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Fault diagnosis for inverter open circuit faults using DC-link signal and random forest-based technique

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ABSTRACT

Three-phase voltage source inverters based on insulated-gate bipolar transistors (IGBTs) are widely used in various industrial applications. Faults in IGBTs significantly affect the performance of the inverter and entire system. Robust and accurate fault detection are the key requirements of fault diagnosis methods. This paper explores a method for diagnosing power switch open circuit faults of a voltage source inverter based on machine learning algorithms. The diagnosis is performed in two steps, firstly the fault is detected by applying the random forest classifier algorithm with the DC-link signal. Next, the fault switch location is performed by additionally using the inverter output AC current signals. The diagnostic results based on simulation data show that the fault can be detected with maximum accuracy. Meanwhile, the accuracy in locating the fault switch is also significantly improved with the additional use of current signals measured at the DC-link. Potential application of electromagnetic field signal is also highlighted for the practical implementation of fault diagnosis.

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1. INTRODUCTION

Three-phase voltage source inverters are widely used in various technical fields such as: power systems of renewable energy sources (wind, solar, and other innovative forms), industrial electric motor drives, energy storage systems, uninterruptible power suppliers, electric vehicles, and other systems in the modern power system. The reliability of the inverter has a great influence on the efficiency in operation of the entire system. Insulated-gate bipolar transistor (IGBT) is a common type of power electronic device in voltage source inverters. During their operation, IGBTs are subjected to high stress, such as electrical, thermal, and mechanical ones, that can lead to their failures or faults. Statistics in the past studies [1], [2] show that failures can occur in both power and control circuits, in which power switches with short circuit and open circuit faults are among the most susceptible components. While IGBT short circuit faults can be detected by the standardized overcurrent protection function built into the electric machine drives, the open circuit condition can still be maintained for a certain period, ensuring operational reliability. However, open circuit faults need to be detected timely manner to avoid spreading the fault to other parts of the system, increasing the severity of the failure. The review study shows that massive studies have been devoted to proposing methods for diagnosing open circuit faults of the power switch in inverters. There are diverse ways to classify diagnostic methods, but they can regularly be divided into signal-based methods, model-based methods, and data-based methods, with the distribution shown in Figure 1 [3].

In signal analysis-based methods, signals are measured and analyzed to obtain fault-related features of the system. The signals could be current, voltage, control, or even electromagnetic signals at the DC-link [4]-[14]. The alternating current supplied to an electric motor is the most commonly used signal for developing open-circuit fault diagnosis methods. For example, some techniques rely on algorithms based on the Park's vector of average motor supply current [4], [5]; the current space vector trajectory [6]; the mean of the absolute value or the phase of the absolutely normalized current [7], the function of current error [8], or abnormal patterns of the current [9]. As an example of a voltage-based approach, the line voltages are used as fault diagnosis variables in [10], in which the sequence components of the voltage are analyzed to detect and locate the faulty switch. Moreover, the temperature can be applied as a signal for fault diagnosis, which is measured or estimated by applying the electrical, optical, or physically contacting methods [11], [12]. In addition, the electromagnetic field signals conducted or emitted from the bus bar of the DC-link can be efficiently used for the invasive techniques of fault diagnosis [13], [14].

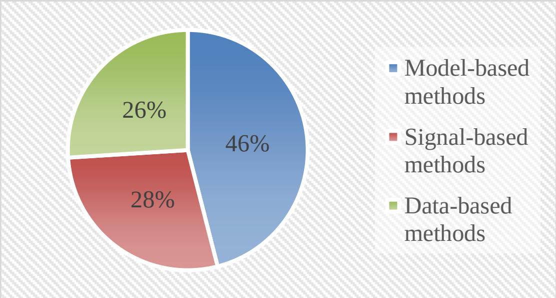


Figure 1. Statistical share of fault diagnosis methods in voltage source inverters

These methods offer the advantage of simplicity, as they utilize standard signals that are often accessible for multiple operational purposes. In addition, they provide the ability of prompt detection of faults. Recent proposals using temperature or DC-link electromagnetic field signals demonstrated significant potential in the improvement of the accuracy in detection of faults [3]. However, the limitation of sensitivity is the main drawback of signal-based methods. Therefore, their efficiency is significantly affected by the noise and the variation of the operating conditions.

Model-based methods are based on the mathematical model of systems that are under analysis to isolate failure by reflecting faulty characteristics in physical systems. The accuracy of the parameters and model plays a vital role in the effectiveness of these methods. The complexity of the model is difficult to develop and that may cause a long duration for fault diagnosis. This is the principle challenging for the application of this technique in real time domain [3]. Methods based on linear or nonlinear observers show the importance in the diagnosis of faults which are difficult to detect in power electronic converters. Furthermore, a lot of observers are able to operate in the conditions of model errors and noises, for instance the state observer proposed in [15]. Other form of observers includes model adaptive reference system [16]-[18]; sliding mode observers [19]. The advantage of these methods is its ability to maintain high accuracy, even when applied to complex systems. However, the main drawback is the necessity for comprehensive model development and time-consuming for the fault diagnosis.

Data-driven methods are based on mathematical techniques to detect and identify the fault. Unlike the methods in the two groups mentioned above, these approaches can be performed independently of information about the model and load conditions. Nonetheless, a significant limitation of these methods lies in their dependence on extensive historical system data and the utilization of machine learning algorithms and data recognition techniques. Moreover, the methods are limited in their ability to detect new or previously unseen failures because they need relevant data for training [3], [20], [21]. Following this, deep learning algorithms are more frequently applied. However, the implementation faces challenges such as high costs for collecting big data. Data such as voltage, current, and temperature, are collected and fed into algorithms to search for abnormalities. The commonly used machine learning algorithms are random forest (RF), support vector machine (SVM), and principal component analysis (PCA) [22] [23], methods based on time series such as autoregressive integrated moving average (ARIMA), long short-term memory (LSTM) [24], [25].

The advantages of these methods are high automation, reduced dependence on technicians, suitable for large-scale and continuous system monitoring. However, large and high-quality data are required to ensure accuracy in training and fault diagnosis. Thus, data-driven methods are a promising direction for developing diagnostic systems. The main drawback of these methods is the need for large amounts of historical data and the cost of data required to train the model, especially in deep learning models. Machine learning methods show high accuracy; however, the complexity of the calculation sometimes reduces the speed of fault diagnosis. Therefore, in practical applications, existing data, model generalization and improved computational efficiency need to be ensured.

In this paper, a two-step fault diagnosis method is proposed for the single switch open-circuit fault. The study demonstrates how the accuracy of the fault diagnosis can be improved by using the DC-link signals. Due to the limitations of raw alternating current signals in fully capturing fault characteristics, direct current signals at the DC-link, combined with spectrum analysis methods, are utilized for effective feature extraction. Once the fault has been fully detected, the raw data of the currents allows the fault switch to be positioned with high accuracy with additional direct current. In experiments, electromagnetic field signals, as the images of direct current in simulation, have been used to detect faults. The results show the feasibility of applying the proposed diagnostic method to real systems.

The structure of the paper is organized into four main sections; i) Section 2 presents the random forest algorithm-based method. It begins with a concise introduction to the fundamental principles of the random forest algorithm, followed by the description of the proposed fault diagnosis method and its adaptation to converter systems; ii) In section 3, the performance of fault diagnosis using AC output current signals is examined, and then the improvement achieved when incorporating DC-link current information is highlighted. Following this, the analysis by considering additional DC-link signals is further extended, focusing on fault detection based on the amplitude of DC-link current harmonics and addressing the task of fault location; and iii) Finally, section 4 concludes the paper by summarizing the main contributions and outlining potential directions for future work.

2. RANDOM FOREST ALGORITHM-BASED METHOD

2.1. Random forest algorithm

This subsection explores the advantages of using random forest for classification tasks, with a focus on its application in fault diagnosis. The RF algorithm is a powerful ensemble learning technique utilized for both classification and regression tasks. Random forest's versatility, flexibility, accuracy, and robustness make it ideal for handling complex and high-dimensional data. It also offers some degree of interpretability that allows engineers to understand the decision-making process and identify key features or conditions leading to a particular fault classification. The fault diagnosis application focuses on choosing just relevant data for analysis, assigning meaningful labels, and using the RF algorithm, whose main steps are shown in Figure 2, to classify faults based on learned patterns.

Furthermore, one of the key advantages of the random forest algorithm lies in its strong capability to generalize to previously unseen data. This property is particularly critical for fault diagnosis systems, in which real-time predictions are required under dynamic operating conditions or in scenarios that were not explicitly included in the training dataset. The ability to generalize beyond the training samples ensures that the diagnostic model can remain effective and reliable despite variations in system behavior or unforeseen disturbances. Recent studies have reported the successful application of random forest in this domain. Specifically, it has been employed to detect and locate open-circuit faults in modular multilevel converters [26], where the inherent structural complexity presents considerable diagnostic challenges. In addition, its effectiveness has been demonstrated in three-phase PWM rectifiers or in three-phase PWM rectifiers [27], further underscoring its robustness and adaptability across different categories of power electronic systems. Collectively, these contributions highlight the random forest algorithm as a promising and versatile approach for fault detection and localization in modern converter applications.

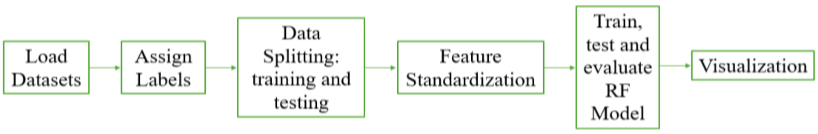


Figure 2. Main steps in the random forest classifier implementation

2.2. Proposed fault diagnosis method

Figure 3 shows the main steps that are implemented in the diagnosis method for the open-circuit fault. To obtain a fast and accurate response, the random forest (RF) algorithm is applied in the fault diagnosis system as a classifier, which uses the amplitude of the first three harmonics of the DC-link signal as a fault feature. For the detection purpose, the output current is only used to extract the fundamental frequency (f_1) for the fast Fourier transform (FFT) analysis. In the stage of detection, two labels of 0 and 1 are used for the classification between the healthy state and the faulty condition.

Once the fault is detected, locating the faulty switch can be carried out by utilizing three output line currents. The following section demonstrates that incorporating the DC-link current can significantly enhance location accuracy. In the algorithm, 7 labels are used to classify the system conditions, including 1 healthy state 0 and 6 faulty conditions for switches (A1, A2, B1, B2, C1, and C2 in Figure 4) from 1 to 6, respectively. In the next section, the potential of utilizing DC-link current providing more useful information for the fault diagnosis will be explored. Following this, the diagnosis method with diagram shown in Figure 1 will be described.

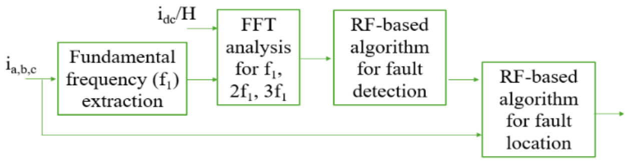


Figure 3. Random forest algorithm-based method for the diagnosis of IGBT open circuit

3. RESULTS AND DISCUSSION

In this section, an IGBT open circuit fault in the voltage source inverter and its diagnosis will be investigated. The inverter is used to feed an induction motor, as shown in Figure 4. In simulation, the fault of 1 in 6 switches is simulated. Furthermore, the operation with different levels of torque is also considered. In experiment, as the DC-link current is challenging to measure due to the complex structure of the DC bus, electromagnetic field signal is utilized, which can be considered as the image of the simulating DC-link current [14].

To construct the training and testing datasets, simulations are performed under the following conditions: i) An induction motor of 1.5 kW is supplied by a voltage source inverter, controlled according to the Volt/Hertz algorithm; ii) The data set includes fault cases at 1 of 6 switches in the inverter when the motor is operating at the rated load. In addition, different load levels (5%, 10%, 50%, 60%, and 100%) are simulated in case of switch A1 failure to verify the change according to the operating condition of the system.

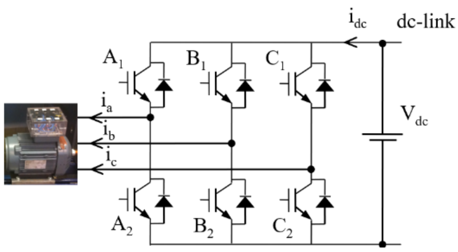


Figure 4. Induction motor fed by an IGBT-based voltage source inverter

3.1. Fault diagnosis with AC output current and improvement with DC-link current

The open circuit faults lead to the distortion in the shape of the AC output currents which feature extraction can be made even with their raw data. Figure 5 shows the distortion of both the AC and DC-link currents when there is an open circuit fault in the switch. It can be seen from Figure 5 that the shape of the current signal changes, as shown in Figure 5(a); and it seems that higher-order harmonic components appear in the DC-link current signal during the fault duration from 0.3 s to 0.6 s, as depicted in Figure 5(b). By simulating the electric motor drive in healthy state and faulty conditions, a dataset was created containing 3000 samples for each single switch fault and 54,989 samples of healthy states.

Figure 6 shows the confusion matrices in two cases: Figure 6(a), the AC currents are used as the signal for feature extraction; and Figure 6(b), both AC and DC-link currents are utilized. Although the raw AC current data are used, the accuracy score of the model is as high as 92.56%. It is much improved to 95.06% when the DC-link current is additionally applied. It means that the feature of the DC-link current is sensitive to the fault and could be a potential signal for diagnosing this type of fault.

However, the results in Figure 6 show that the number of samples corresponding to the healthy state that are incorrectly labeled as a fault is higher than the number of mislocalization cases (correct fault state but wrong switch). Therefore, in the next section, a proposed method with two steps will be introduced, in which the detection could be first carried out. Following this, the location algorithm is conducted, which can be implemented as an offline analysis, to locate the faulty switch.

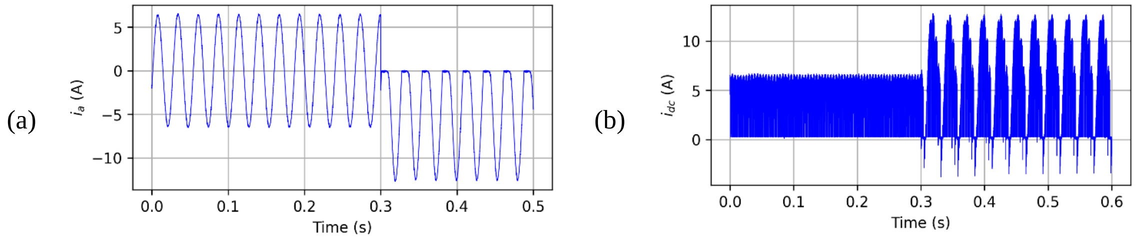


Figure 5. Open circuit of upper switch A1: (a) AC output current-phase A, and (b) DC-link current (simulation)

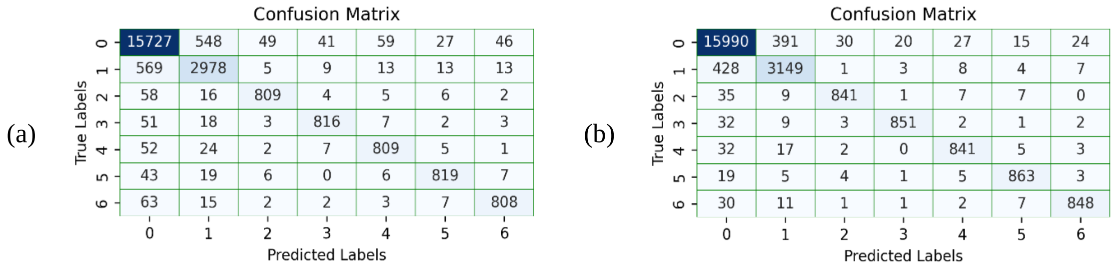


Figure 6. Confusion matrix, datasets of (a) AC currents and (b) AC and DC-link currents

3.2. Fault diagnosis using additional DC-link signal

In this section, the fault diagnosis with two main steps was described below based on the diagram presented in Figure 3.

3.2.1. Fault detection based on the amplitude of DC-link current harmonics

Indeed, the distortion of the DC-link current has been verified by a significant increase in the amplitude of its first three harmonic components [14]. To further validate this approach, a raw dataset was constructed, consisting of 3000 samples collected at a rate of 10 kHz under normal operating conditions, which were labeled as class 0, and an additional 2000 samples recorded under the open-circuit condition of switch A1. This dataset was subsequently processed using the fast Fourier transform (FFT) to extract the amplitudes of the first three harmonic components, which serve as the primary indicators for fault detection. The extracted features were then utilized to generate the training data for the random forest classifier, where 20% of the total samples were reserved for testing. As illustrated in Figure 7, the classifier successfully distinguished between healthy and faulty states with high accuracy. It should also be noted that the dataset incorporated not only the fault condition of switch A1 but also the faults of other switches under various load levels, thereby enhancing the robustness of the evaluation. Based on these results, it can be concluded that the proposed method achieved the maximum fault detection accuracy in the test set.

3.2.2. Fault location

The fault location can be implemented in both online and offline manners. The dataset for all the faulty conditions is utilized for the classification. Figure 8 shows the confusion matrix for locating the faulty switch with the model achieving an accuracy of 98.28%. In summary, with the proposed two-step fault detection and location method, the diagnostic accuracy has been significantly improved. Furthermore, fault detection can be performed with the highest accuracy, allowing the identification of whether the system is operating under an open circuit condition of a power switch.

3.3. Proposal signal for practice application

When applying the fault diagnosis in practice, the electromagnetic signal is measured instead of the current since the measurement is difficult due to the geometric structure of the DC bus. Hall sensors with several advantages have been recommended for measuring local electromagnetic field signals (Figure 9) [14]. Figure 10 illustrates the variation of the AC current as well as the DC-bus electromagnetic field signal. The signal distortion can be seen during the fault period from 0.3 s to 0.6 s, as shown in Figure 10(a).

The distortion of the electromagnetic signal seems to correspond to the variation of the current, as depicted in Figure 10(b). Furthermore, the waveform is also significantly distorted with the appearance of high-order harmonics, especially the first three components. Applying a similar approach as in the simulation, the amplitudes of the first three harmonic components are extracted for fault detection. The RF model is then used for classification with high accuracy, as shown in Figure 11.

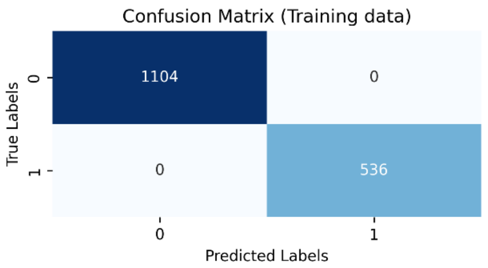


Figure 7. Confusion matrix for fault detection (simulation)

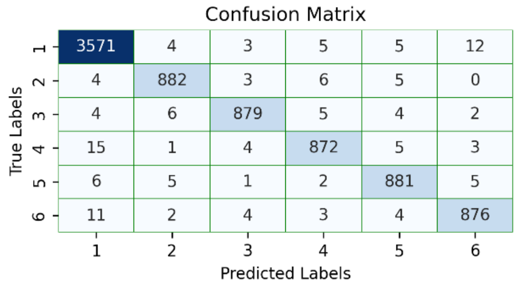


Figure 8. Confusion matrix for location of a faulty switch

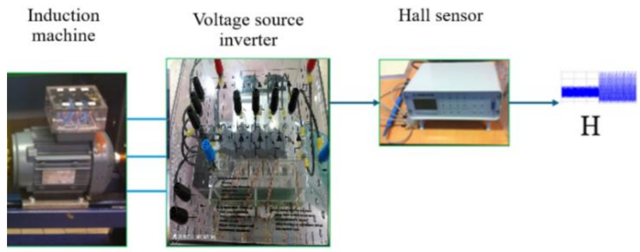
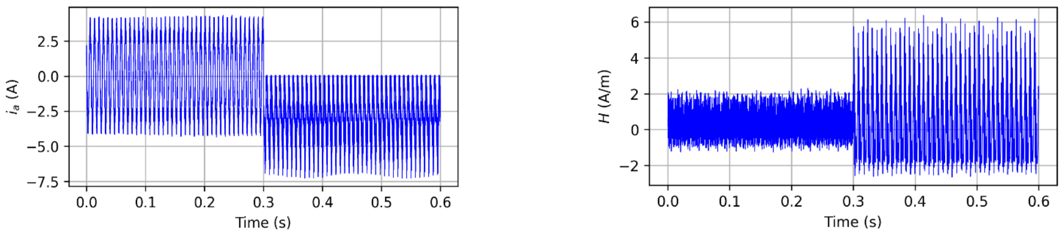


Figure 9. Hall sensor for the measurement of the electromagnetic field signal at the inverter DC bus



(a) (b)

Figure 10. Open circuit of upper switch A1: (a) AC output current (phase A) and (b) electromagnetic field signal

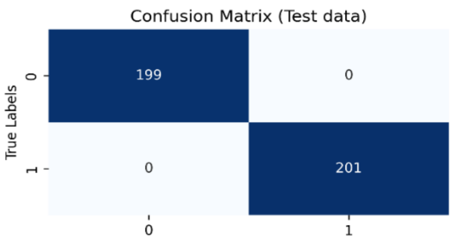


Figure 11. Confusion matrix for fault detection (experiment)

4. CONCLUSION

The application of the random forest algorithm to the diagnosis of an open circuit fault of a power switch in a two-level converter has been explored in this study. Analysis of the measured signal at the DC-link demonstrates that fault-related information extracted from this location enables significantly higher accuracy in fault diagnosis. Furthermore, with the fault detection step using the amplitude of the first three harmonic components of the measurement signal at the DC-link, the fault can be detected with very high accuracy. As a future study, applying a data set for both fault detection and localization and combining appropriate feature extraction methods can further improve the structure, accuracy, and speed of fault detection.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Hoang-Giang Vu	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓		
Dang Toan Nguyen	✓		✓		✓				✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest regarding the publication of this paper.

DATA AVAILABILITY

Not applicable.

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