Convolutional Neural Network-Based Open-Circuit Fault Diagnosis for 5L-HNPC Inverters

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Convolutional Neural Network 기반 하이브리드 5L-HNPC 인버터의 개방회로 고장진단

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ABSTRACT

A deep learning-based fault diagnostic approach for a three-phase five-level hybrid neutral-point-clamped (5L-HNPC) inverter is proposed in this paper. The proposed method detects a single switch open-circuit fault by utilizing a 1-D convolution neural network to extract the periodic characteristic of fault information. The suggested data-driven deep learning-based method is simpler and more accurate under varied system conditions.

1. Introduction

Multilevel inverters are suggested due to their benefits, as they greatly minimize switch voltage stress. However, as the voltage level and number of switches grow, so does the likelihood of an open fault in switching devices. There is no hardware used to detect open-circuit faults. Model-based, knowledge-based, and data-driven techniques are the three most popular approaches for fault diagnosis [1]. Identifying key features in a dataset for a machine learning-based method involves feature extraction. 1-D CNN, on the other hand, processes data in the Convolutional Neural Network without utilizing specialized techniques to extract features [2].

Through 1-D CNN, this study provides a single open-circuit fault of a five-level hybrid neutral-point-clamped (HNPC) inverter. This data-driven strategy is used to increase diagnostic accuracy and robustness in a variety of working conditions. Finally, the validity of the proposed method is verified through simulation.

2. Analysis of Open-Circuit Faults

2.1 Fault Analysis of Five-Level HNPC Inverters

Fig. 1 depicts the circuit architecture of a three-phase five-level HNPC inverter topology. The HNPC topology is made up of two HB cells and one 3L-NPC cell per phase, as well as eight active switches, two diodes, and four series-connected common capacitors. There are five switching states on this inverter. When a switching device open-circuit defect occurs in the S_{x2} or S_{x7},, the output current has a similar waveform, showing that these two switches have no significant effect on the output current and making it difficult to precisely detect the faulty device. However, the effect of the faulty switching state on each switch varies based on the position of the faulty switch.

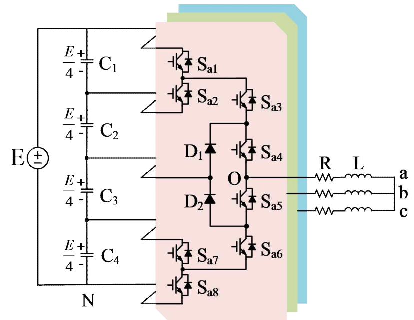

Fig. 1 Three-phase five-level hybrid neutral-point clamped inverter

3. 1-D CNN-Based Fault Diagnosis

3.2 Data Acquisition and Preprocessing

Deep learning is a data-driven learning method that extracts patterns and characteristics from data. In this research, PLECS simulations are employed to collect data. Table 1 displays the simulation parameters used in this work. A waveform with a two-cycle length of a fundamental frequency (40 ms) is extracted by taking into consideration all three phases of a three-phase five-level HNPC consisting of 24 fault states and 1 normal state, with a sampling frequency of 10 kHz. The training dataset consists of three-phase pole voltage data with three modulation indexes (0.3, 0.6, and 1.0) and two fundamental frequencies (10 Hz and 50 Hz). Low fundamental frequency data learning is required for a wide range of fault diagnosis. This occurred because the periodic properties of the data for low-frequency are not entirely contained within the fixed input length of the CNN.

As shown in Fig. 2, two methods are used to collect large amounts of data while avoiding duplication. First, data is extracted to consider the transient condition after causing a fault at 10 transient cases in order to make high accuracy regardless of the fault occurrence time. Second, using data

Table 1 Five-Level HNPC Inverter parameters

C	2 mF	R	9 Ω
V_{dc}	5000 V	L	8 mH
Sampling Frequency	10 kHz	Fundamental Frequency	50 Hz

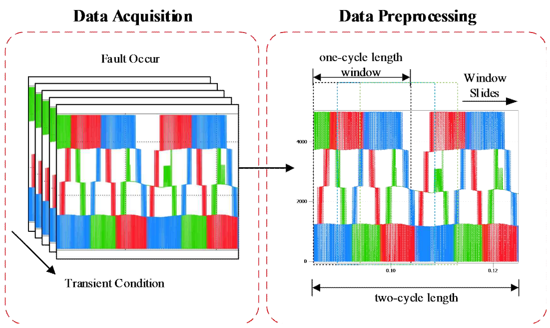

Fig. 2 Data generation from pole voltage waveform

segmentation the two-cycle length of waveform data is window-sliced with a one-cycle length of a fundamental frequency (20 ms). Three-pole voltage data for 25 fault cases with 21,320 fault data is used for training.

3.2 1-D CNN Model Architecture

Fig. 3 depicts the proposed fault diagnostic algorithm's 1-D CNN model architecture, which includes three 1-D convolutional layers to extract the feature map from the input data. The stride and padding strategies can help to minimize the number of convolutional layer parameters. For the activation function, a rectified linear unit (ReLU) is used after each convolutional layer. After the activation function, max pooling is used to minimize network computation amount and boost computational speed. The Fully Connected Network (FCN) is replaced by a Global Average Pooling (GAP) layer since a fully connected network increases the size and computing volume of deep learning, thus the GAP layer is utilized to address that problem. The existing Fully Connected Layer (FCL) makes layer channels from a vector of lines using flattening. Finally, the softmax output function calculates the probability of recurrence in 25 fault cases. In this study, Adam is utilized to optimize the model, and cross-entropy is employed as the loss function. Each batch has 100 samples, and the epoch is 30.

3.3 Performance Evaluation

A Pole voltage waveform containing 49,692 fault data is used to validate the feasibility of open-circuit fault diagnosis using 1-D CNN. To provide a reliable application, classification models were validated in 16 different conditions in which the system should detect and identify each faulty switch despite the modulation index and fundamental frequency.

Table 2 shows the accuracy verification table according

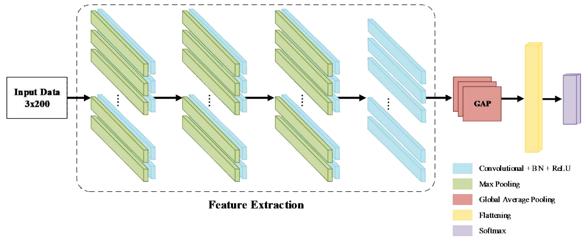

Fig. 3 1-D CNN model architecture

Table 2 Validation data accuracy for different system condition

MI	fundamental frequency			
	20 Hz (1800 rpm)	30 Hz (900 rpm)	50 Hz (1500 rpm)	60 Hz (1800 rpm)
0.1	99.45 %	99.83 %	100 %	100 %
0.5	98.89 %	99.02 %	100 %	100 %
0.8	100 %	98.78 %	100 %	100 %

to each condition, when training three modulation indexes (0.3, 0.6, and 1.0) and two fundamental frequencies (10 Hz and 50 Hz) the fault diagnosis method can work for every validation data with the accuracy without problem even for low fundamental frequency.

4. Conclusion

In this paper, a single-switch open-circuit fault diagnosis method for five-level HNPC inverters based on 1-D CNN has been proposed. Based on three-phase pole voltage data, the 1-D CNN model was trained by using window slicing and considering the transient condition to improve the performance. The proposed method was validated to shown reliability and robustness of proposed method with high average accuracy reached 99.66 % under 12 different conditions which were not trained in the deep learning model.

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) (No. 2022R1A4A1031885).

References

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