Open-circuit fault diagnosis of traction inverter based on improved convolutional neural network

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Abstract. In the traction system of high-speed EMUs, the inverter's Insulated Gate Bipolar Transistor (IGBT) often occurs open-circuit (OC) faults. However, traditional fault diagnosis relies mainly on signal processing to extract fault features, which is susceptible to environmental interference, resulting in poor generalization ability of the model. Aiming at this problem, a fault diagnosis method based on an improved convolutional neural network is proposed. Firstly, the three-phase stator current signal is preprocessed by wavelet domain denoising. Secondly, fault features are independently learned through a convolutional network. Finally, a fully-connected layer is used for fault diagnosis. The experimental results show that this method could resolve the OC fault diagnosis problem of the inverter's IGBT effectively, and also achieve higher accuracy under the interference of noise, and the diagnosis can be made at 0.01s after the fault occurs.

1. Introduction

In recent years, traction systems have been widely used in China's high-speed railways. In the traction system, it is essential to determine whether the inverter works normally. However, inverters are prone to failure due to their complex working environment and frequent exposure to high temperatures [1]. The results show that IGBT is the most prone to failure in the inverter, and the most common faults are IGBT short-circuit (SC) or open-circuit (OC) faults [2]. It is easy to cause over voltage or over current when SC fault occurs. To avoid this problem, a protection circuit is usually selected in the circuit; however, When OC fault occurs, it is often difficult to detect and locate, and it will cause additional losses [3]. Therefore, it is of considerable significance to find a method that can efficiently diagnose OC faults of the inverter.

At present, inverter fault diagnosis methods are mainly divided into three methods based on analytical models, signal processing, and data-driven [4]. In analytical models, two kinds of functional models based on health and fault state are proposed to construct the corresponding residual signal for diagnosis, which has fast diagnosis time and strong robustness [5]. An observer diagnosis method based on the adaptive threshold is proposed, the fault detection time is short, and the fault location is accurate [6]. The advantage of the analytical model is high accuracy, but as the scale of the system continues to grow larger, it is often difficult or impossible to build accurate mathematical models due to its increasing complexity and nonlinear feature. In signal processing, Normalized Park's Vector technique and adaptive threshold are used to diagnose faults, which can diagnose both IGBT open
circuit faults and current sensor faults at the same time [7]. The energy vectors were obtained by Discrete Wavelet Transform of the three-phase current, and the Euclidean distance between each two energy vectors was calculated, thus achieving fault detection and location [8]. The advantages of the signal processing method are low cost and low calculation. However, the actual signal measurement often contains some noise. Noise interference will have a greater impact on the diagnosis effect. In data-driven, Fast Fourier Transform and ReliefF algorithm are used to extract fault characteristics, and fault diagnosis is carried out by combining the Extreme Learning Machine and Random Vector Function Link, which achieves good results in real-time fault diagnosis [9]. Concordia Transformation is used to calculate the slope of the current trajectory and input it into Random Forest as a fault feature for fault diagnosis [10]. A method of inputting three-phase current and its synthesized characteristics into depth neural network is proposed, and the reliability of the method is verified by on-line fault diagnosis [11]. Fault characteristics were extracted by a discrete Wavelet Transform (WT), and the fault was classified and diagnosed by Neural Network (NN) [12]. Fast Fourier Transform (FFT) was proposed to extract fault characteristics, and then fault diagnosis was conducted through the Bayesian network (BN) [13]. A fault diagnosis method based on the combination of Deep Belief Networks and Least Square Support Vector Machine (DBN-LSSVM) is proposed, proving with good diagnostic accuracy and low diagnosis delay time [14]. The data-driven methods have the advantages of low cost and fast diagnosis, but they need a large number of data samples, which are difficult to obtain. This paper proposes an OC inverter fault diagnosis method based on an improved convolutional neural network (Wavelet Domain Denoising and Convolutional Neural Network, WDD-CNN).

2. Traction inverter system and fault analysis
In high-speed EMUs, the traction system is mainly composed of pantographs, transformers, rectifiers, inverters, induction motors, and control systems. Figure 1 presents the working principle diagram of the traction inverter system. The inverter consists of six IGBTs (T1-T6 in Figure 1) and six freewheeling diodes (D1-D6 in Figure 1) connected in anti-parallel to it. Vector Control and SVPWM modulation technology are adopted for control strategy. The vector transformation converts the feedback three-phase stator current and rotation speed into voltages \( U_{\text{ref}}^q \) and \( U_{\text{ref}}^d \) in the DQ coordinate system. Trigger pulses are generated by \( U_{\text{ref}}^q \) and \( U_{\text{ref}}^d \) through SVPWM modulation, to control the IGBT conduction interval, so that the inverter can convert the DC voltage into AC voltage to supply the three-phase asynchronous motor. Due to the length of the paper, please refer to the literature for the specific principle of the traction inverter system [15].

![Figure 1. Work principle of the traction inverter system.](image-url)
The traction inverter contains six IGBTs, in which single OC fault or multiple OC faults at the same time may occur. The probability that two or more IGBTs fail at the same time is far less than that of one or two IGBTs. Moreover, when two or more IGBTs fail at the same time, the fault features cannot be reflected in the current signal. Therefore, one or two IGBTs of the inverter have OC faults at the same time are investigated in our paper. Among them, there are 6 types of faults in one IGBT, 15 types of OC faults in two IGBTs at the same time, when the system is running normally, it is also regarded as one operating state, with a total of 22 types of operating states. The 22 operating states can be divided into four typical categories: (1) No failure occurred; (2) One IGBT failed; (3) Two IGBTs of the same-phase bridge arm failed simultaneously; (4) Two IGBTs of different-phase bridge arms failed simultaneously.

In this paper, a simulation model of a traction inverter system is established in MATLAB Simulink, the following are the simulation waveform diagrams of the three-phase stator currents under four types of typical faults:

Figure 2. The waveform diagrams of stator currents: (a) Run in normal; (b) T1 OC; (c) T1 and T4 OC; (d) T1 and T6 OC.

Figure 2(a) shows the waveform of three-phase current during normal operation of the system. After the system starts to operate and reaches stability, the three-phase current has a phase difference of 120 degrees in sequence; Figure 2(b) shows the waveform of three-phase current when T1 has an OC fault, causes the current of the positive half cycle of phase A to not pass, phase A has only a negative half cycle current, and because the sum of the three-phase currents of A, B and C is zero, the currents of the two phases of B and C are distorted to a certain extent; Figure 2(c) shows the three-phase current when T1 and T4 have an OC fault, the phase A current cannot pass at all. Therefore, the two-phase currents of B and C must add up to 0, so that the amplitudes of the two phases of B and C are equal and the phase difference is 90 degrees; Figure 2(d) shows the three-phase current waveform when T1 and T6 have OC fault, the phase A current cannot pass the current of the positive half cycle, and
phase B cannot pass the current of the negative half cycle. To maintain the sum of the three-phase current to 0, the amplitude of the three-phase current has a large distortion.

In summary, when one or two OC faults occur on the IGBT of the inverter, the three-phase current of the stator will change significantly in amplitude. The OC fault diagnosis of the inverter can be implemented by using the amplitude characteristics of the three-phase current, and this change conforms to certain rules. In the WDD-CNN algorithm mentioned in this paper, WDD will reduce the noise characteristics of the fault feature, which will reduce the interference of the actual environment, thereby greatly improving the robustness of the algorithm model; CNN uses convolution to traverse the fault feature, this will extract the deep-level features of the fault. The innovation of this article is: Firstly, the advantages of WDD and CNN are combined, making the algorithm model very robust and able to achieve high accuracy; Secondly, this paper adopts the method of extracting data samples by sliding window, which enables the algorithm model to perform fault diagnosis in a short time after the failure occurs.

3. WDD-CNN network architecture and data preprocessing

3.1. WDD-CNN network architecture

In this paper, the three-phase stator current signal is used as the input of WDD-CNN, and the state stamp of OC faults in 6 IGBTs as the output of the network. The WDD-CNN network model is shown in Figure 3(a). In the wavelet denoising layer, the db4 wavelet function is used to decompose the current signal into 4 layers, and the soft threshold is set to 4.5. Figure 3(b) shows the process of wavelet denoising:

![Figure 3. WDD-CNN network architecture: (a) Network architecture; (b) The process of wavelet denoising.](image)

Besides, the four pooling layers and fully connected layers use the Relu function as the activation function to increase the nonlinear fitting ability of the network, as shown in Function (1):

$$
\text{relu}(x) = \begin{cases} 
  x & \text{if } x \geq 0 \\
  0 & \text{if } x < 0 
\end{cases}
$$

(1)

The output layer uses the Sigmoid function as the activation function. The specific algorithm is shown in Function (2):

$$
\text{sigmoid}(x) = \frac{1}{1 + e^{-x}}
$$

(2)

The loss function uses the Sigmoid cross-entropy function, where $y$ is the label of the fault and $y$ is the output value of the algorithm model, as shown in Formula (3):

$$
\text{loss} = (-y) \ln \left( \text{sigmoid}(y) \right) + (1-y) \ln \left( 1 - \text{sigmoid}(y) \right)
$$

(3)
3.2. Data preprocessing

To enhance the robustness of the model and obtain more data samples, ten simulation experiments were conducted at the load torque of 30 N·m, 60 N·m, 90 N·m, 120 N·m, 150 N·m, 180 N·m, 210 N·m, 240 N·m, 270 N·m, and 300 N·m. The simulation time is set as 2s, the fault triggering time is 1s, and the sampling time is 0.001s. The 22 states of the system were simulated under ten different load torques, and a total of 220 (22×10 = 220) original data samples were obtained.

This paper uses a sliding window to extract data to increase the number of data samples. Based on the sliding window method of extracting data, the window starts to extract data from the 500th sampling point, and every 10 sampling times, it always extracts 1000 sampling points to the end and draws 50 times in each original sample data. The specific method is as follows:

1) The first sample draws the sampling points between 500-1500;
2) The second sample draws sampling points between 510-1510;
3) And so forth, sampling points between 1000-2000 are extracted.

The sample data expansion is 220 × 50 = 11,000. In some samples, only 10 fault data points may be included, and others are normal data points. If the algorithm in this paper can accurately identify these samples as fault samples, it is considered that the algorithm can diagnose the fault after 0.01s (10 data points × sampling time 0.001s) after the fault occurs.

According to the type of IGBT failure, a 6-bit data label is made for the sample data. If the IGBT is operating normally, it is represented by 0; if the IGBT has an OC fault, it is represented by 1. For example, when the system is running normally, the label is 000000; when T1 has an OC fault, the label is 100000. The corresponding labels for each running state are shown in Table 1:

| Fault type | Labels | Fault type | Labels |
|------------|--------|------------|--------|
| Run normal | 000000 | T16 OC | 000010 |
| T1 OC      | 000000 | T23 OC | 000001 |
| T2 OC      | 000000 | T24 OC | 000001 |
| T3 OC      | 001000 | T25 OC | 000001 |
| T4 OC      | 001000 | T26 OC | 000001 |
| T5 OC      | 000010 | T34 OC | 001000 |
| T6 OC      | 000010 | T35 OC | 001000 |
| T12 OC     | 010000 | T36 OC | 001000 |
| T13 OC     | 010000 | T45 OC | 000110 |
| T14 OC     | 010000 | T46 OC | 000110 |
| T15 OC     | 000010 | T56 OC | 000011 |

To get as close to the actual situation as possible, Gaussian noise is added into all data samples. The principle of adding noise is shown in Function (4):

$$z(t) = f(t) \times e(t)$$  \hspace{1cm} (4)

Where \(z(t)\) is the feature data after adding noise, \(f(t)\) is the original feature data, and \(e(t)\) is Gaussian noise with a mean value of 1 and a variance of 1.2.

4. Training results and evaluation

4.1. WDD-CNN model training

According to the principle of the hold-out method, the sample data when the load torque is 30, 60, 90, 120, 150, 180, 210 and 240 N·m are taken as the training set, a total of 8800 sample data, and the load torque is 270 N·m and 300 N·m are taken as the test set, with a total of 2200 sample data.

Experiment 1. Training and testing process for simulation data sets
The WDD-CNN model is trained directly on the simulation data sets. Figure 4 and Figure 5 are the loss and accuracy change curves of the simulation data sets during the training process. In the end, the training set loss value was reduced to 0.0001, the test set loss value was reduced to 0.0003, the training set accuracy rate was 99.95%, and the test set accuracy rate was 99.0%.

Experiment 2. Training and testing process for noisy data sets

The WDD-CNN model is trained on the noisy data sets. Figure 6 and Figure 7 show the loss and accuracy change curves of the noisy data sets during the training process, respectively. The convergence rate of the loss value and the accuracy rate has decreased. It can be seen that the noise does have some negative effects on the fault diagnosis. However, because the WDD-CNN model has better noise reduction and reinforcement learning capabilities, the loss value of the WDD-CNN network on the test set is finally reduced to 0.0019, and the accuracy rate reaches 96.65%.

Data samples are taken at 0.01s when the fault occurs, and the average time to identify a data sample is 0.005s, then the fault can be identified at 0.015s after the fault occurs.

4.2. Analysis and evaluation of experimental results

In this paper, three evaluation indicators which are called Hamming loss, Precision, and Recall are introduced to evaluate WDD-CNN. The specific definition is as in Formulas (5) - (7):

\[
\text{Hamming loss} = \frac{1}{M} \sum_{i=1}^{M} \frac{|Y_i - P_i|}{N} \tag{5}
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \tag{6}
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \tag{7}
\]
Where $M$ is the number of samples, $N$ is the number of labels, $Y_{ij}$ is the true label of the jth component of the ith sample, and $P_{ij}$ is the prediction label of the jth component of the ith sample, FP indicates that the true label is 0 and the predicted label is 1, and FN indicates that the true label is 1 and the predicted label is 0, and TN indicates that both the true label and the predicted label are 0.

Figures 8(a) and 8(b) are the changes in Hamming loss, Figures 8(c), and 8(d) are the changes in Precision, Figures 8(e), and 8(f) are the Recall rates graph of change.

It can be seen that in the simulation data sets, the test Hamming loss is reduced to 0.00475, the accuracy rate is increased to 99.47%, and the recall rate is increased to 98.78%; in the noisy data sets, the test Hamming loss is decreased to 0.007, and the accuracy rate is increased to 99.02% The recall rate rose to 98.41%.

Figure 8. The waveform diagrams of three evaluation indicators: (a) Hamming loss of simulation data; (b) Hamming loss of noisy data; (c) Precision of simulation data; (d) Precision of noisy data; (e) Recall of simulation data; (f) Recall rate of noisy data.

To further verify the diagnostic performance of WDD-CNN, this paper compares it with the following five existing diagnostic methods: the neural network (NN), CNN, and WT-NN, FFT-BN,
DBN-LSSVM methods proposed in [12-14]. Table 2 shows the accuracy rates of various diagnostic methods on the test set:

| Diagnosis method | NN  | CNN | WT-NN | FFT-BN | DBN-LSSVM | WDD-CNN |
|------------------|-----|-----|-------|--------|-----------|---------|
| Simulation data  | 85.2| 96.9| 93.4  | 91.2   | 98.4      | 99.0    |
| Noisy data       | 55.2| 86.2| 76.0  | 66.4   | 80.8      | 96.6    |

5. Conclusions

In this paper, to resolve the traction inverter IGBTs open circuit faults problem, a simulation model is established, and the stator current waveform diagram of one or two IGBTs of the inverter when an OC fault occurs at the same time is discussed. Then, an improved CNN model by combining the WDD method is proposed to reduce the noise in the fault datasets from the current input signal. By implementing the CNN process, the output 6-bit fault label would determine the diagnosis results through a fully-connected layer. By adding Gaussian noise into the simulated data sets, the WDD-CNN method is compared with other related algorithms. Experimental results reveal that our proposed algorithm could achieve better performance on all evaluation indicators, with a good 99.0% accuracy rate. Even under the interference of noise data, our model could reach a relatively high accuracy, which validates better generalization ability, and the diagnosis can be made at 0.015s after the fault occurs.

Although the method proposed in this paper can achieve better diagnostic results, the method has not been diagnosed in actual systems. The next step will be to build a simple and practical system platform to further verify the feasibility of this method. Eventually, it is expected that this method can be applied to the actual railway system.

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References
[1] Smet V, Forest F, Huselstein J J, Richardeau F and Berkani M 2011 Ageing and Failure Modes of IGBT Modules in High-Temperature Power Cycling IEEE Transactions on Industrial Electronics 58(10) 4931-41
[2] De Mello Oliveira A B, Moreno R L and Ribeiro E R 2018 Short-Circuit Fault Diagnosis Based on Rough Sets Theory for a Single-Phase Inverter IEEE Transactions on Power Electronics 34(5) 4747-64
[3] Amini J and Moallem M 2016 A fault-diagnosis and fault-tolerant control scheme for flying capacitor multilevel inverters IEEE Transactions on Industrial Electronics 64(3) 1818-26
[4] Gao Z, Cecati C and Ding S X 2015 A survey of fault diagnosis and fault-tolerant techniques— Part I: Fault diagnosis with model-based and signal-based approaches IEEE Transactions on Industrial Electronics 62(6) 3757-67
[5] Wu F and Zhao J 2015 A real-time multiple open-circuit fault diagnosis method in voltage-source-inverter fed vector controlled drives IEEE Transactions on Power Electronics 31(2) 1425-37
[6] Jlassi I, Estima J O, El Khil S K, Bellaaj N M and Cardoso A J M 2016 A robust observer-based method for IGBTs and current sensors fault diagnosis in voltage-source inverters of PMSM drives IEEE Transactions on Industry Applications 53(3) 2894-905
[7] Jlassi I and Cardoso A J M 2019 A Single Method for Multiple IGBTs, Current-and Speed-Sensor Faults Diagnosis in Regenerative PMSM Drives IEEE Journal of Emerging and Selected Topics in Power Electronics
[8] Wu F, Hao Y, Zhao J and Liu Y 2017 Current similarity based open-circuit fault diagnosis for
induction motor drives with discrete wavelet transform Microelectronics Reliability 75 309-16

[9] Xia Y, Xu Y and Gou B 2019 A Data-Driven Method for IGBT Open-Circuit Fault Diagnosis based on Hybrid Ensemble Learning and Sliding-Window Classification IEEE Transactions on Industrial Informatics 16(8) 5223-33

[10] Liu C, Kou L, Cai Gw, Zhou J N, Meng Y Q and Yan Y H 2019 Knowledge-based and Data-driven Approach based Fault Diagnosis for Power-Electronics Energy Conversion System 2019 IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm) IEEE 1-6

[11] Kou L, Liu C, Cai G W, Zhang Z, Zhou J N and Wang X M 2020 Fault diagnosis for three-phase PWM rectifier based on deep feedforward network with transient synthetic features ISA transactions

[12] Dhumale R and Lokhande S 2016 Neural network fault diagnosis of voltage source inverter under variable load conditions at different frequencies Measurement 91565-75

[13] Cai B, Zhao Y, Liu H and Xie M 2016 A data-driven fault diagnosis methodology in three-phase inverters for PMSM drive systems IEEE Transactions on Power Electronics 32(7) 5590-600

[14] Shi T, He Y, Wang T and Li B 2019 Open Switch Fault Diagnosis Method for PWM Voltage Source Rectifier Based on Deep Learning Approach IEEE Access 7 66595-608

[15] CamposDelgado D U and EspinozaTrejo D R 2010 An observer-based diagnosis scheme for single and simultaneous open-switch faults in induction motor drives IEEE Transactions on Industrial Electronics 58(2) 671-9