptive ability to different loads.

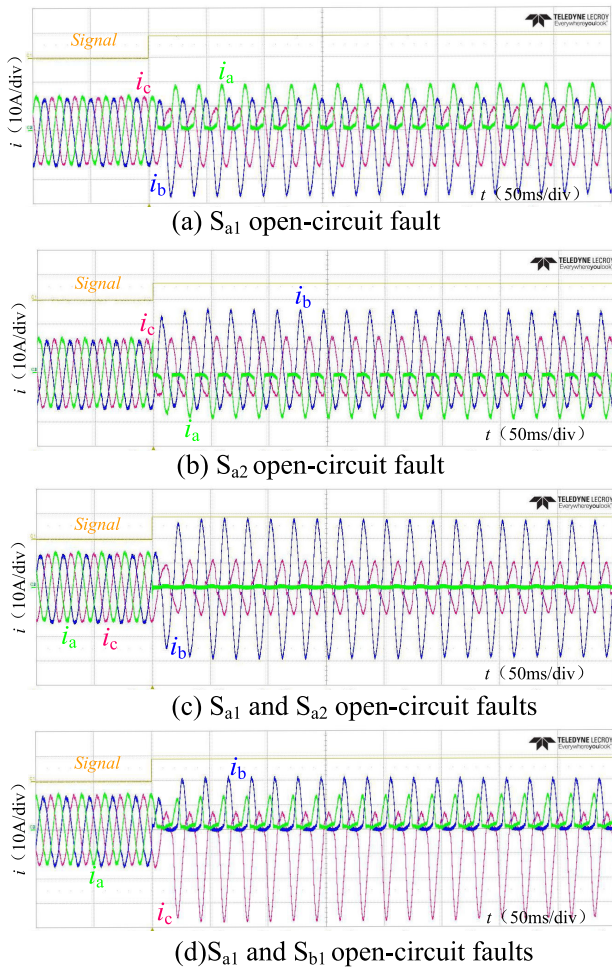


FIGURE 4. Three-phase fault current waveforms with 16Ω load.

A. FEATURE TRANSFORMATION BASED ON KNOWLEDGE

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 $\omega=100\pi$.

The expression for the Concordia transformation are given by [34]

$$\begin{bmatrix} i_\alpha \\ i_\beta \\ i_0 \end{bmatrix} = m * \begin{bmatrix} 1 & -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \\ i_c \end{bmatrix} \quad (2)$$

where $m = \sqrt{\frac{2}{3}}$.

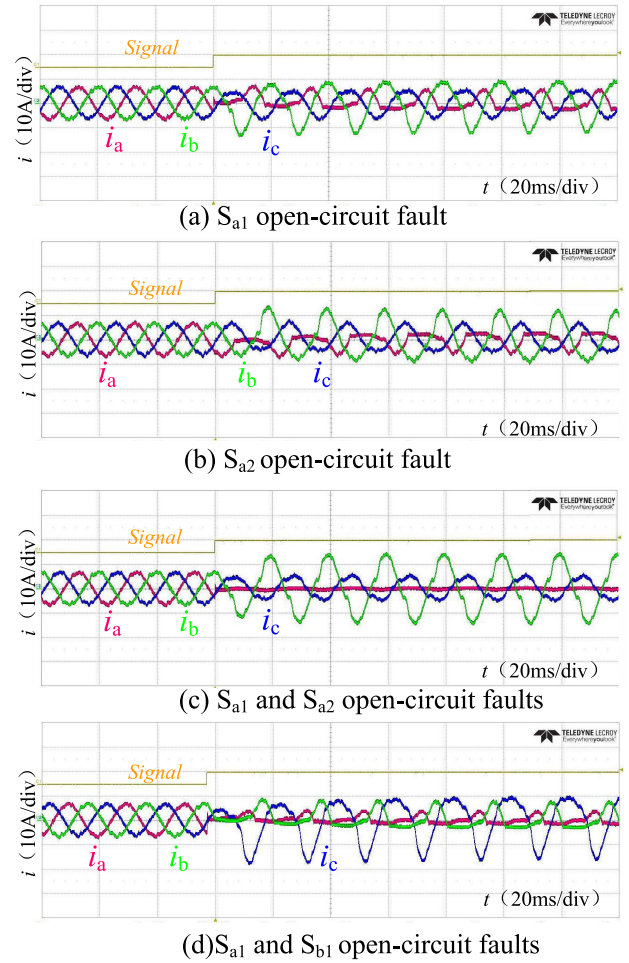


FIGURE 5. Three-phase fault current waveforms with 32Ω load.

Assuming that $i_a + i_b + i_c = 0$, and then

$$\begin{cases} i_\alpha = \sqrt{\frac{3}{2}} i_a \\ i_\beta = i_b \sqrt{2} + \frac{1}{\sqrt{2}} i_c \end{cases} \quad (3)$$

Based on the above formulas, it can be obtained that the expressions of the current trajectory can be described as follows

$$i_\alpha^2 + i_\beta^2 = (mA)^2 \quad (4)$$

Relations (1) and (3) are then employed to obtain the slope, which can be expressed as follows

$$\psi_1 = \frac{i_\alpha(t)}{i_\beta(t)} = \frac{\sqrt{3}}{1 + 2 \frac{i_b}{i_a}} = \frac{\sqrt{3}}{1 + 2 \frac{\sin(\omega t - \frac{2}{3}\pi)}{\sin(\omega t)}} \quad (5)$$

And then the slope ψ_2 can be expressed as

$$\begin{aligned} \psi_2 &= \frac{i_\alpha(t) - i_\alpha(t-T)}{i_\beta(t) - i_\beta(t-T)} \\ &= \frac{\sqrt{3}}{1 + 2 \frac{i_b(t) - i_b(t-T)}{i_a(t) - i_a(t-T)}} \\ &= \frac{\sqrt{3}}{1 + 2 \frac{\sin(\omega t - \frac{2}{3}\pi) - \sin(\omega t - \frac{2}{3}\pi - T)}{\sin(\omega t) - \sin(\omega t - T)}} \end{aligned} \quad (6)$$

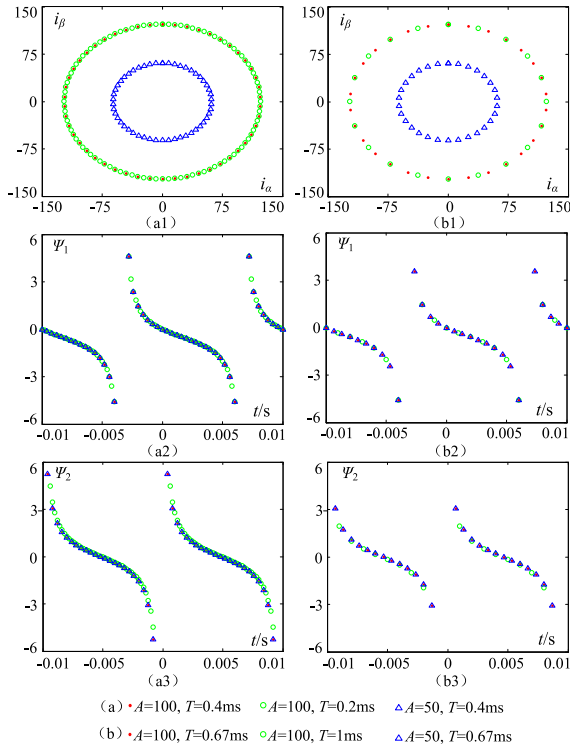


FIGURE 6. Current trajectories and slopes under different T and A .

It is obvious that ψ_1 and ψ_2 are only related to sampling interval T and time t , meanwhile they are not affected by the load. Fig.6 shows the current trajectories and slopes under different T and A . Fig.6(a1) and Fig.6(b1) show the current trajectories, which are circular current trajectories whose radii are affected by the amplitude A of three-phase sinusoidal AC currents. Fig.6(a2) (a3) (b2) and (b3) show the slopes, which are only affected by sampling interval T and time t , but not by amplitude A . Therefore, the slopes will be adopted as the direct features to train fault diagnosis classifier.

Based on the similar idea, another a novel current trajectory and slope are also demonstrated in this paper, which takes advantage of the algorithm similar to the above method to feature transformation, and thus extracts the feature without relation to amplitude A . The current trajectories about (i_a, i_b) , (i_a, i_c) and (i_b, i_c) are oblique ellipses (as shown in Fig.7), whose shape is not affected by the amplitude A , but the minor axis semidiameter and major axis semidiameter are affected by the amplitude A .

The expressions of oblique ellipse can be described as follows

$$\frac{(x \cos \theta - y \sin \theta)^2}{a^2} + \frac{(x \sin \theta + y \cos \theta)^2}{b^2} = 1 \quad (7)$$

where a is major axis semidiameter, b is minor axis semidiameter, and θ is rotation angle.

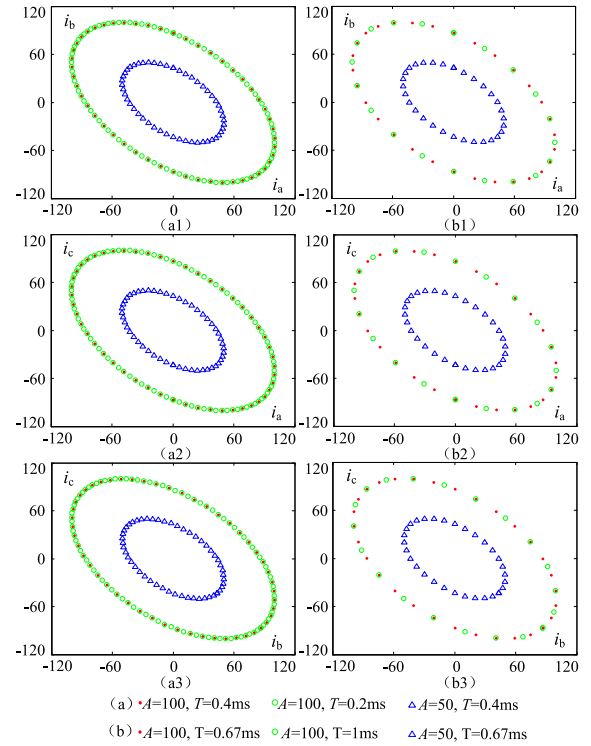


FIGURE 7. New current trajectories under different T and A .

Assuming that $x = i_a$ and $y = i_b$, then

$i_a = 0, i_b = -\frac{\sqrt{3}}{2}A$ when $\omega t = 0$, substitute $x = i_a$ and $y = i_b$ into (7), it can be gotten that

$$\frac{3A^2 \sin^2 \theta}{4a^2} + \frac{3A^2 \cos^2 \theta}{4b^2} = 1 \quad (8)$$

$i_a = \frac{\sqrt{3}}{2}A, i_b = 0$ when $\omega t = \frac{2\pi}{3}$, substitute $x = i_a$ and $y = i_b$ into (7), it can be gotten that

$$\frac{3A^2 \cos^2 \theta}{4a^2} + \frac{3A^2 \sin^2 \theta}{4b^2} = 1 \quad (9)$$

$i_a = \frac{\sqrt{3}}{2}A, i_b = -\frac{\sqrt{3}}{2}A$ when $\omega t = \frac{\pi}{3}$, substitute $x = i_a$ and $y = i_b$ into (7), it can be gotten that

$$\frac{3A^2(1 + \sin 2\theta)}{4a^2} + \frac{3A^2(1 - \sin 2\theta)}{4b^2} = 1 \quad (10)$$

According to the formula (7)(8)(9)(10), it can be deduced that the expressions of oblique ellipse is as follows

$$(x + y)^2 + \frac{(x - y)^2}{3} = A^2 \quad (11)$$

Further research found that (i_a, i_b) , (i_a, i_c) and (i_b, i_c) all conform to the formula (11), and where x and y are symmetrical, that is, interchangeable. According to the formula (11), it also can be seen that the new current trajectory of three-phase sinusoidal AC currents is only affected by the amplitude A . Fig.7 indicate that the trajectories of (i_a, i_b) , (i_a, i_c) and (i_b, i_c) under different conditions are oblique ellipses, which are coincident with the formula (11).

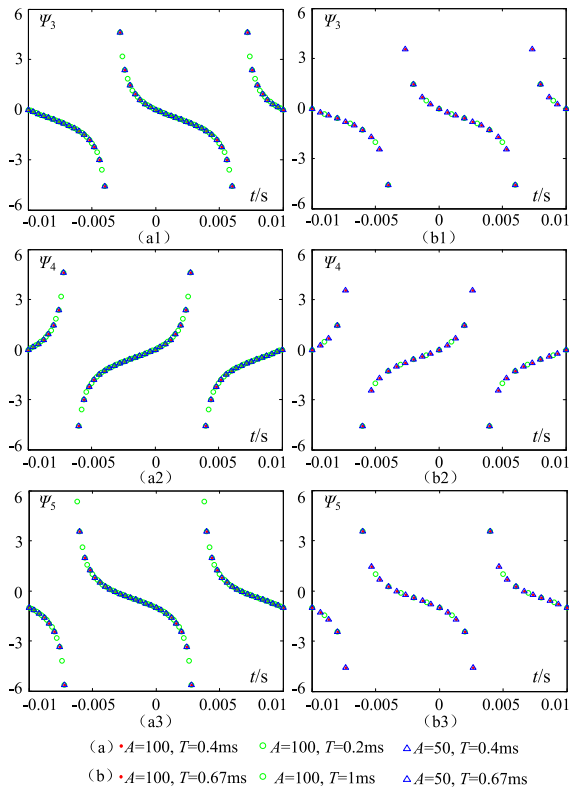


FIGURE 8. New slopes under different T and A .

Since the new current trajectory of three-phase sinusoidal AC currents is affected by the amplitude A . Therefore, the slopes of the new current trajectories are further studied.

The slope of ψ_3 can be expressed as

$$\psi_3 = \frac{i_a(t)}{i_b(t)} = \frac{\sin(\omega t)}{\sin(\omega t - \frac{2}{3}\pi)} \quad (12)$$

The slope of ψ_4 can be expressed as

$$\psi_4 = \frac{i_a(t)}{i_c(t)} = \frac{\sin(\omega t)}{\sin(\omega t + \frac{2}{3}\pi)} \quad (13)$$

The slope of ψ_5 can be expressed as

$$\psi_5 = \frac{i_b(t)}{i_c(t)} = \frac{\sin(\omega t - \frac{2}{3}\pi)}{\sin(\omega t + \frac{2}{3}\pi)} \quad (14)$$

Fig.8 shows the slopes of new current trajectories under different T and A . It can be seen that ψ_3 , ψ_4 and ψ_5 are only affected by the sampling interval T and time t , while they are not affected by the amplitude A . Therefore, the slopes also can be adopted as the direct features to train fault diagnosis classifier.

According to the above research, the transformed features can be obtained by taking the A-phase current as the first

phase current, whose expressions can be described as

$$\begin{cases} i_{A\alpha} = i_a \sqrt{\frac{3}{2}} \\ i_{A\beta} = i_b \sqrt{2} + \frac{i_a}{\sqrt{2}} \\ \psi_{A1} = \frac{i_{A\alpha}(k)}{i_{A\beta}(k)} \\ \psi_{A2} = \frac{i_{A\alpha}(k) - i_{A\alpha}(k-1)}{i_{A\beta}(k) - i_{A\beta}(k-1)} \\ \psi_{A3} = \frac{i_a(k)}{i_b(k)} \\ \psi_{A4} = \frac{i_a(k)}{i_c(k)} \\ \psi_{A5} = \frac{i_b(k)}{i_c(k)} \end{cases} \quad (15)$$

where $(\psi_{A1}, \psi_{A2}, \psi_{A3}, \psi_{A4}, \psi_{A5})$, the slopes of the current trajectories, are the transformed features. And $k-1$ and k are the previous and the present measured currents. Similarly, taking the B-phase and C-phase current as the first phase current, respectively, the $(\psi_{B1}, \psi_{B2}, \psi_{B3}, \psi_{B4}, \psi_{B5})$ and $(\psi_{C1}, \psi_{C2}, \psi_{C3}, \psi_{C4}, \psi_{C5})$ also can be obtained.

Fig.9 and Fig.10 show the slopes of the current trajectories when the open-circuit fault occurs in IGBT S_{a1} and S_{a2} under different loads, where (a1)-(a6) are under the condition of open-circuit fault in S_{a1} , (b1)-(b6) are under the condition of open-circuit fault in S_{a2} , (a1) and (b1) show the original fault waveform, and the other sub-graphs show the slopes of the current trajectories, respectively. It can be seen that the original fault waveforms of different loads are different, while the slopes of the current trajectories are very similar under different loads. That is to say, the slopes of the current trajectories have the ability to adapt to different loads. The robustness of slopes of the current trajectories, under the other open-circuit faults and loads, tell a similar story, so only open-circuit fault occurs in IGBT S_{a1} and S_{a2} under 16Ω and 32Ω are given here, as following.

Based on the result of feature transform, the original fault data are now transformed to $(\psi_{A1}, \psi_{A2}, \psi_{A3}, \psi_{A4}, \psi_{A5})$, $(\psi_{B1}, \psi_{B2}, \psi_{B3}, \psi_{B4}, \psi_{B5})$ and $(\psi_{C1}, \psi_{C2}, \psi_{C3}, \psi_{C4}, \psi_{C5})$ representing 15 features, meanwhile the slopes of the current trajectories have the adaptive ability to different loads.

B. TRAINING AND EVALUATION OF FAULT DIAGNOSIS CLASSIFIER

Knowledge-based and data-driven approaches have their own advantages and disadvantages. On the one hand, the knowledge-based method is seriously affected by sufficient knowledge of the specific domain, but the fault models of the power-electronics energy conversion system are particularly difficult to establish, and few researchers have studied them. Therefore, the knowledge may not be enough to establish complete models in all the cases. On the other hand, the data-driven method is highly depend on training data, but the training data are often limited. Therefore, a data-driven fault

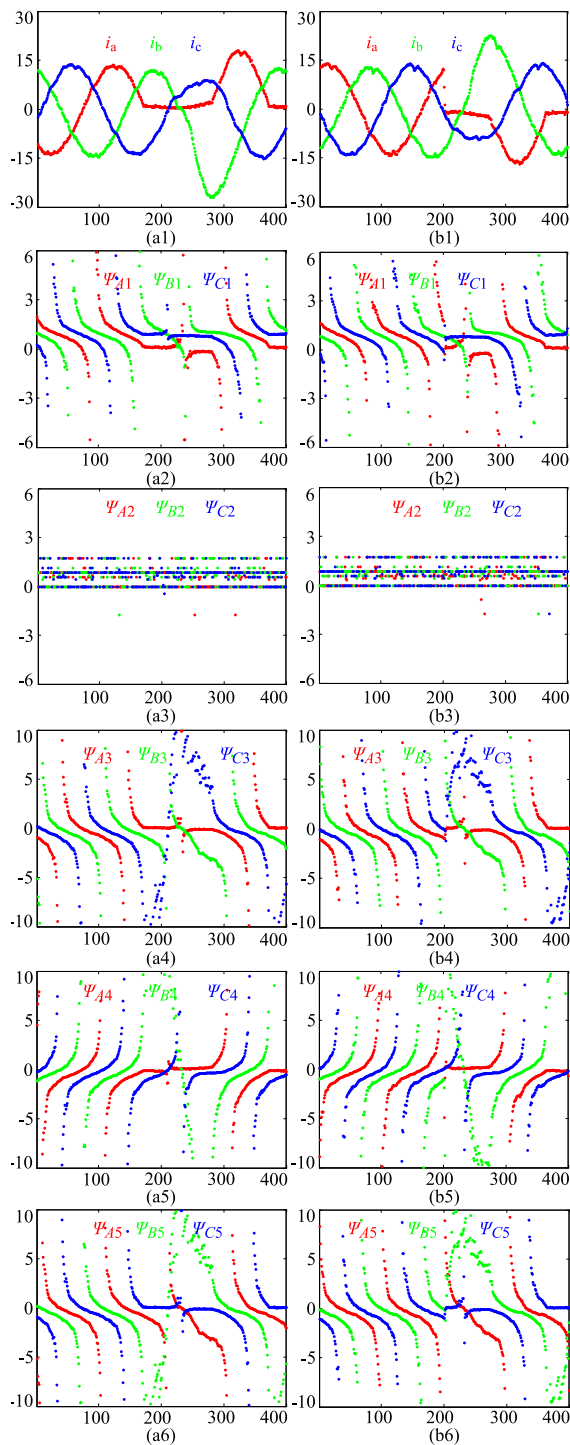


FIGURE 9. Fault features when load is 16 Ω .

diagnosis classifier, trained on the limited data, is extremely difficult to achieve reliable fault diagnosis performance in this case.

To overcome these defects and deficiencies, the knowledge-based and data-driven approach are combined to improve the fault diagnosis performance in this study. It would be highly desirable to feature transform based on knowledge, after that to learn the rules from transformed

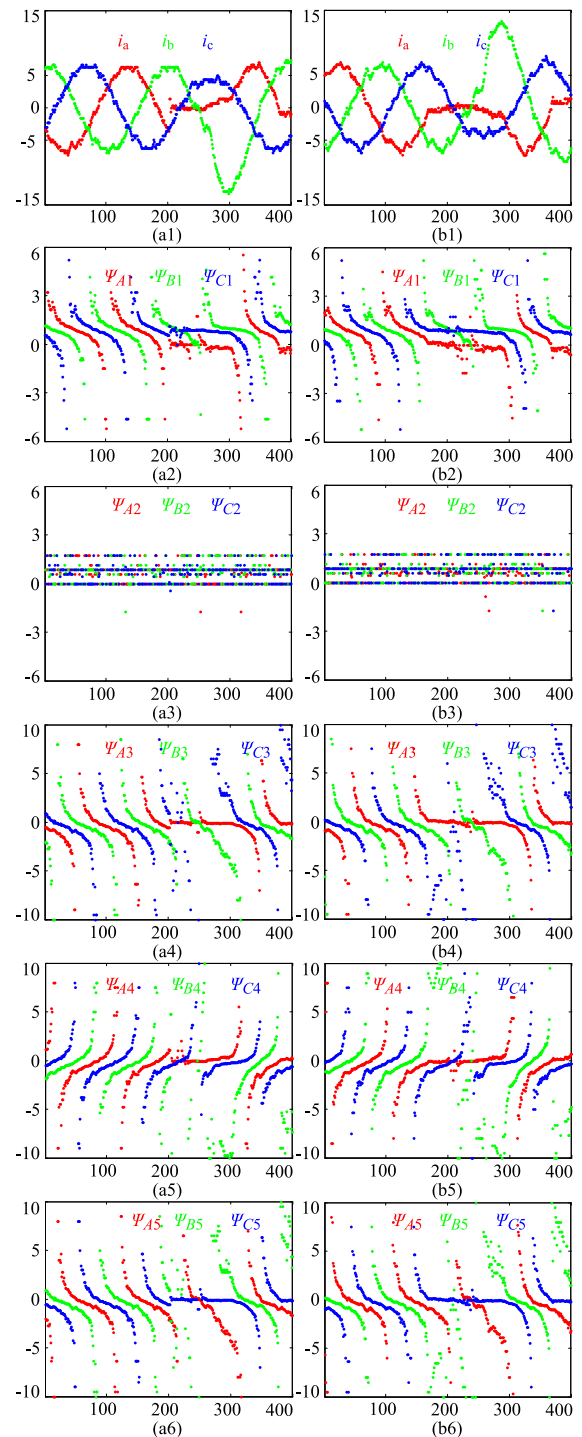


FIGURE 10. Fault features when load is 32 Ω .

data using advanced data-driven techniques. It would make the intelligent fault diagnosis method less reliance on the knowledge about fault models or raw fault data, so that novel applications could be done faster, and more significant, it also makes the fault diagnosis toward more intelligent. In order to prove the validity and effectiveness of the proposed method, a comparison between data-driven method and the proposed method is presented to illustrate the need for a new fault diagnosis system.

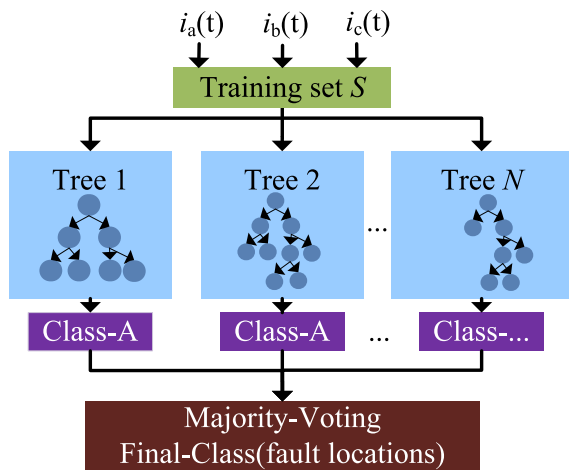


FIGURE 11. Flow chart of data-driven approach.

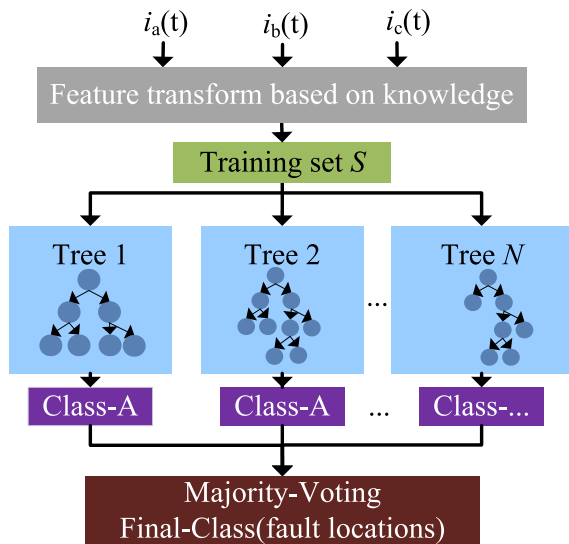


FIGURE 12. Training process of knowledge-based and data-driven approach.

The training process of data-driven and the training process of knowledge-based and data-driven are given as shown in Fig.11 and Fig.12, where the random forest was chosen as the data-driven method. With the help of many decision trees, the random selection of samples and features, random forest algorithm is a powerful supervised machine learning algorithm, which has the advantages of tolerating noise and extreme values, solving the over-fitting problem, meanwhile it is not sensitive to the errors in data itself [35]. During the training process, random forest classifier can be formalized as: given n labeled samples $D = (x_1, y_1), (x_2, y_2), \dots, (x_k, y_k), \dots, (x_n, y_n)$, where $x_k = (i_a(k), i_b(k), i_c(k))$ is a 3-dimensional features vector and y_k is the label of the k^{th} sample (as shown in Table 3). The random forest, a supervised machine learning model, can learn the relationships between the fault data (historical three-phase AC fault currents data) and the labels (fault locations). Compared with the single data-driven

TABLE 3. Some fault samples and fault labels.

Fault IGBT	i_a	i_b	i_c	Actual output	Target output
Normal state	0	-13.986	12.935	000000	000000
S_{a1}	2.029	9.003	-12.941	100000	100000
S_{a2}	-1.291	11.660	-7.850	010000	010000
S_{b1}	-4.556	0.701	10.996	001000	001000
S_{b2}	-1.623	-0.626	-10.257	000100	000100
S_{c1}	11.992	-9.786	0.701	000010	000010
S_{c2}	2.3618	-6.714	-0.959	000001	000001
S_{a1} and S_{b1}	0.664	-0.332	5.645	101000	101000
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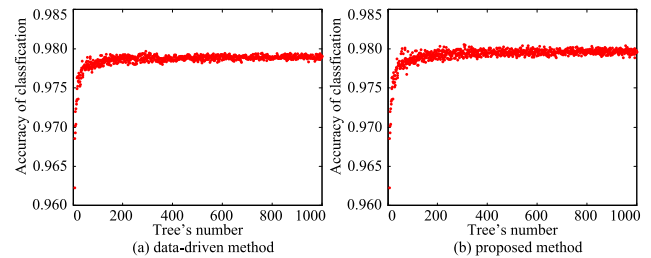


FIGURE 13. Influence of trees' number on performance in RFs.

method, the proposed method introduces a knowledge-based approach to feature transform. After inputting fault samples, the features can be transformed $(\psi_{A1}, \psi_{A2}, \psi_{A3}, \psi_{A4}, \psi_{A5})$, $(\psi_{B1}, \psi_{B2}, \psi_{B3}, \psi_{B4}, \psi_{B5})$ and $(\psi_{C1}, \psi_{C2}, \psi_{C3}, \psi_{C4}, \psi_{C5})$ by the knowledge-based approach. And then the data-driven method is adopted to train the fault diagnosis classifier. By using this method, the influence of load on fault features can be eliminated.

The whole data set is divided into training and test sets, where 16,800 fault samples are randomly selected from 24,000 fault samples of each fault condition as the training set, and the remainder fault samples are selected as the test set. The training set is used to train the model, and the test set is used as the unknown data to assess the model performance. The proposed method requires longer computational time in the training process of fault diagnosis classifier, but the mature fault diagnosis classifier can provide a good online monitoring performance while less computation is required.

The number of random forest decision trees is set based on empirical experience, which is set according to the classification results with trees' number ranging from 1 to 1000. As shown in Fig.13, Fig.13(a) shows the average identification accuracy of the single data-driven method, where the average identification accuracy is the highest at 262 being 0.9797. And Fig.13(b) shows the average identification accuracy of the proposed method, where the average identification accuracy is the highest at 305 being 0.9805 in Fig.13(b).

Table 4 and Table 5 show the average classification accuracies of data-driven method and the proposed method, respectively. The mature fault diagnosis classifiers are trained by the fault samples under 16 Ω load. While the results on the test set indicated the effectiveness of the fault diagnosis classifiers, the fault data from other loads are adopted to validate the robustness of the proposed method.

TABLE 4. Average classification accuracies of data-driven method.

Fault IGBT	16Ω		32Ω	
	diagnostic accuracy	misdiagnosis rate	diagnostic accuracy	misdiagnosis rate
Normal state	0.9794	0.0206	0.7930	0.2070
S_{a1}	0.9793	0.0207	0.8488	0.1512
S_{a2}	0.9800	0.0200	0.7654	0.2346
S_{b1}	0.9784	0.0216	0.7561	0.2439
S_{b2}	0.9801	0.0199	0.7912	0.2088
S_{c1}	0.9797	0.0203	0.8378	0.1622
S_{c2}	0.9800	0.0200	0.7221	0.2779
S_{a1} and S_{b1}	0.9793	0.0207	0.8023	0.1977
S_{a1} and S_{b2}	0.9801	0.0199	0.8200	0.1800
...				

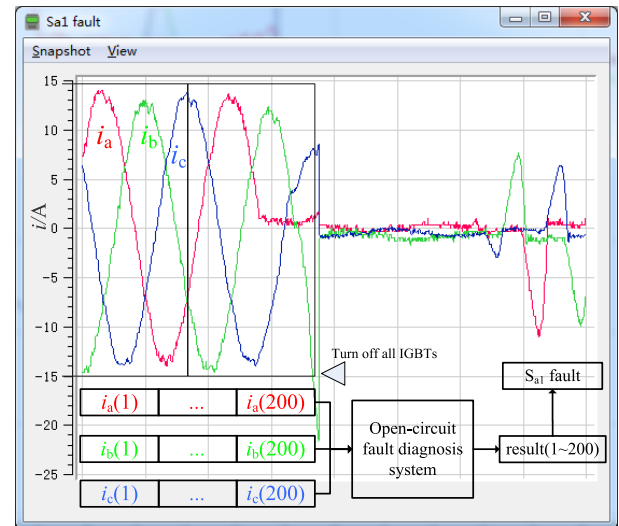
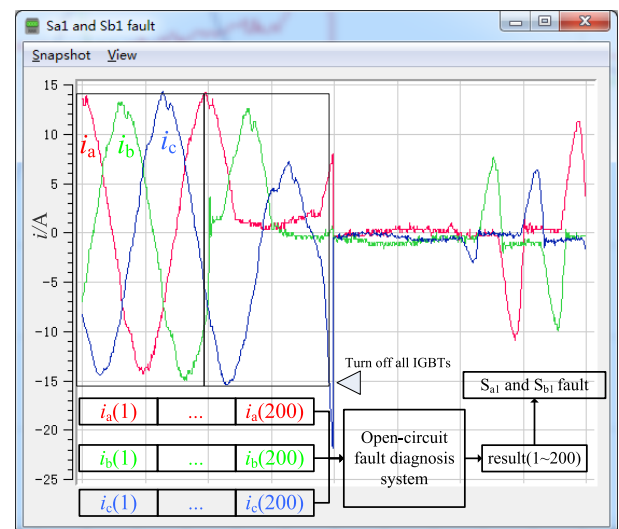
TABLE 5. Average classification accuracies of proposed method.

Fault IGBT	16Ω		32Ω	
	diagnostic accuracy	misdiagnosis rate	diagnostic accuracy	misdiagnosis rate
Normal state	0.9798	0.0202	0.9789	0.0211
S_{a1}	0.9766	0.0234	0.9762	0.0238
S_{a2}	0.9832	0.0168	0.9821	0.0179
S_{b1}	0.9773	0.0227	0.9768	0.0232
S_{b2}	0.9834	0.0166	0.9822	0.0178
S_{c1}	0.9766	0.0234	0.9760	0.0240
S_{c2}	0.9839	0.0161	0.9824	0.0176
S_{a1} and S_{b1}	0.9769	0.0231	0.9765	0.0235
S_{a1} and S_{b2}	0.9801	0.0199	0.9793	0.0207
...				

According to Table 4, the mature fault diagnosis classifier based on data-driven method, trained with the fault samples under 16Ω load, has poor applicability to the fault samples under 32Ω load. By contrast, it can be seen from Table 5 that the mature fault diagnosis classifier based on the proposed method is not only applicable to the fault samples under 16Ω load, but also to the fault samples under 32Ω load. As shown in Table 4 and Table 5, when the fault samples under 32Ω load, the average classification accuracies of the proposed method are over 97%, which are better than those of data-driven method. The results prove that the proposed method is much better when the fault samples under different loads, and the data-driven method rely too much on training data. Meanwhile it is fully confirmed that the proposed method can adapt to the influence of different loads on fault samples.

IV. ONLINE FAULT DIAGNOSIS EXPERIMENTS FOR THREE-PHASE POWER-ELECTRONICS ENERGY CONVERSION SYSTEM

In order to further verify the effectiveness of the proposed diagnosis method, online fault diagnosis experiments are conducted for different open-circuit faults of IGBTs in an actual three-phase PWM rectifier platform. The fault diagnosis schematic of power-electronics energy conversion system is as shown in Fig. 1. The whole experimental platform mainly includes a three-phase PWM rectifier, a control system based on FPGA and a fault diagnosis system based on a low-cost industrial computer. In order to realize online fault diagnosis on the premise of ensuring system safety, the multiple

(a) S_{a1} fault with 16Ω load(b) S_{a1} and S_{b1} fault with 16Ω load**FIGURE 14. Online fault diagnosis experiments.**

timescale method is adopted in the whole fault diagnosis process. The modular design method is used in the FPGA program, which include control system, data cache and data transmission. The sampling clock and sampling frequency of control system are 128kHz and 25.6kHz, respectively. The data caching process is to re-sample the samples of the control system and then store them temporarily, and the clock and frequency of resampling are all 10kHz. And meanwhile the data is sent to the fault diagnosis system every 20ms.

The mature fault diagnosis classifier can provide a good online monitoring performance with less computation. The performance of the other open-circuit faults tell a similar story, so only some fault diagnosis experiments under 16Ω load are given here. As shown in Fig.14, online monitoring system will receive 200 sets of fault samples every 20ms, and then the diagnosis system can give 200 sets diagnosis results (as shown in Fig.15), which will send protection commands

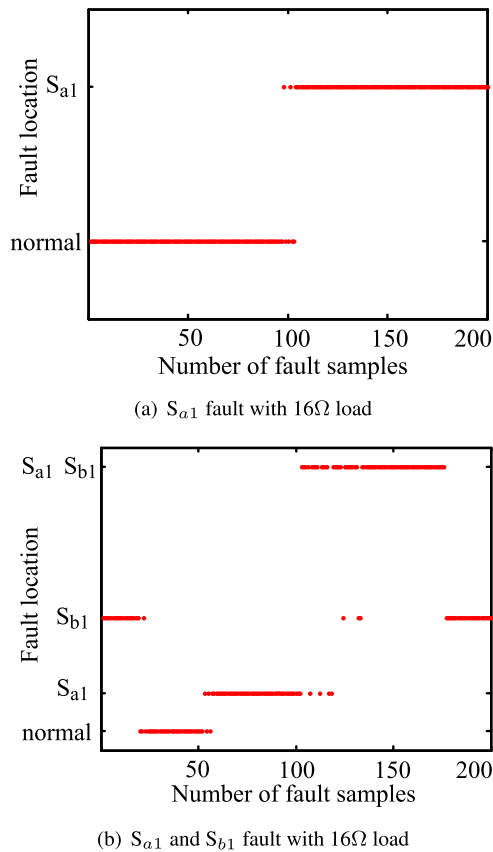


FIGURE 15. Online fault diagnosis results.

to the control system once the fault is detected. As can be seen from Fig.14, when a fault occurs, the fault diagnosis system will protect the system before the system does not cause serious secondary fault.

Fig.15 shows the 200 sets diagnosis results of the 200 sets fault samples in Fig.14. According to the results shown in Fig.15(a), it can be seen that the diagnosis results of the front 100 samples are under normal state, and the next 100 diagnosis results are under the condition of open-circuit faults in IGBT S_{a1} . Therefore, the final open-circuit fault location is IGBT S_{a1} . Again, as shown in Fig.15(b), when the open-circuit faults happen in IGBTs S_{a1} and S_{b1} , the 200 sets diagnosis results are (S_{b1} fault)→(normal)→(S_{a1} fault)→(S_{a1} and S_{b1} fault)→(S_{b1} fault) in turn. Therefore, it is not difficult to see that the faults locations occur in IGBTs S_{a1} and S_{b1} from the diagnosis results. The results show that the proposed fault diagnosis method can successfully detect and locate the open-circuit faults in IGBTs of the three-phase PWM rectifier.

V. CONCLUSION

This paper proposes a novel intelligent fault diagnosis method for open-circuit faults of IGBTs in three-phase power-electronics energy conversion system based on knowledge-based and data-driven methods. Knowledge in different fields is also different, and it is difficult to be universal. It has been certified that the slopes of two current trajectories are

not affected by the loads in this paper. The slopes of two current trajectories can be obtained by feature transformation of three-phase AC currents, and the slopes are adopted to train the fault diagnosis classifier based data-driven method (the random forest algorithm), which has the adaptive ability to different loads. The random forest algorithm and the slopes of current trajectories are combined to train the fault diagnosis classifier, which can not only reduce the dependence on fault model, but also reduce the dependence on training data.

Finally, in order to further verify the effectiveness of the proposed diagnosis method, online fault diagnosis experiments are conducted for different open-circuit faults of IGBTs in an actual three-phase PWM rectifier platform. The multiple timescale method is adopted in the whole fault diagnosis process, which can realize online fault diagnosis on the premise of ensuring system safe. And the results show that the proposed fault diagnosis method can successfully detect and locate the open-circuit faults in IGBTs of the three-phase PWM rectifier. In addition, the proposed method can also be applied to most of three-phase power-electronics energy conversion systems.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Weicheng Wang: Writing - original draft, Methodology, Formal analysis. Lei Kou: Writing - original draft, Methodology, Software. Quan-De Yuan: Validation, Writing - review & editing, Software. Jia-Ning Zhou: Validation, Writing - review & editing. Chuang Liu: Resources, Methodology, Writing - review & editing. Guo-Wei Cai: Writing - review & editing.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this article.

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