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Complete List of Authors:	Li, Zhan; Zhejiang University, College of Electrical Engineering Gao, Yuan; University of Nottingham, Electrical and Electronics Engineering Zhang, Xin (GAE); Nanyang Technological University, School of Electrical and Electronic Engineering Wang, Borong; Zhejiang University, College of Electrical Engineering Ma, Hao; Zhejiang University, College of Electrical Engineering

Keywords:	Inverters, Fault diagnosis, Hybrid solution methods, Circuit modeling, Data models

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A Model-Data-Hybrid-Driven Diagnosis Method for Open-Switch Faults in Power Converters

Zhan Li, *IEEE Member*, Yuan Gao, *IEEE Student Member*, Xin Zhang, *IEEE Senior Member*, Borong Wang, *IEEE Student Member*, Hao Ma, *IEEE Senior Member*,

***Abstract*—To combine the advantages of both model-driven and data-driven methods, this paper proposes a model-data-hybrid-driven (MDHD) method to diagnose open-switch faults in power converters. This idea is based on the explicit analytical model of converters and the learning capability of artificial neural network (ANN). The process of the method is divided into two parts: offline model analysis and learning, and online fault diagnosis. For both parts, model-driven and data-driven are combined. With the model information and data-based learning capability, a fast diagnosis for various operating conditions can be achieved without high computation burden, tricky threshold selection and complex rulemaking. This can greatly contribute to the practical application. The open-switch fault diagnosis in a two-level three-phase converter is studied for method validation. For this converter, an ANN is trained with two input elements, seven output elements, and two neurons in the hidden layer. Experimental results are given to demonstrate good performance.**

Keywords—artificial neural network (ANN), data-driven, fault diagnosis, model-driven, open-switch

I. Introduction

Power converters play key roles as interfaces of controlling and transferring power in electrical traction systems, renewable energy systems, and other applications. However, power converters are the most vulnerable parts of the integrated power systems [1]. To prevent further damage in the systems, fast detection and protection of power converters' faults are of great importance and thus have attracted much attention [2].

In power converters, power switches are most likely to be damaged [3]. However, the protection of open-switch faults is still far to be a standard feature in applications. Conventional methods for diagnosing open-switch faults in converters mainly include knowledge-driven and data-driven methods. The former is based on the fault analysis of the converter; while in the latter, the fault analysis is replaced by machine learning or signal processing algorithms because faulty characteristics can be extracted from the collected data.

Knowledge-driven methods can be further divided into current signal-based [4,5], voltage signal-based [6,7], and model-based [8,9]. Voltage signal-based methods can diagnose the fault within one switching period; however, extra sampling and diagnosis circuits are needed. In contrast, current signal-based methods are simple and only require existing signals, however, they are more dependent on operation conditions and the diagnosis time is long. **Model-based methods are based on the analytical model, like the average model. The analytical model can reflect the fault occurrence in a timely way, which is not limited to operating conditions. Therefore, model-based methods can achieve fast diagnosis speed and apply to various operating conditions, e.g. in both inverter mode and rectifier mode. Nevertheless, they are complex in rulemaking and threshold selection.**

Data-driven methods are becoming increasingly popular due to the development of machine learning (ML) algorithms and computing ability. Algorithms such as backpropagation neural network [10], support vector machine [11], extreme learning machine [12], and random forest [13] have been applied to fault diagnosis for power converters. To reduce input elements and improve robustness, some statistic algorithms, including fast Fourier transformation [14], discrete wavelet transformation [15], principal component analysis [16], are adopted to process the data and extract features before training. Besides, different algorithms can be combined to enhance their capability [17]. **These data-driven methods do not require modeling, fault analysis and rulemaking. However, they usually require large amounts of training data and computation. Besides, it is difficult to apply these data-driven methods to real-time fast fault diagnosis.**

To combine the advantages of both model-driven and data-driven methods, a model-data-hybrid-driven (MDHD) method is proposed. The process of the method is divided into two parts: offline model analysis and learning, and online fault diagnosis. In the offline part, the fault diagnosis variables, namely the ANN inputs, are selected based on the analytical circuit model and further optimized by trial-and-error with ANN. Then the trained ANN is used online to diagnose the fault. With the model information, the ANN can be trained with fewer neurons and samples. Besides, fast diagnosis speed can be achieved in various operation conditions. On the other hand, complex fault analysis, rulemaking and threshold selection are avoided due to the learning capability of ANN, which makes the method easy to use and suitable for more complicated applications.

II. Proposed MDHD Method

A. Basic Principle

The process of the proposed MDHD method is depicted in Fig.1. The process would be the same for different topology applications. The process can be divided into offline model analysis and learning (Step1~Step5), and online fault diagnosis (Step6~Step7).

Step 1 (Model-driven): Build analytical models of power converters. For different topologies, it is suggested to build the circuit model related to the voltages across or connecting power devices, because these voltages are directly related to the conditions of power devices. Therefore, the models can be informative about the faults and react quickly to the fault occurrence.

Step 2 (Model-driven): Get the fault diagnosis variable selection pool ($x_1 \ldots x_K$). All variables in the analytical model are fault diagnosis variable candidates as a selection pool. The final diagnosis variables will be optimized in Step 4.

Step 3 (Data-driven): Get training samples from simulations or experiments.

Step 4 (Data-driven): Optimize diagnosis variables by trial-and-error. In this step, the fault diagnosis variables are further selected by trial-and-error with the collected training samples, resulting in the minimum number of required fault diagnosis variables. This can help reduce the ANN calculation. It is important to note that this step is compounded with Step 5, because different kinds of diagnosis variables as the ANN inputs chosen from the selection pool should be tried by training ANN and the training performances are compared at the end.

Step 5 (Data-driven): Build the ANN for online fault diagnosis. The ANN is trained with collected samples to map the relationships between fault diagnosis results and fault diagnosis variables.

Step 6 (Model-driven): Calculate diagnosis variables ($x_1 \ldots x_D$) for ANN inputs. The fault diagnosis variables are calculated with analytical models built in Step 1. In this paper, the average model is applied.

Step 7 (Data-driven): Diagnose faults with the trained ANN. In this step, the practical real-time values of fault diagnosis variables are sent to the ANN. The ANN serves as an online expert to diagnose the fault

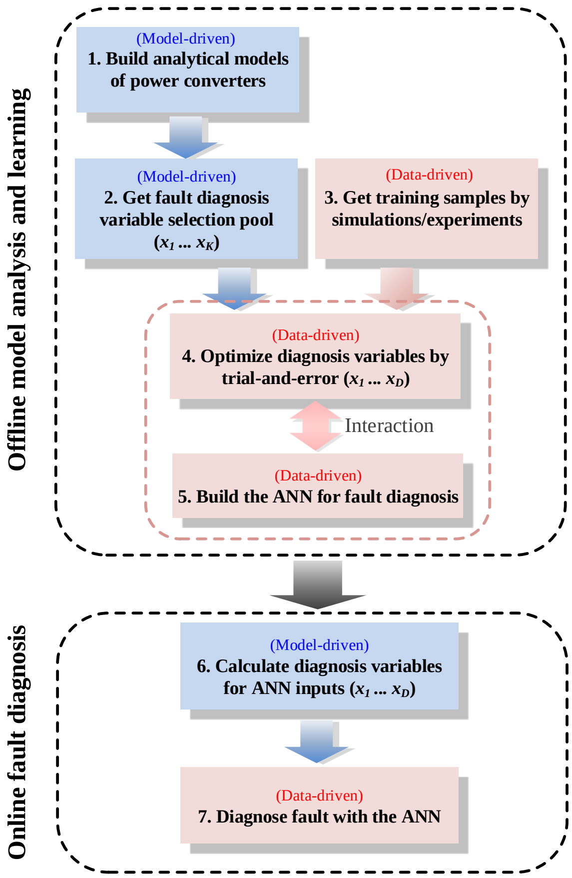


Fig. 1. Process of the proposed MDHD method.

The model-driven part of the MDHD method is important and beneficial, especially in a more complicated circuit. The importance and benefits of the model-driven part can be concluded as:

1) Achieve fast diagnosis speed. The diagnosis variables chosen based on the model, eg. ΔV_{ab} and ΔV_{bc} in the three-phase converter, react quickly to the fault occurrence. Therefore, fast diagnosis speed can be achieved.

2) Reduce inputs of the data-driven part. The model-driven part can help select the diagnosis variables which are the most informative about the fault. Hence the inputs of the data-driven part can be reduced, thereby reducing the calculation burden and training time of ANN.

3) Simplify the learning process. The fault diagnosis variables based on the model are less dependent on operating conditions, like load conditions and operating modes. Thus, the training samples and the learning process can be simplified.

The benefits of the data-driven parts are that the rulemaking and threshold selection can be automatically made by data learning rather than manual complex analysis. This is important when circuits are complicated, where the diagnosis rulemaking and threshold selection are difficult.

B. Model-Driven Part

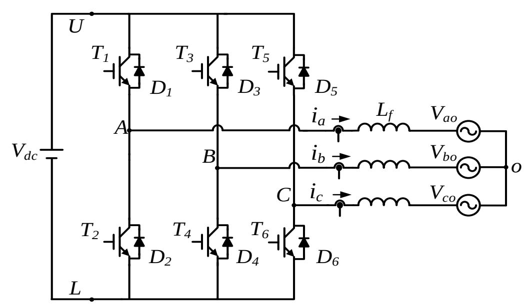
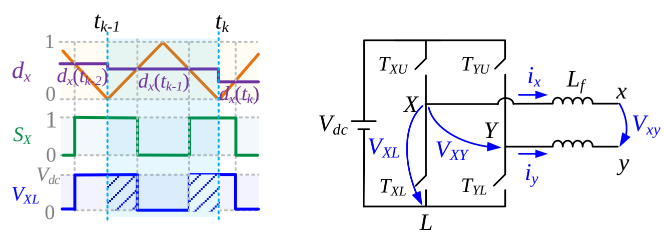


Fig. 2. The grid-tied two-level three-phase converter



(a) PWM modulation (b) Simplified circuit.

Fig. 3. Model analysis of the converter.

Fig.2 shows a grid-tied two-level three-phase converter. Output currents, grid voltages, and DC voltage are sampled for control. The driving signal S_X ($X = A, B, C$) is defined as: S_X=1, the upper switch is on; S_X=0, the lower switch is on.

According to the illustration in Fig.3 and Kirchoff voltage law, the continuous model of the converter is given in (1).

$$\begin{cases} V_{dc}(t)S_{AB}(t) = L_f \dfrac{di_{ab}(t)}{dt} + V_{ab}(t) \\ V_{dc}(t)S_{BC}(t) = L_f \dfrac{di_{bc}(t)}{dt} + V_{bc}(t) \end{cases} \tag{1}$$

Where $S_{AB}(t) = S_A(t)$-$S_B(t)$, $S_{BC}(t) = S_B(t)$-$S_C(t)$, $i_{ab}(t) = i_a(t)$-$i_b(t)$, $i_{bc}(t) = i_b(t)$- $i_c(t)$.

However, when open-switch faults occur, the equations in (1) are no longer valid. The deviations between the left sides and right sides of the equations are defined as

$$\begin{cases} \Delta V_{AB}(t) = V_{dc}(t)S_{AB}(t) - L_f \dfrac{di_{ab}(t)}{dt} - V_{ab}(t) \\ \Delta V_{BC}(t) = V_{dc}(t)S_{BC}(t) - L_f \dfrac{di_{bc}(t)}{dt} - V_{bc}(t) \end{cases} \tag{2}$$

In practice, signals are normally sampled every switching period. The signal $x(t)$ sampled at k^{th} moment t_k is marked as $x(t_k)$. According to the average model introduced in [8], (1) can be discretized as

$$\begin{cases} \Delta V_{AB}(t_k) = V_{dc}(t_k)d_{AB}(t_{k-1}) - \dfrac{L_f}{T_s}(i_{ab}(t_k) - i_{ab}(t_{k-1})) - V_{ab}(t_k) \\ \Delta V_{BC}(t_k) = V_{dc}(t_k)d_{BC}(t_{k-1}) - \dfrac{L_f}{T_s}(i_{bc}(t_k) - i_{bc}(t_{k-1})) - V_{bc}(t_k) \end{cases} \tag{3}$$

(3) is the analytical model for variable selection in Step 2 and calculation in Step 6.

C. Data-Driven Part

a) Fundamentals of ANN

A particular ML approach used in this study is the feedforward ANN. It should be noted other ML algorithms can also be applied. ANNs can approximate any given input/output data relationship with arbitrary precision [18]. As shown in Fig.4, a basic forward ANN comprises an input layer, one or more hidden layers, and an output layer. The neuron numbers in input and output layers are determined by sample designs while the neuron number in hidden layers can be changed [19].

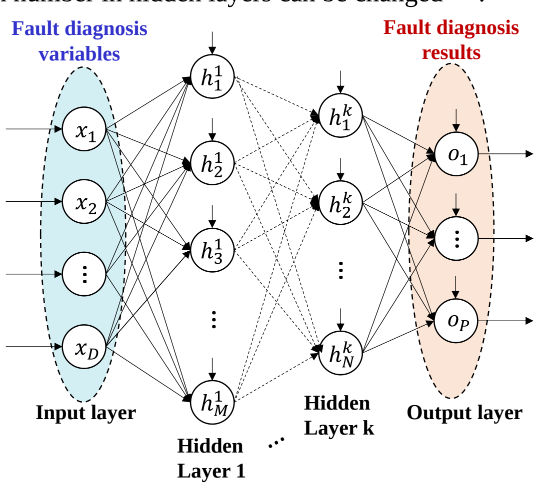


Fig. 4. Feedforward ANN.

In Layer 1 (input layer), the output of each neuron equals the related input data after normalization. Regarding a neuron h_i^l in a hidden layer l, firstly the outputs of all the last-layer neurons p_j^{l-1} ($j = [1..N_{l-1}]$, N_{l-1} is the neuron number of Layer $l-1$) are multiplied with given weights ω_{ij}^l and then the bias b_i^l is added. After that, the result is further processed through an activation function f_σ to give the neuron's output p_i^l [20]. Namely,

$$p_i^l = f_\sigma\left(\sum_{j=1}^{N_{l-1}} \omega_{ij}^l p_j^{l-1} + b_i^l\right), i = 1, .., N_l \tag{4}$$

In the same way, this output becomes one of the inputs for the next layer $(l+1)$. Finally, the output layer L uses the linear function to integrate signals of Layer $L-1$ for the desired output p_i^L. The final output process for the target pattern problem will be discussed later.

TABLE I. DESIGNED ANN INPUTS AND OUTPUTS

Input elements	$\Delta V_{AB}(t_k)$, $\Delta V_{BC}(t_k)$
Output elements	P_{FT1}, P_{FT2}, P_{FT3}, P_{FT4}, P_{FT5}, P_{FT6}, P_{NF}

b) ANN Training

Variables in the analytical model in (3), ($\Delta V_{AB}(t_k)$, $V_{dc}(t_k)d_{AB}(t_k)\ldots V_{bc}(t_k)$), are the fault diagnosis variables candidates as a selection pool. Inspired by fault analysis in previous literature and through trial-and-error with the collected training samples, the final fault diagnosis variables (ANN inputs) for the focused converter are chosen as in TABLE I. Only two input elements ($\Delta V_{AB}(t_k)$, $\Delta V_{BC}(t_k)$) are needed. Six outputs (P_{FT1}~P_{FT6}) stand for the conditions of six switches in the two-level converter. The 7th output (P_{NF}) denotes normal operation. The range of each output is set as [0, 1].

To improve robustness, a counter decision strategy is applied. Six counters Ctr_1~Ctr_6 correspond to six faults F_{T1}~F_{T6}. For example, when P_{FT1}>0.8 and P_{NF}<0.2, Ctr_1 pluses one. Otherwise, Ctr_1 resets to zero. Once Ctr_1 reaches the threshold N_{th}, the T_1 fault is confirmed. Selecting threshold N_{th} is a tradeoff between diagnosis speed and robustness. In this paper, N_{th} is set to 5.

There are seven patterns: the fault in a sole switch (P_{FT1}~P_{FT6}) and normal operation (P_{NF}). Therefore, seven sets of data are collected for ANN training. When a switch fault occurs, only half period of the operation is affected, during which the faulty characteristics are observable. Therefore, the data during the affected half period is collected. As shown in Fig.5, 80% of data in the affected half period is collected as samples.

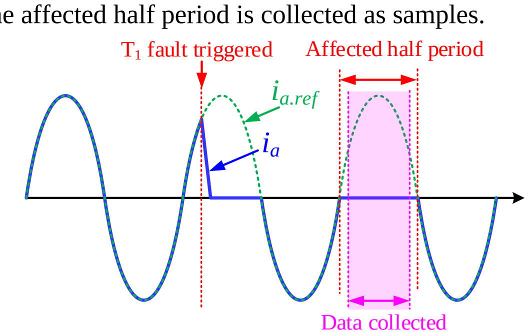


Fig. 5. Illustration of training data collection.

Training samples are collected from simulations in Simulink. Specifications of the studied converter are shown in TABLE II. For each fault pattern P_{FT1}-P_{FT6}, the samples are collected under four operation conditions: inverter mode (IM) 1.8kW, IM 0.9kW, rectifier mode (RM) 1.8kW, RM 0.9kW. For the normal pattern P_{NF}, the collection conditions are: 0kW→IM 0.9kW→IM 1.8kW→RM 1.8kW→RM 0.9kW→IM 0.2kW. The total number of training samples is 2943.

As the seven ANN outputs are all 0-1 classification, neural network pattern recognition (NNPR) application in Matlab is used for training which is a dedicated APP for classification learning problems. Different from ANN regression/fitting, NNPR training limits all predictions (p_i^L in the output layer) into (0, 1) by the Softmax function for classifications:

$$\mu_i = \exp\,(p_i^L)/\sum_{i=1}^{N_L} \exp\,(p_i^L). \quad (5)$$

Therefore, the NNPR generates the probabilities for 7 elements in the output layer.

The training can be finished in several seconds due to the small number of training samples, which makes it convenient for trial-and-error until ANN input elements, structure and performance are obtained. Finally, an ANN with a single hidden layer is applied using only two neurons as shown in Fig.6. The training results are shown in Fig.7. The accuracy is nearly 100%.

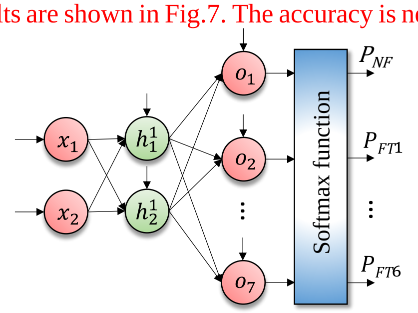


Fig. 6. Trained ANN structure in experiments.

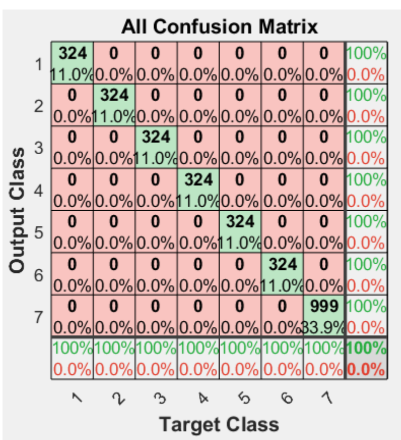


Fig. 7. Training results.

TABLE II. SPECIFICATION OF THE CONVERTER IN EXPERIMENTS

DC voltage	400V
Grid Phase voltages(rms)	110V, 50Hz
Rated power	1.8kW
Actual filter inductances	9mH, 0.3Ω
Filter inductances in diagnosis	11mH, 0.3Ω; 11mH, 0.3Ω; 7mH, 0.3Ω;
Switching/Sampling frequency	10kHz

III. EXPERIMENTAL RESULTS

Experiments are carried out to validate the proposed method. The experiment rig is shown in Fig.8. Particularly, 20% variations are added to the filter inductances. This aims to verify the robustness of the ANN against parameter variations. Experimental results are displayed in Fig.9~Fig.12. It should be noted that the voltage and current waveforms are captured from oscilloscopes. The ANN output and fault diagnosis waveforms are calculated and plotted by MATLAB with signals collected from the DSP on the control board.

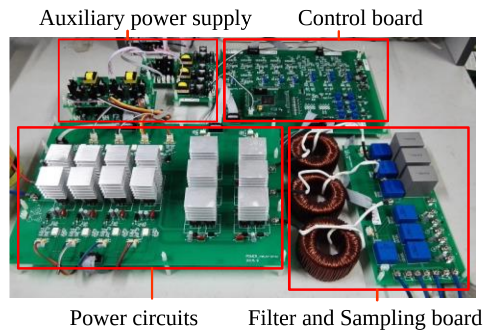


Fig. 8. Experiment rig.

Fig.9 shows the experimental result under normal operation with random power changes ranging from IM 1.2kW to RM 1.2kW. The power changes are different from the trained conditions. It can be observed that with 20% inductance variations and under severe power changes, no false alarm is triggered.

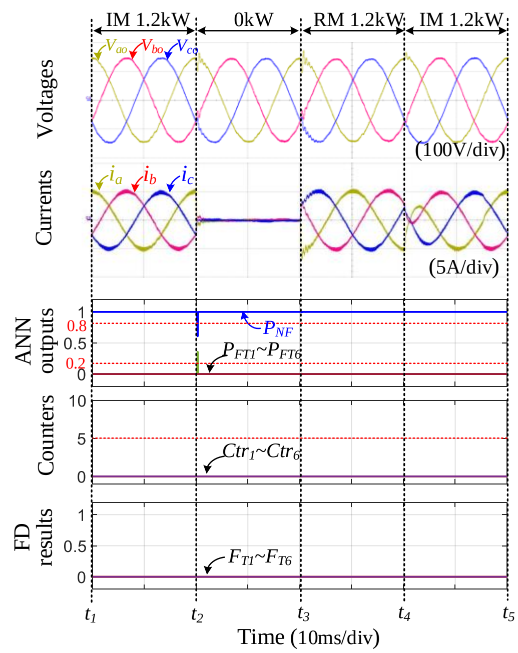


Fig. 9. Experimental results under normal operation with power changes.

Experiments in Fig.10~Fig.12 aim to verify the diagnosis performance in various operation conditions. The power is RM 1.2kW and IM 0.23kW in Fig.10 and Fig.11 respectively. The grid voltages in Fig.12 are unbalanced. The faults are triggered at t_1. Immediately the output P_{NF} changes to 0 and P_{FT1} to 1. Then Ctr_1 increases. When Ctr_1 reaches N_{th}, namely 5, the fault in T_1 is diagnosed.

The experimental results can be concluded as:

a) The method is featured with strong robustness against power changes and parameter variations, as shown in Fig.9.

b) The diagnosis is fast. The fault diagnosis time in Fig.10 is only 0.5ms (2.5% fundamental period, 5 switching periods).

c) The method is effective in both inverter and rectifier modes, in heavy and light loads, as shown in Fig.10 and Fig.11. Besides, it is immune to grid unbalance, as shown in Fig.12.

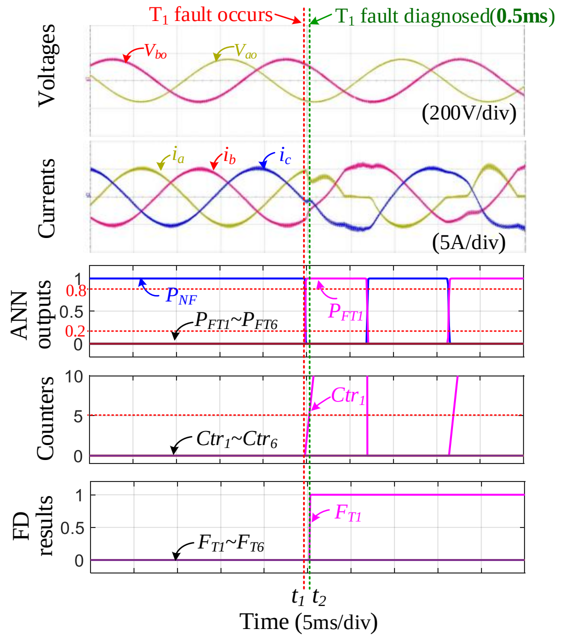


Fig. 10. Experimental results of T_1 fault diagnosis under 1.2kW in rectifier mode.

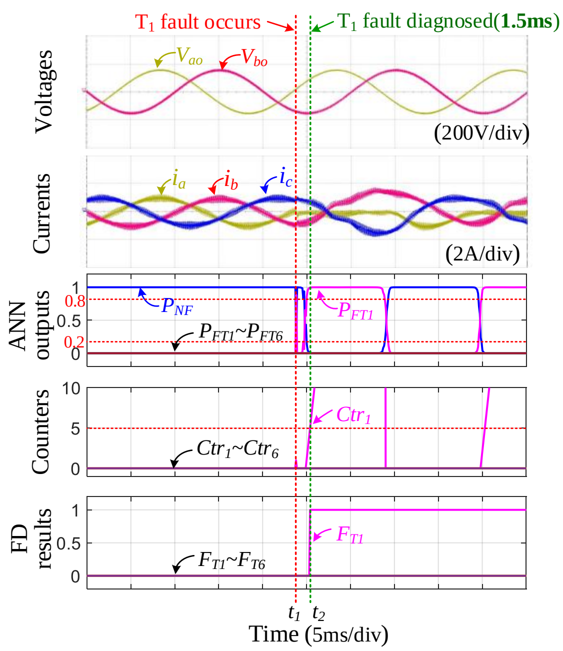


Fig. 11. Experimental results of T_1 fault diagnosis under 0.23kW in inverter mode.

IV. Comparison with Up-to-Date Methods

The proposed MDHD method is compared briefly with the recent model-driven methods [8,9] and data-driven methods [12,17] in terms of speed, robustness and complexity. The comparison results are given in TABLE III.

Both the model-driven methods and the proposed MDHD method can achieve fast diagnosis speed. The fault can be diagnosed within several switching periods. However, the fault diagnosis time for the data-driven method can be up to half of the fundamental period. All these methods show good robustness. The data-driven methods show the highest complexity due to heavy training and calculation. The model-driven methods are more complex in rulemaking and threshold selection than the data-driven, especially for more complicated circuits. It can be seen the proposed method shows a good balance in speed, robustness, and complexity.

TABLE III. Brief Comparison with Up-to-Date Methods

Methods	Speed	Robustness	Complexity
Model-driven [8,9]	Fast	High	Medium
Data-driven [12,17]	Slow	High	High
Proposed MDHD	Fast	High	Medium-Low

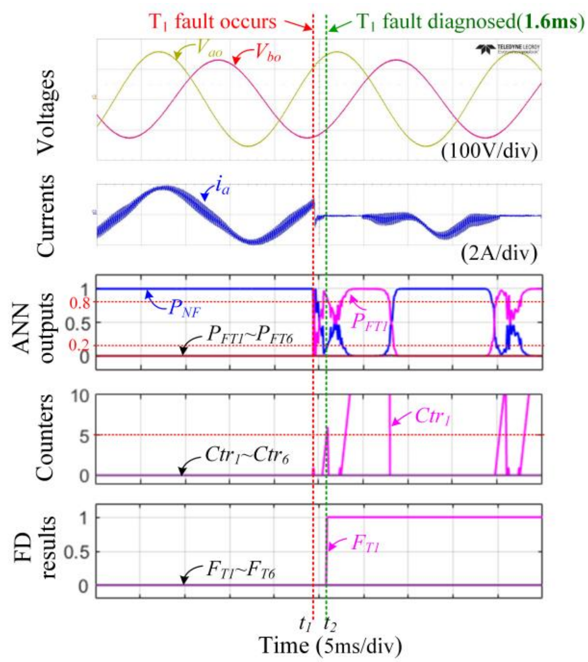


Fig. 12. Experimental results of T_1 fault diagnosis under unbalanced grid condition in inverter mode.

V. Conclusion

This paper presents a model-data-hybrid-driven open-switch faults diagnosis method for two-level three-phase converters. Model information and learning capability of ANN are combined comprehensively to achieve fast diagnosis with simple implementation. For the studied converter, an ANN is designed with two input elements, seven output elements, and two neurons in the hidden layer. The training samples are collected from simulations and the trained ANN is verified by experiments. Experimental results show the method is featured with strong robustness and fast diagnosis speed (0.5ms, 2.5%

fundamental period at the fastest). Fast diagnosis, simple computation, and easy training make this method easy to use. Moreover, the proposed idea is promising to be applied in more complex topologies. The process of the method is the same for different topology applications.

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