신호 및 데이터 기반 3상 PWM 인버터의 다중 스위치 고장 진단

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Multiple Open-Switch Fault Diagnosis for Three-Phase PWM Inverter Based on Signal and Data-Driven Approach

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ABSTRACT

This paper proposes a hybrid data-driven approach for diagnosing open-circuit faults in multiple switches of inverters by combining Multi-Task Learning (MTL) with the Hilbert transform and envelope method. As the number of potential faulty switches increases, the data requirements also increase. The proposed method enhances fault detection accuracy while reducing the data. Simulation results have proven reliability, achieving an accuracy of 99.49 % across different conditions.

1. Introduction

Three-phase PWM inverters are widely used in industrial applications, including variable-speed motor drives, uninterruptible power supplies, and renewable energy systems. Open-circuit fault detection is commonly utilizing three main approaches: model-based, knowledge-based, and data-driven techniques [1]. In the context of data-driven fault diagnosis, 2-level inverters have a simple topology. However, the likelihood of multiple switch faults increases the data requirements for accurate diagnosis. Reducing sample size is essential, especially when using experimental data, as extensive data acquisition can risk permanent damage to the system [2].

Effective feature extraction is essential for identifying key characteristics in a data-driven approach. To simplify the algorithm, the Hilbert transform and envelope algorithm are used for phase fault detection. Once a faulty phase is identified, the three-phase current data is sent to a Multi-Task Learning (MTL) algorithm, efficiently identifying faulty switches. In multiple fault scenarios, MTL facilitates simultaneous learning of various fault attributes across the three phases, enhancing diagnostic accuracy and robustness.

2. Open-Circuit Fault with Data-Driven Approach

2.1 Fault Analysis

Fig. 1 illustrates a three-phase 2-level inverter topology, which includes six switches across all three phases. Deep learning is a data-driven method that extracts patterns and features from data requiring a substantial amount of data during training. Consequently, as the switch faults increase, the amount of data needed also increases. Fig. 2 shows a comparison between the conventional and the proposed methods. In the conventional approach, 41 samples are required to identify a triple-switch fault. However, with the proposed method, only 3 potential fault samples are needed for accurate diagnosis.

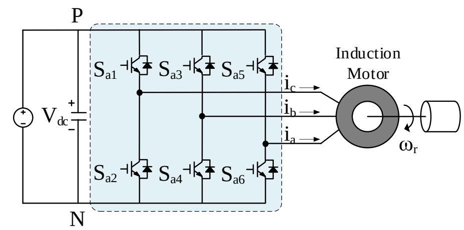

Fig. 1. A three-phase two-level PWM inverter topology.

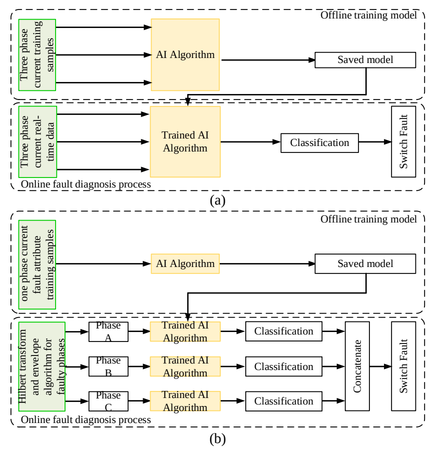

Fig. 2. Framework of the fault diagnosis.

2.2 Framework of the Proposed Fault Diagnosis

A simplified algorithm for fault diagnosis combines hybrid signal-based and data-driven approaches. As shown in Fig. 2(b), this framework illustrates the framework of the proposed method. The Hilbert transform and envelope algorithm are employed to detect faulty phases. This mathematical approach analyzes amplitude variations in the inverter output voltage data, facilitating detection across multiple phases[3]. The Hilbert transform can be expressed as

$$\hat{x}(t)=\frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(\tau)}{t-\tau}d\tau, \qquad (1)$$

$$z(t)=x(t)+j\hat{x}(t). \qquad (2)$$

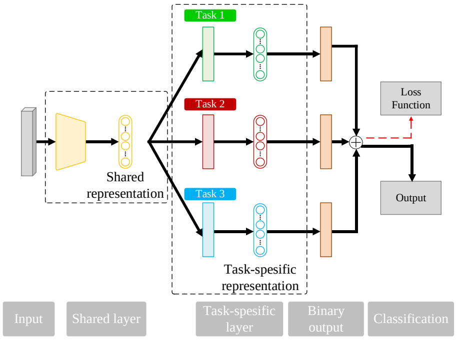

Fig. 3. Multi-task learning architecture.

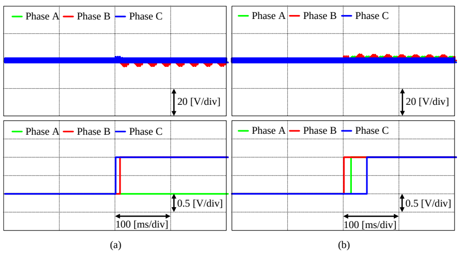

Fig. 4. Fault-phase detection using Hilbert transform.

This integral produces a signal that is a 90-degree phase-shifted version of the original signal $x(t)$, where t is the point in time the transform is evaluated, τ is the variable of integration, $\hat{x}(t)$ is the Hilbert transform of $x(t)$, $z(t)$ is the analytical signal, and j is the imaginary unit. For the envelope $A(t)$, the magnitude of the analytical signal is utilized:

$$A(t) = |z(t)| = \sqrt{x(t)^2 + \hat{x}(t)^2}. \tag{3}$$

The output from this step focuses on the relevant faulty phases. Moreover, the current data from these phases are fed into three separate MTL algorithms. Task 1 focuses on faults where the current remains zero during the positive cycle, Task 2 targets faults where the current stays zero during the negative cycle, and Task 3 identifies faults where the current is zero for the entire cycle.

As shown in Fig. 3, the MTL algorithm is structured with shared layers, which capture common fault features across all tasks, and task-specific layers that focus on individual tasks. The total loss from each task should be minimized to diagnose faulty switches effectively.

2.3 Data Acquisition

In this paper, PLECS simulations are utilized to collect data. The training dataset comprises three-phase current data at two speeds (500 rpm and 1000 rpm) and two loads (0 Nm and 4 Nm). Waveforms are extracted by considering all three phases across three faulty states. However, the proposed method requires only a single phase to train the algorithm, as the three parallel MTL models use the same trained model.

3. Evaluation of Performance

To validate the feasibility of detecting faulty phases using the Hilbert transform and envelope algorithm, two possible switch faults are illustrated in Fig. 4. As shown, all possible switch faults can be accurately detected, as indicated by the fault flag. To evaluate the performance of the proposed method, the trained model using phase A is shown in Fig. 5, achieving 100 % accuracy with validation data from phase B. To ensure reliable application, Table 1 presents the accuracy validation for untrained data, demonstrating that the fault diagnosis method is effective across 16 different conditions.

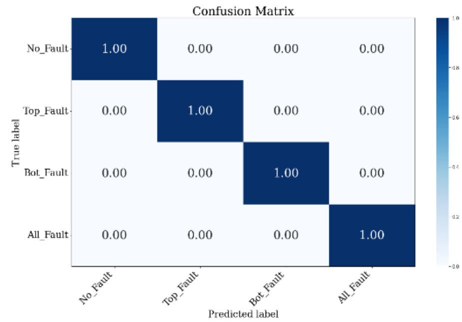

Fig. 5. Validation on phase B using model trained on phase A.

Table 1. Validation results for various conditions

Training data	Validation data accuracy [%]			
System condition	800 rpm, 1 Nm	800 rpm, 5 Nm	1200 rpm, 1 Nm	1200 rpm, 5 Nm
500 rpm, 0 Nm	99.93	99.54	99.91	99.40
500 rpm, 4 Nm	99.67	99.95	99.51	99.89
1000 rpm, 0 Nm	98.88	98.70	99.86	99.63
1000 rpm, 4 Nm	98.61	98.85	99.67	99.80

3. Conclusion

This paper has proposed a method to simplify fault diagnosis for multiple switches in a 2-level PWM inverter. Using three-phase voltage data, it employs the Hilbert transform and envelope algorithm to detect faulty phases. Once detected, the faulty current data is fed into an MTL model to diagnose which switches are faulty. The proposed method demonstrates reliability and robustness, achieving an accuracy of 99.49 % under 16 different conditions.

References

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