Research Article

Comparison and Analysis of the Influence of Different Data Transformation Methods on the Fault Identification of Flexible DC Transmission Lines by Convolutional Neural Network

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Received 6 June 2021; Revised 30 July 2021; Accepted 25 August 2021; Published 6 September 2021

Academic Editor: Mohammad Amin Hariri-Ardebili

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In the fault classification and identification of flexible DC transmission lines, it is inevitable to use the voltage and current characteristics of the transmission line. All kinds of data transformation methods can highlight the hidden characteristics of the original fault electrical quantity. Various artificial intelligence algorithms can further reduce the difficulty of transmission line fault classification. For such fault classification methods, this paper first builds a four-terminal flexible direct current transmission system model on PSCAD/EMTDC platform and obtains data by simulating different faults of transmission lines. Then, empirical mode decomposition (EMD), wavelet transform (WT), fast Fourier transform (FFT), and variational mode decomposition (VMD) are performed on the obtained data, respectively. Finally, the transformed data and original data are used as inputs to classify by convolutional neural network (CNN). The influence of one data transformation method and different combinations of two data transformation methods on CNN classification results is explored. The simulation results show that when only one data transformation method is used, CNN has the best classification effect for the data after VMD transformation. The classification accuracy and recall rate are both increased from 96.9% and 96.3% without data transformation to 99.88%. When VMD and FFT are combined, CNN classification results’ accuracy and recall rate are further improved to 99.96%.

1. Introduction

Modular multilevel converter based high voltage direct current (MMC-HVDC) has many advantages, such as modular structure, low harmonic content, the independent control system of active and reactive power, and low switching loss at runtime. Therefore, MMC-HVDC has shown broad application prospects in isolated island power supply, offshore wind power integration, power supply in large cities, weak AC grid connection, long-distance large-capacity transmission, and asynchronous interconnection [1–4].

The DC transmission network is a low inertia system [5]. When the DC transmission line fails, the fault current of the line will rise rapidly, which seriously affects the regular operation of the DC transmission network and the converter. In order to ensure the regular operation of the system, it is necessary to identify the fault type after the fault occurs accurately and then remove the fault in a short time [6].

DC transmission line fault classification and identification are mainly divided into fault traveling wave identification and artificial intelligence algorithms identification methods. The fault traveling wave identification method has been applied in AC transmission line fault protection as early as possible, so its development is earlier, and the technology is relatively mature. The artificial intelligence algorithm to identify DC transmission line fault development is relatively late, but recent years have also made significant research results.

When the transmission line of the power system fails, the fault point will propagate the fault traveling wave to both ends of the transmission line. The protection of the ultra-high-speed operation proposed according to the fault traveling wave theory is the traveling wave protection. The
principle of traveling wave protection can detect faults according to the characteristics of fault traveling waves. The traveling wave at the beginning of the fault contains the fault information of the current traveling wave, voltage traveling wave, or their combination. When traveling wave protection is applied to fault identification of AC transmission lines or DC transmission lines, the accuracy of fault identification can be further improved with data transformation methods such as Fourier transform and wavelet transform. At present, there are many valuable research results on the construction of traveling wave protection based on the transformation of the original traveling wave by different data transformation methods. In [7], the fast Fourier transform was performed on the characteristic current signal after the fault, and then the transformed spectrum signal was classified by setting the threshold. However, the scientificity of the selected threshold is not verified, and the classification accuracy needs to be further verified. Reference [8] carried out wavelet transform on the obtained single-ended electrical quantities to realize the rapid classification and identification of transmission line faults. However, when applied to the multiterminal DC distribution system, it may affect the operation performance due to the lack of a clear protection boundary. In [9], the wavelet transform was used to decompose the fault signal of the transmission line, and the high-frequency signal was extracted to realize the classification of the lightning fault and line fault. However, the classification accuracy would decrease with the increase of transmission line length. In [10], the initial and postfault traveling waves of voltage and current are decomposed by empirical mode decomposition. The inherent model components obtained by decomposition are used to realize line protection, but the overall protection time needs 5 ms. In [11], the dual-tree complex wavelet transform with the advantage of antifrequency band aliasing was used to accurately extract the high frequency of the fault, and the difference in the maximum modulus of the line polar wave under different fault conditions was used for fault identification and pole selection. However, the setting of the protection threshold was easy to cause misjudgment of the fault type, and the influence of lightning was not considered. In [12], principal component analysis (PCA) is used to form a cluster point family of DC fault data to realize fault identification, but the protection method based on PCA does not consider the influence of high transition resistance.

Although the traveling wave protection method is relatively mature, the identification of transmission line faults by fault traveling wave is affected by the traveling wave transmission speed. With the continuous development of transmission technology and the increasing length of transmission lines, traveling wave identification will face significant challenges. The data-driven artificial intelligence classification algorithm is not affected by the transmission speed of fault traveling waves. It can only rely on fault data to realize the classification and identification of transmission line faults. Using different data transformation methods to transform fault data also has a certain influence on the classification accuracy of artificial intelligence algorithms. In recent years, the combination of data transformation and artificial intelligence algorithms has also made many valuable transmission line fault classification and identification achievements. Reference [13] proposed that the wavelet method was used to extract the frequency characteristics, and the neural network was used for fault diagnosis. This method did not consider the rapidity requirement of HVDC system fault diagnosis. Literature [14] proposed a fault detection method based on an artificial neural network for a three-terminal two-level flexible DC transmission system. This method requires a large amount of fault data to train an artificial neural network, but the longest detection time can reach about 4 ms, which cannot meet the rapid fault detection requirements of MMC-MTDC with DC circuit breakers. In [15], the wavelet singular signal was used as the feature, and the support vector machine was used to classify and identify the faults of transmission lines under different fault conditions. However, the synthetic minority over-sampling technology adopted by it generates a new minority of samples through linear interpolation, which has the risk of overfitting. Reference [16] first applied wavelet transform to extract feature information of fault voltage and fault current and then used extreme learning machine to realize fault identification and location, but this study only focused on single-stage grounding fault of double-terminal DC transmission system. Reference [17] designed a fault detection scheme based on wavelet transform and deep neural networks. The branch current measured value sampled by relay was extracted by discrete wavelet transform, and all available data were input into deep neural network. Three deep neural networks (DNN) were used to realize the fault identification, fault phase selection, and fault location of transmission lines. However, three DNNs need to be trained separately, and the training work is more complex. In [18], the fast Fourier transform and discrete wavelet transform were used to extract the feature of voltage and current after fault, and then the adaptive neurofuzzy inference system was applied to realize the classification and identification of fault types. However, this method was not suitable for situations of unbalanced load and asynchronous sampling. Reference [19] first carried out Fourier transform and wavelet transform on the voltage of the transmission line after the fault. Then it used the two-layer artificial neural network to identify and classify the fault of the transmission line successively on the transformed characteristic data. However, this study did not analyze the rapidity of the DC circuit breaker. In [20], the wavelet singular entropy value is extracted from the fault current, and then the fuzzy logic is used to realize the fault classification. However, it only extracts the feature of the fault current, so it cannot effectively identify the single-phase grounding fault and the two-phase grounding short circuit fault.

In order to explore the influence of different data transformation methods on CNN classification of flexible DC transmission lines and meet the rapid requirements of DC transmission line fault classification and identification, this paper first obtains the fault data of the DC transmission line within 2.5 ms after a fault and transforms the original data by EMD [21], WT [22], FFT [23], and VMD [24]. Then, the transformed data and the original data are used as input
to classify the CNN. The effects of one data transformation method and different combinations of two data transformation methods on CNN classification results are explored.

2. Four-Terminal MMC-HVDC System

For a multiterminal MMC-HVDC transmission network, each converter station will have multiple lines connected to it. When a line of the converter station fails, other lines connected to the converter station will show overcurrent phenomenon. In order to isolate faults correctly, it is necessary to quickly and correctly judge various faults occurring on different lines. In this paper, based on using four data transformation methods to process fault data, CNN is used to learn the internal law of DC voltage and current at the outlet of converter station under different fault types and different fault conditions. Based on data, fault classification is realized.

In this paper, the four-terminal MMC-HVDC system is taken as an example to study, and the four-terminal MMC-HVDC system model is shown in Figure 1.

In the system, three DC transmission lines, L1, L2, and L3, are connected by the DC bus, and a passive network connects line L2. The lengths of the three DC transmission lines are 50 km, 80 km, and 100 km, respectively. Three faults are set for each line: positive grounding fault, negative grounding fault, and bipolar short circuit fault. In Figure 1, the V and A of the bus and each line at the bus outlet represent the positive and negative voltage, positive and negative current of each transmission line, respectively, as the selected characteristic electrical quantity.

3. Four Data Transformation Methods

After obtaining the fault data of electrical measurement points, if only the change rate between adjacent data points is calculated, the data characteristics cannot be highlighted, thus affecting classification accuracy. In this paper, EMD, WT, FFT, and VMD, four data transformation methods commonly used in data processing, are used to preprocess the obtained fault data.

Taking the positive grounding fault of transmission line L1 as an example, the transient short circuit fault of the transmission line is set at 2 s, the fault duration is 0.01 s, and the fault is cleared at 2.01 s. For fault line L1 and nonfault line L2, when there is no data transformation, the positive current \( i_{L1} \) of transmission line L1 and the positive current \( i_{L2} \) of transmission line L2 are shown in Figures 2 and 3.

Figures 2 and 3 highlight the current waveform at fault times from 2 s to 2.01 s. It can be seen from the comparison between Figures 2 and 3 that the current \( i_{L2} \) of the fault phase L1 fluctuates more violently than that of the nonfault phase L2, and the time to return to regular operation after fault removal is longer.

3.1. EMD. EMD does not need to set the basis function when decomposing the signal and can decompose the signal according to the time scale characteristics of the data itself. Theoretically, EMD can decompose any signal and has significant advantages in processing nonstationary time series signals. The basic steps of the EMD algorithm for signal decomposition are as follows.

For any signal \( x(t) \), all the extremums are calculated first, and the maximum and minimum values of the difference between all extremums are calculated to obtain the envelope signals \( s_{\text{max}}(t) \) and \( s_{\text{min}}(t) \). The mean value \( m_1(t) \) of the envelope signal is calculated:

\[
m_1(t) = \frac{s_{\text{max}}(t) + s_{\text{min}}(t)}{2}
\]

The intrinsic mode function (IMF) \( c_1(t) \) of signal \( x(t) \) can be calculated by formula (1) as follows:

\[
c_1(t) = x(t) - m_1(t).
\]

The residual \( r_1(t) \) obtained from \( c_1(t) \) is

\[
r_1(t) = x(t) - c_1(t).
\]

Repeat the above steps, and the original signal can be decomposed into multiple IMFs and a corresponding residual. After decomposing the original signal \( n \) times, the original signal \( x(t) \) can be expressed as

\[
x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t).
\]

The residual \( r_n(t) \) can be obtained by combining formula (3):

\[
\begin{align*}
  r_1(t) - c_2(t) &= r_2(t) \\
  r_2(t) - c_3(t) &= r_3(t) \\
  \vdots \\
  r_{n-1}(t) - c_n(t) &= r_n(t).
\end{align*}
\]

Since there is no basis function in EMD decomposition, signal decomposition is entirely dependent on the time scale characteristics of the data itself, so the maximum number of layers of EMD decomposition cannot be set. In this paper, EMD is used to decompose the obtained voltage and current wave. For the waveform with slight fluctuation, EMD can only decompose a layer of IMF and residual. In order to ensure the unity of data, all voltage and current waveforms are selected as the first layer of IMF.

EMD is applied to the fault current between 2 s and 2.01 s in Figures 2 and 3. The transformed waveform is shown in Figures 4 and 5.

3.2. WT. WT is a method to analyze the time and frequency of the signal at the same time. The signal is multiscale refined through the expansion and translation of the wavelet. Finally, the time subdivision is achieved at high frequency, and the frequency subdivision is achieved at low frequency. Therefore, more details of the signal can be obtained.

Admissibility condition \( C_w \) can be obtained by adding a limit condition to square integrable function \( \psi(t) \):
where \( \psi(t) \) is the mother wavelet function of the wavelet transform, which is a fast-decaying oscillation function with zero mean. The wavelet basis function \( \psi_{a,b}(t) \) can be obtained after scaling and translation:

\[
C_{\psi} = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty, \tag{6}
\]

\[
\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right), \quad a, b \in \mathbb{R}; a \neq 0. \tag{7}
\]

In formula (7), \( a \) is the stretching factor, and \( b \) is the translational factor. The scaling factor \( a \) controls the scaling of the wavelet function. The larger \( a \) is, the wider the wavelet function is and the smaller the amplitude is. The translation
factor $b$ controls the translation of wavelet function, and its translation corresponds to time.

For any finite signal $f(t)$, the basic wavelet transform formula $WT(a, b)$ is

$$WT(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \ast \left(\frac{t - b}{a}\right) \, dt.$$  \hspace{1cm} (8)

When using WT to process data, different wavelet bases are needed for different problems. In the processing of power signals, the dbN wavelet system has a better effect than other wavelets, and $N$ is the order of the dbN wavelet. Among them, db1 is the simplest Harr wavelet. Except for db1, other dbN wavelets have no explicit expressions. The characteristics of dbN series wavelets are that, with the increase of order, the larger the vanishing matrices’ increase, the better the frequency band division effect. However, it will weaken the time-domain support increasing the calculation amount seriously. Therefore, it will increase the calculation time and make the real-time performance worse. Because this paper needs to quickly determine the fault type after the system failure, considering the timeliness requirements, this paper selects db2 as the wavelet basis for the three-layer wavelet transform of data. The specific decomposition structure is shown in Figure 6.

It can be seen from Figure 6 that the original signal $x$ is decomposed into low-frequency signal $r_3$ and high-frequency signals $c_{1}, c_{2}$, and $c_{3}$. The low-frequency signal retains the approximate information in the original signal, and the high-frequency signal contains the detailed information in the original signal.

The above WT is applied to the fault current between 2 s and 2.01 s in Figures 2 and 3. The detail coefficients extracted after transformation are shown in Figures 7 and 8.

3.3. FFT. Fourier transform analyzes the different components contained in the original waveform by using different sinusoidal signals. Fourier transform can decompose any waveform into the sum of countless sinusoidal signals with different frequencies. Using Fourier transform, the signal in the time domain can be converted to frequency domain for analysis, highlighting the frequency domain information in the signal.

Periodic voltage and current waveforms $f(t)$ can be expressed as periodic functions with period $T$: 
For formula (9), its Fourier series can be expressed as
\[
f(t) = a_0 + \sum_{n=1}^{\infty} \left( a_n \cos n\omega t + b_n \sin n\omega t \right).
\]
(10)

In formula (10), \(a_0\) is the DC component, \(n\) is the harmonic number, \(a_n\) is the cosine coefficient of \(n\) harmonic, \(b_n\) is the sine coefficient of \(n\) harmonic, and \(\omega\) is the fundamental angular frequency.

According to Euler formula:
\[
\begin{align*}
    e^{j\omega t} &= \cos \omega t + j \sin \omega t, \\
    e^{-j\omega t} &= \cos \omega t - j \sin \omega t.
\end{align*}
\]
(11)

Formula (10) can be translated into formula (12):
\[
\begin{align*}
    f(t) &= a + \sum_{n=1}^{\infty} \left[ \frac{1}{2} a_n (e^{j\omega t} + e^{-j\omega t}) - \frac{1}{2} j b_n (e^{j\omega t} - e^{-j\omega t}) \right] \\
    &= a + \sum_{n=1}^{\infty} \left( \frac{a_n - j b_n}{2} e^{j\omega t} + \frac{a_n + j b_n}{2} e^{-j\omega t} \right) \\
    &= \sum_{n=1}^{\infty} F_n e^{j\omega t}.
\end{align*}
\]
(12)

In formula (12), \(F_n = (1/2)(a_n - j b_n)\).

For the continuous function \(f(t)\) with fundamental angular frequency \(\omega\) in the time domain, when it satisfies the Dirichlet condition and is absolutely integrable, its Fourier transform is
\[
F(\omega) = \int_{-\infty}^{\infty} f(t) e^{-j\omega t} \, dt.
\]
(13)

In mathematical analysis, the signals of continuous Fourier transform analysis are continuous. The discrete signal is stored in the modern signal processing system, and the analysis needs to apply discrete Fourier transform. For the discrete signal \(f(n)\) with \(N\) sampling points, the discrete Fourier transform formula is
\[
F(k) = \sum_{n=0}^{N-1} f(n) e^{-j(2\pi nk/N)}, \quad k = 0, 1, 2, \ldots, N-1.
\]
(14)

In formula (14), \(N\) is the number of sampling points, \(f(n)\) is the original discrete signal, and \(F(k)\) is the spectrum after discrete Fourier transform.

Fast Fourier transform is a fast and efficient calculation method of discrete Fourier transform. When the number of transformed data sampling points \(N\) is larger, the time saving of fast Fourier transform is more obvious.

FFT is applied to the fault current between 2 s and 2.01 s in Figures 2 and 3, and the corresponding frequency characteristics are shown in Figures 9 and 10.

3.4. VMD. VMD is an adaptive signal processing method, which can set the number of modal components obtained by signal decomposition, and the modal components obtained by decomposition have their central frequencies. VMD takes the sum of modal components as the constraint condition and takes the minimum bandwidth of modal components as the optimization goal to construct the modal component solution model. The signal decomposition is completed by iterative calculation. The specific decomposition process is as follows.

According to the decomposition principle of VMD, assuming that the original signal \(f(t)\) is decomposed into \(K\) IMF components, the optimization objectives and constraints corresponding to the mathematical model of VMD are
\[
\begin{align*}
    &\min_{\{u_k, \omega_k\}} \left\{ \sum_k \left[ \| \left( \delta(t) + \frac{1}{\pi t} \right) u_k(t) \right\|_2^2 \right\}, \\
    &\text{s.t.} \quad \sum_k u_k(t) = f(t).
\end{align*}
\]
(15)

In formula (15), \(f(t)\) is the original signal, \(u_k(t)\) is the \(k\)th intrinsic mode component obtained by decomposition, \(\omega_k\) is the central frequency of \(u_k(t)\), and \(\delta(t)\) is a Dirac function.

Based on the optimization objective of formula (15), the augmented Lagrange expression \(L\) is constructed:
\[
L(u_k, \omega_k, \lambda) = a \sum_k \left\| \left( \delta(t) + \frac{1}{\pi t} \right) u_k(t) \right\|_2^2 + \left\| f(t) - \sum_k u_k(t) \right\|_2^2 + \lambda \left( \sum_k u_k(t) - f(t) \right).
\]
(16)
Figure 7: Detail coefficients extracted by WT in $i_{21}$.

Figure 8: Detail coefficients extracted by WT in $i_{31}$.

Figure 9: Fault current spectrum in $i_{21}$. 
In formula (16), $\lambda$ is a Lagrange multiplier, and $\alpha$ is a quadratic penalty factor.

The alternating direction method of the multiplication operator is used to optimize the augmented Lagrangian expression iteratively. The method is based on $\arg\min[L(\omega_k, \omega_k, \lambda)]$ to solve $u_{kn+1}^{n+1}$ and the center frequency of the modal component $\omega_{kn+1}^{n+1}$:

$$
\begin{cases}
\omega_{kn+1}^{n+1} = \omega_k, \\
u_{kn+1}^{n+1}(\omega) = \frac{\sum_{i=1}^{k+1} u_i(\omega) + \lambda^k(\omega)/2}{1 + 2\alpha(\omega - \omega_k)^2}, \omega_{kn+1}^{n+1} = \frac{\int_0^\infty \omega |u_k(\omega)|^2 d\omega}{\int_0^\infty |u_k(\omega)|^2 d\omega}.
\end{cases}
$$

\[\lambda^{k+1} = \lambda^k + \tau(f(\omega) - \sum_{i=1}^{k+1} u_i(\omega)). \tag{18}\]

The termination condition of VMD iterative calculation is

$$
\sum_k \|u_{kn+1}^{n+1} - u_k^n\|^2 < \varepsilon. \tag{19}\]

In formula (19), usually set $\varepsilon = 1.0 \times 10^{-6}$. If formula (19) holds, the iterative calculation is stopped, and the calculated modal component set $\{u_k(t)\}$ is output. If not, iterative calculations continue.

Although VMD can set the number of modal components of signal decomposition, when the number of decomposition layers is too large, the resulting modal components are discontinuous, and the regularity is seriously reduced. After several tests, the CNN classification results are the best when three-layer VMD is applied to the fault current $i_{31}$, and $i_{31}$ and the third layer modal component IMF3 are taken. Three-layer VMD is applied to the fault current between 2 s and 2.01 s in Figures 2 and 3, and the three-layer modal components obtained are shown in Figures 11 and 12.

4. CNN Structure of Fault Classification

4.1. CNN Brief Introduction. In recent years, CNN has shown significant advantages in image classification, image super-resolution reconstruction, and other fields and is widely used [25]. With the increasing scale of power systems, the amount of data for fault classification is also increasing. The standard feedforward neural network is not suitable for large-scale processing data. Therefore, this paper takes CNN as an example to realize fault classification.

Typical CNN generally includes convolution layer, pooling layer, full connection layer, and output layer. When classifying large-scale data, the input matrix is enormous and contains multiple electrical quantities. CNN can map feature extraction and reduce the dimension of input data through convolution layer and pooling layer and finally output classification results through full connection layer and output layer.

4.2. CNN Network Structure. The CNN used in this paper is based on LeNet-5 [26, 27], and the specific network structure is shown in Table 1.

4.3. CNN Input and Output Data Composition. For CNN, the input data are a two-dimensional matrix, and the row number of the matrix is the total amount of data obtained through simulation. The matrix is listed as the measured characteristic electrical quantity. Because each data transformation method transforms the electrical quantity, and each CNN classification is to transform the data and the original data as input, the data transformation method will only increase the number of columns of the matrix. It will not affect the number of rows of the matrix. Taking the four-terminal model established in this paper as an example, the time window for each data acquisition is 2.5 ms after the failure. When the sampling frequency is maintained at 20 kHz, there are 50 data points in each sampling time window. Therefore, the number of matrix rows corresponding to each sampling window is 50. Each data point contains electrical measurements of each line at the simulation time, with a total of 3 transmission lines and 1 bus, 4 electrical measurement points per line, and 16 original electrical quantities. So the number of matrix columns corresponding to each sampling window is 16. The data dimension of each sampling window is $50 \times 16$. After applying four data transformation methods of EMD, WT, FFT, and VMD to the 16 original electrical quantities, four groups of transformed fault data can be obtained, and each group contains 16 transformed electrical quantities. When exploring the influence of one data transformation method on CNN classification, the four groups of transformed electrical volumes are respectively combined with the original data as...
CNN input, and the data dimension of each sampling window in the input data is $50 \times 32$. When exploring the influence of different combinations of two data transformation methods on CNN classification, two groups of data among the four groups of transformed data are combined with the original data as CNN input, and the data dimension of each sampling window in the input data becomes $50 \times 48$.

In order to ensure that the trained CNN can accurately classify faults at different locations of transmission lines, the training data must include fault data at different locations of transmission lines. The specific training data acquisition conditions are shown in Table 2. In the table, $L$ is the length of the transmission line, and the fault distance is the distance between the fault point and the electrical measurement point. For test data, according to the same acquisition method, the test data acquisition conditions are shown in Table 3.

For convenience, 1PG, 1NG, and 1PN are used in Tables 2 and 3 to represent the positive grounding fault, negative grounding fault, and bipolar short circuit fault of transmission line $L1$. The fault representation methods of transmission lines $L2$ and $L3$ are similar, and NF represents the normal operation state.

A total of 11 fault samples, 10 fault categories, and 110 data acquisition windows are obtained from the training data by Table 2, and 5500 data are finally obtained. For the test data obtained by the method in Table 3, there are 10 fault samples, 10 fault categories, and a total of 100 data acquisition windows. Finally, 5000 data are obtained.

5. Result Analysis

In this paper, MATLAB is used to transform the obtained data by EMD, WT, FFT, and VMD. Then, based on TensorFlow, CNN is used to classify the data. The influence of different data transformation methods and different combinations of different data transformation methods on CNN classification results is compared.

The trained CNN model is used for the test data after VMD transformation, and the confusion matrix of classification results is shown in Figure 13.

The column in Figure 13 represents the true category of the transmission line running state, and the column represents the prediction category classified by CNN. Figure 13 uses 1PG, 1NG, and 1PN to represent the positive grounding fault, negative grounding fault, and bipolar short circuit fault of transmission line $L1$. The fault representation methods of transmission lines $L2$ and $L3$ are similar, and NF represents the normal operation state. Based on the confusion matrix shown in Figure 13, the accuracy and recall of CNN prediction results can be calculated. Taking the positive grounding of line $L1$ (1NG) as an example, there are 497 data pieces with the same predicted value, and the actual number of 1PN has 500 data pieces. Therefore, the recall rate of 1PN
is $497/500 = 99.4\%$, and the number of 1PN predicted is 497 data pieces. Therefore, the accuracy rate of 1PN is $497/497 = 100\%$. In this way, each type of classification’s accuracy and recall rate is shown in Table 4.

According to this method, the accuracy and recall rate of CNN classification results after data processing by other data transformation methods are calculated.

Based on MATLAB and TensorFlow, this paper compares CNN algorithm with other commonly used artificial intelligence algorithms for classification, including $k$-nearest neighbor algorithm (KNN), Naive Bayes (BYS), bootstrap aggregating (BAG), classification and regression tree (CART), and support vector machine (SVM). The classification results of each algorithm are compared as follows.

5.1. Influence of a Data Transformation Method on Different Classification Algorithms. Tables 5 and 6 are the comparison of the accuracy and recall rate of different classification algorithms after applying a data transformation method to the raw data.

The rows in Tables 5 and 6 represent different data transformation methods, and the columns represent six different classification algorithms. By comparing the classification results in Tables 5 and 6, it can be seen that, for different data transformation methods, the classification results of several classification algorithms have similar changes. The overall classification effect of CNN is better than other classification algorithms.

5.2. Effects of Different Combinations of Two Data Transformation Methods on Different Classification Algorithms. In order to further study the influence of different data transformation methods on the classification results of the classification algorithm, it is found through many experiments that when three or more data transformation methods are used for combination, not only is the classification speed slow due to the expansion of data dimension, but also the classification results are not ideal. When two data transformation methods are used for combination, specific data sets can improve classification accuracy. The classification accuracy and recall rate of different classification algorithms after different combinations of two data transformation methods are compared.

Tables 7 and 8 show the comparison of the accuracy and recall rates of different classification algorithms after applying two data transformation methods to the data.

The rows in Tables 7 and 8 represent different combinations of two data transformation methods, and the columns represent six different classification algorithms. By comparing the classification results in Tables 7 and 8, it can be seen that the classification results of several classification algorithms have similar changes according to the different
By comparing the classification results in Tables 5 to 8, it can be obtained that, for a data transformation method and different combinations of two data transformation methods, the classification results of several classification algorithms have similar variation rules, and the CNN classification results are better than those of other algorithms as a whole. The following will take CNN as an example to analyze the influence of a data transformation method and different combinations of two data transformation methods on CNN classification results.
5.3. Comparison of the Influence of a Data Transformation Method on CNN Classification Results. Figure 14 compares CNN classification accuracy and recall rate after applying different data transformation methods. The horizontal coordinate is different data transformation methods, and the ordinate is the average accuracy and recall rate of CNN classification results.

According to the statistical information in Figure 14, each data transformation method improves the CNN classification results, and VMD is the most obvious. After VMD transformation, the accuracy of CNN classification results increases from 96.9% to 99.88%, and the recall rate increases from 96.3% to 99.88%.

Figures 15 and 16 show the comparison of classification accuracy and recall rate of different fault types by CNN under different data transformation methods.

In Figures 15 and 16, the horizontal coordinates are 9 fault types and normal operation states of transmission lines, and the ordinate coordinates are the classification accuracy and recall rate corresponding to different operation states of transmission lines.

It can be seen from the comparison information shown in Figures 15 and 16 that the data after VMD transformation have the highest classification accuracy and recall rate and ensure the stability of CNN for different fault classification accuracy and recall rate. The accuracy and recall rate of different fault classifications remain between 99.4% and 100%, so the broken line graph obtained by different fault classification accuracy and recall rate is relatively smooth and approximate to a straight line.

5.4. Comparison of Different Combinations of Two Data Transformation Methods on CNN Classification Results. Figure 17 compares the CNN classification accuracy and recall rate of two different data transformation methods and different combinations. The horizontal coordinates are different data transformation combinations, and the ordinate is the average accuracy and recall rate of CNN classification results.

According to the statistics in Figure 17, the accuracy and recall rate of CNN classification results have been further improved only in the combination of VMD and FFT, and the accuracy and recall rate have been increased from 99.88% to 99.96%. For other data combination methods, due to the influence of the data after WT and EMD transformation, it is easy for CNN to mistake the confusing information as the
eigenvalue for extraction in classification, which leads to the decrease of classification accuracy.

Figures 18 and 19 show the comparison of classification accuracy and recall rate of different fault types by CNN under different data transformation combinations. The horizontal coordinates are 9 fault types and normal operation states of transmission lines, and the ordinate coordinates are the classification accuracy and recall rate corresponding to different operation states of transmission lines.

It can be seen from the comparison of different fault classification accuracy and recall rates shown in Figures 18 and 19 that, under the combination of VMD and FFT, the stability of CNN for different fault classification accuracy and recall rates is further improved. Its classification accuracy and recall rates are increased from 99.4% and 100% to 99.8% and 100%. Due to the influence of WT and EMD transformed data, CNN has a certain degree of decline in the accuracy and recall stability of different fault classifications.
Figure 15: Comparison of classification accuracy of each fault.

Figure 16: Comparison of classification recall of different faults.
Figure 17: CNN classification results under the combination of different data transformation methods.

Figure 18: Comparison of classification accuracy.
6. Conclusion

In order to explore the influence of different data transformation methods on CNN classification of flexible DC transmission lines, this paper first builds a four-terminal flexible DC transmission network model and then obtains the fault data within 2.5 ms after transmission line fault by simulation. The original fault data are transformed by EMD, WT, FFT, and VMD. Finally, the transformed data and original data are used as input to CNN for classification. The influence of one data transformation method and different combinations of two data transformation methods on CNN classification results is explored. The experimental results show that when only one data transformation method is applied, CNN has the best classification effect on the data after VMD transformation, and the accuracy and recall rate of CNN classification results are 99.88%. When two different data transformation methods are applied to the original data, CNN has the best classification effect on the data after VMD and FFT combination, and the accuracy and recall rate of CNN classification results are further improved to 99.96%, which can meet the accuracy and rapidity requirements of flexible DC transmission line fault identification.

Data Availability

The data used to support the findings of this study have been deposited in the DEEDS repository (https://datacenterhub.org/deedsdv/publications/view/583).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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