Open-Circuit Fault Diagnosis of Power Rectifier Using Deep Convolutional Neural Network

Ruoyue Wang
Shenghua Department of Central South University, Yuelu District, Changsha, Hunan, 410012
xfwry@sina.com

Abstract. Aimed to automatically provide accurate fault diagnosis of data from failed power electronics, various studies have been researched based on different approaches. Recently, data driven methods based on deep learning have required increasing attention because of their automatic feature learning abilities. Nonetheless, one of the challenges using these methods in practice is how to obtain the most representative fault features and ensure the better predication performances at the same time. This paper is in respect of the open-circuit fault diagnosis of the phase-controlled three-phase full-bridge power rectifier using deep convolutional neural network (DCNN) for extracting and further classifying fault features. The process mainly includes four steps. Firstly, a presupposed approach of DCNN which is applied to automatically capture the paramount fault features from the raw data is briefly introduced. Then a structure of DCNN is designed to extract the features from output data. Furthermore, the model and framework of the fault diagnosis system are developed to diagnose the open-circuit fault of the power rectifier. Finally, the effectiveness of the proposed method is validated using simulation results. Experiments illustrate that the DCNN model can achieve high accuracy in different fault cases and present great capability of diagnosing fault types in open-circuit fault of power rectifiers.

1. Introduction
With the prosperity of power electronic devices, power rectifier has been wildly applied to variable speed constant frequency generator, uninterruptible power supply, high-voltage DC transportation and electronic motor drive, etc. Power rectifiers present superior performance because of the controlled power semiconductors with high frequency and outstanding control quality [1]. However, power semiconductors are prone to suffer from failure which further causes converter failure due to the poor working environment, over-current, over-voltage and aging. It has been estimated that 38% of the faults in variable electronic engineering fields are because of the failure of power switches [2]. Although there are different ways to improve the reliability of the system, failure is ineluctable. Therefore, it’s necessary to detect the early fault once it occurs and recognize the type of the fault as quickly as possible to enhance the reliability [3].

Most of the rectifier failure would appear on the power electronic switches, mainly including open-circuit faults (OCFs) and short-circuit faults (SCFs) [4]. The SCFs which are usually caused by overvoltage and inappropriate trigger pulses will lead to flow of high currents. Under most circumstances, the SCFs will be eventually turned into OCFs by being detected and then triggered the protection system such as fast fuse [5]. While the SCFs are always devastating and shut down the
rectifier immediately, the OCFs do not make the system shut down but could cause phase imbalance which generally degrade the performance of the rectifier. Moreover, the OCFs can’t be detected by the standard protection circuits, so it’s essential to recognize the importance of diagnosing the open-circuit faults to enhance the reliability of the power electronic rectifier [6].

To solve the problem of open-circuit fault diagnosis, traditional fault diagnosis approaches mainly include model-based method which has higher sample efficiency. However, it decreases the asymptotic performance because it’s difficult to create models for the complicated systems so that the data-based method usually uses easy linear models to identify the systems [7]. Therefore, some new approaches have been applied for fault diagnosis such as data-driven method [8].

The data-based method using artificial to diagnose the fault include two steps. Features are firstly extracted from the current or voltage data in the power rectifier on the basis of time-frequency approach and spectral analysis [9]. Then the extracted features should be recognized by classification algorithms such as Artificial Neural Network (ANN), Support Vector Machine (SVM) [10] and K-means clustering approach [11].

Nevertheless, there are some limitations when dealing with feature extraction which is the key to the fault diagnosis. For example, although traditional ANN has successfully applied manual feature extraction, it largely depends on the complex expert diagnostic signal process and spends lots of time selecting the most representative features [12], which therefore encourages scientists to investigate novel methods to automatically collect extracted features from the raw data. For example, scientists have been utilized Deep Neural Network (DNN) to automatically capture the features in fault diagnosis for years.

To deal with above mentioned problems of traditional approaches, a Convolutional Neural Network (CNN) method based on DNN is developed for power machinery fault diagnosis. In this paper, the proposed approach is utilized to the open-circuit fault diagnosis of phase-controlled three-phase full-bridge rectifier. Firstly, the wave form of the output voltage is measured through the measuring elements in the power rectifiers and the values of the output voltage are put into the input layer. After that the fault features are automatically extracted during the process of CNN based on DNN and put out in the output layer. Then the extracted fault features are compared with the standard fault features in order to select the accurate type of the fault diagnosis of the rectifier by comparing, based on which an original approach is put forward to design the structure of the Deep Convolutional Neural Network (DCNN). Eventually, the failure can be recognized, and the diagnosis accuracy and other results will be proved in the simulation. In summary, the main contributions of this paper are exhibited as follows:

(1) For the first time, Deep convolutional Neural Network is utilized for the open-circuit fault diagnosis of phase-controlled three-phase full-bridge rectifier whose paramount fault features can be automatically extracted from the original output voltage data.

(2) A novel system model based on CNN is established and trained, from which the comparison results between the extracted data and standard data could be required to acquire the exact type of the fault.

(3) The simulation model of fault diagnosis system is presented which presents excellent performance according to the model accuracy curve, model loss curve and confusion matrix.

The rest of this paper is arranged as follows. The proposed model of deep convolutional neural network is briefly introduced and then the design of the DCNN structure is presented in Section 2. In Section 3 the fault model classification and the system of phase-controlled three-phase full-bridge rectifier are proposed. Then the simulation results are investigated in Section 4. Finally, general conclusions are discussed in Section 5.

2. The proposed model

The structure of the proposed open-circuit fault diagnosis of power rectifier method is demonstrated in Figure 1. It mainly includes three modules: (1) raw voltage data acquisition module; (2) pre-processing module; and (3) deep convolutional neural network module. To be specific, the pre-
processing module is aimed to acquire the data samples and labels from raw voltage data. The deep convolutional neural network module is applied to extract the most representative features and then identify different faults.

2.1. Deep convolutional neural network (DCNN) for open-circuit fault diagnosis

In this paper, in order to extract more detailed fault features, we set five blocks, each of which contains convolution-average pooling structure, as illustrated in Figure 2. The first block is designed to process the input voltage data, followed by four other convolution-average pooling blocks with similar structure and a flatten layer. Then the extracted features are put into the fully connected layer for nonlinear combination to acquire the output. Finally, the output is fed into classification layer to export different fault category labels.

For each convolutional layer, the basic process of which includes: firstly the feature filter (FF) is constructed for a certain class of the input signal, and then the feature map (FM) is obtained by extracting the feature from the voltage signal by using the filter mentioned above. Finally, the rectified linear unit activation (ReLU) is applied:

$$relu(x) = \max(0, x) = \begin{cases} x, & x > 0 \\ 0, & x \leq 0 \end{cases}$$

(1)

Because the ReLU can more efficiently avoid gradient explosion and gradient disappearance. Since there are no other complex activation functions such as exponential functions, and the dispersion of activities reduces the overall computational cost of the neural network at the same time, it can also simplify the calculation process.

For each pooling layer, the basic pooling operation involves: the whole voltage signal is scanned from the top left corner of the feature map according to the pooling window, during which the scanning is first from the left to the right and then from top to bottom.
Table 1 demonstrates the specifications of the number of neurons, filter size and stride and the dropout operations are executed to all the convolutional layers with the probability of 0.2.

| Layers  | Type            | Number of neurons | Filter size | Stride |
|---------|-----------------|-------------------|-------------|--------|
| Block 1 | Convolution 1   | 1×10×8            | 8           | 1      |
|         | Average pooling | 1×2×8             | 8           | 2      |
| Block 2 | Convolution 2   | 1×10×32           | 32          | 1      |
|         | Average pooling | 1×2×32            | 32          | 2      |
| Block 3 | Convolution 3   | 1×10×64           | 64          | 1      |
|         | Average pooling | 1×2×64            | 64          | 2      |
| Block 4 | Convolution 4   | 1×10×128          | 128         | 1      |
|         | Average pooling | 1×2×128           | 128         | 2      |
| Block 5 | Convolution 5   | 1×10×256          | 256         | 1      |
|         | Average pooling | 1×2×256           | 256         | 2      |

2.2. Deep convolutional neural network training

In order to train the DCNN model, in the case of using the Softmax function, the output should be converted to probabilities of the label given the input:

\[
p(l_m | f_m(X_j;\theta)) = \frac{\exp(f_m(X_j;\theta))}{\sum_{k=1}^{M} \exp(f_k(X_j;\theta))}\]

where \(\theta\) is the parameters of the function \(f\), \(M\) denotes the figure of output labels and \(j\) is the sample.

Then, by minimizing the error function, the DCNN model is trained to achieve the highest probabilities to the right labels:

\[
\theta^* = \arg \min_{\theta} \frac{1}{N} \sum_{j=1}^{N} L(y_j, p(l_m | f_m(X_j;\theta)))
\]

where \(L\) denotes the cross-entropy function:

\[
L(y_j, p(l_m | f_m(X_j;\theta))) = -\sum_{m=1}^{M} q(y_j = l_m) \log p(l_m | f_m(X_j;\theta))
\]

where \(q(y_j = l_m)\) is the value of true label associated with the \(m\)-th output.

The deep convolutional neural network training process involves the backward propagation, which can be divided into two procedures. The first is the stage of data transmission from the first layer to the last layer, namely the forward propagation stage. In the second procedure, when the result of current propagation is inconsistent with the expectation, the error is trained from the last layer to the first layer known for the backward propagation procedure. The training process of DCNN is:

1. Initialize the weight and bias of DCNN.
2. The input data is propagated forward through the convolution layers, the pooling layers, and the full-connected layer to calculate the output value.
3. Calculate the error between expected value and the output value.
The error is sent back to the DCNN model if the error is greater than the expected value. Then the error of the full-connected layer, the pooling layers and the convolution layers are acquired in turn. The training ends if the error is equal to or less than our expected value.

(5) Update the weight and bias. And then go back to the second step.

The structure of the CNN training process is shown as Figure 3.

$$\text{Figure 3. DCNN training process.}$$

3. Open-circuit fault diagnosis of three-phase full-bridge rectifier

3.1. Fault model of three-phase full-bridge rectifier

Taking the practicability and complexity into account, phase-controlled three-phase full-bridge rectifier as the system for open-circuit diagnosis is considered in this paper, which is presented in Figure 4.

$$\text{Figure 4. System model of three-phase full-bridge rectifier.}$$

In this paper, we think the faults in the rectifier are caused by broken thyristors. Considering the actual fault conditions, we assume that there are at most two thyristors become broken at the same time. Therefore, the faults can be separated into 4 types as follows:

Fault type 1: Only one thyristor is broken, which includes 6 cases: T1 broken, T2 broken, T3 broken, T4 broken, T5 broken, and T6 broken.

Fault type 2: Two thyristors of the same bridge are broken at the same time, which include 3 cases: T1 and T4 broken, T3 and T6 broken, T5 and T2 broken.

Fault type 3: Two thyristors of different bridges and the same side, which contains 6 cases: T1 and T3 broken, T1 and T5 broken, T3 and T5 broken, T4 and T6 broken, T4 and T2 broken, T6 and T2 broken.

$$\text{Figure 5. Simulation model of three-phase full-bridge rectifier.}$$
Fault type 4: Two thyristors of different bridge and different sides, which contains 6 cases: T1 and T6 broken, T1 and T2 broken, T3 and T4 broken, T3 and T2 broken, T5 and T4 broken, T5 and T6 broken.

After classifying the faults, we could code them with six-digit binary numbers in order to be recognized in later fault diagnosis. The fault codes are presented in Table 2.

**Table 2.** Fault codes of the rectifier.

| Fault Classification | Fault | Code       |
|----------------------|-------|------------|
| Normal               | No    | 001001     |
| Fault Type 1         | T1    | 010001     |
|                      | T2    | 010010     |
|                      | T3    | 010011     |
|                      | T4    | 010100     |
|                      | T5    | 010101     |
|                      | T6    | 010110     |
| Fault Type 2         | T1, T4| 011001     |
|                      | T3, T6| 011010     |
|                      | T5, T2| 011011     |
| Fault Type 3         | T1, T3| 100001     |
|                      | T1, T5| 100010     |
|                      | T3, T5| 100011     |
|                      | T4, T6| 100100     |
|                      | T2, T4| 100101     |
|                      | T2, T6| 100110     |
| Fault Type 4         | T1, T6| 101001     |
|                      | T1, T2| 101010     |
|                      | T3, T4| 101011     |
|                      | T3, T2| 101100     |
|                      | T5, T4| 101101     |
|                      | T5, T6| 101110     |

4. Simulations

4.1. Simulation model

The simulation model is constructed in PSIM presented in Figure 5 in order to examine the accuracy of the fault diagnosis of the phase-controlled three-phase full-bridge rectifier on the basis of DCNN method. To simulate the practical condition of power rectifiers, the rectifier simulation model is operated under 50 Hz and random noise. The output voltage is measured by the voltage measurement element and collected under 5 kHz. To get enough voltage data samples for later fault diagnosis, 200,000 voltage data are acquired in each fault condition. Every 500 of these voltage data are regarded as a sample in which the first 100 data are for training and the last 400 data are for testing. The main
parameters are set as follows: learning rate of DCNN model is set as 0.001, batch size is set as 10, epoch is set as 100 and validation split is set as 0.2 which means there will be 20 percent of the whole data are applied for verification.

4.2. Results and discussions

The fault of the diagnosis system in this paper are divide into 22 types including the normal one and triggering angle which can be modified by adjusting the control signals is set as 30° in the following discussions. The model accuracy and loss of the open-circuit fault diagnosis system with random noises are shown in Figure 6 and Figure 7. As we can see, the accuracy of the system is very low at first but increased rapidly as the epoch promoting and finally average accuracies of training and validation both reach nearly 100%. Accordingly, model loss is very high initially and start to decrease from 100% to approximately 0 when the epoch increases. This could be explained that the epoch should be great enough to extract detailed features and ensure the accuracies of training and validation.

![Figure 6. Model accuracy.](image6)

![Figure 7. Model loss.](image7)

Furthermore, more specific normalized confusion matrix is presented in Figure 8, where there are 500 samples including 200,000 output voltage data for each case and the fault codes in Table 1 are applied. From the matrix, the predicted label and true label are almost exactly coincide, which suggests that this DCNN model can be successfully used to determine and diagnose the fault types trough the extracted features, and further verify the effectiveness of the open-circuit fault diagnosis of power rectifier using deep convolutional neural network.

![Figure 8. Normalized confusion matrix.](image8)
5. Conclusion
This paper demonstrates DCNN-based method for open-circuit diagnosis of phased-controlled three-phase full-bridge rectifier. The success of the proposed method is examined by using several simulation results which include different failure operating conditions. The diagnosis results present DCNN model can extract the representative fault features and recognize the fault types accurately. This work provides a promising future for fault diagnosis of more complicated systems apart from the power rectifiers.

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