[1] Jianbao Guo
[1] Hang Liu
[1] Lei Feng
[2] Lifeng Zu
[2,*] Taihu Ma
[2] Xiaole Mu

Fault Diagnosis Method of Flexible Converter Valve Equipment Based on Ensemble Empirical Mode Decomposition and Temporal Convolutional Networks

Journal of Electrical Systems

Abstract: - The flexible converter valve is a crucial component of the flexible transmission system, and its proper functioning is directly related to the power system's reliability. This study proposes a method for diagnosing faults in flexible converter valve equipment based on ensemble empirical mode decomposition and temporal convolutional networks. The method involves measuring voltage signal data in the power submodule of the flexible converter valve, decomposing and reconstructing the voltage signal using ensemble empirical mode decomposition to extract frequency variation patterns and fault features. Subsequently, a temporal convolutional network is introduced, and a device fault diagnosis model is constructed by learning the evolution law of voltage signals in time series. The experimental results demonstrate that the proposed method has high fault diagnosis accuracy and robustness with an average F1-score of 89.58% and an average area under the curve (AUC) of 94.38%, which are higher than other methods by at least 1.39% and 1.03%.

Keywords: Flexible converter valve equipment; fault diagnosis; ensemble empirical mode decomposition; temporal convolutional networks.

I. Introduction

The flexible DC converter valve is the core equipment of flexible DC transmission systems, capable of converting between AC and DC and flexibly controlling the output and input of voltage, current, reactive power, and active power. Its normal operation is vital for the stability and reliability of power systems [1]. However, due to harsh working environments and prolonged operation of the equipment, failures of flexible DC converter valve equipment occur frequently, posing significant challenges to the maintenance of power systems [2,3]. Therefore, researching efficient and accurate fault diagnosis methods for flexible DC converter valve equipment holds important theoretical significance and practical value.

Many scholars and experts have extensively researched diagnosing such electrical equipment failures. Among them, data-driven fault diagnosis methods are currently a widely studied area of interest [4]. Data-driven methods for fault diagnosis of electrical equipment generally involve feature extraction and diagnostic model establishment. Traditional feature extraction methods, such as wavelet transform [5] and empirical mode decomposition [6], have certain advantages in signal decomposition and data processing. However, due to the nonlinearity and non-stationarity of signals, traditional methods have limitations in the fault diagnosis of flexible DC converter valve equipment, as they cannot capture such equipment's essential and in-depth features [7]. Ensemble Empirical Mode Decomposition (EEMD) [8] is a signal processing method that can effectively handle nonlinear and non-stationary signals and has good noise suppression capabilities [9,10]. It has been widely applied in many fields, e.g., vibration signal analysis [11], image processing [12], and weather forecasting [13].

The establishment of a traditional diagnostic model applies machine learning methods such as random forests (RF) [14], logistic regression (LR) [15], and back propagation neural networks (BPNN) [16]. However, due to the poor performance of these methods when applied to nonlinear data and their tendency to overfit on large datasets, they fail to establish accurate fault diagnosis models. Deep learning methods, on the other hand, gradually transform initial "low-level" feature representations into "high-level" feature representations through multi-layer processing. With "simple models," they can accomplish complex learning tasks, e.g., classification. Therefore, deep learning methods such as One-dimensional Convolutional Neural Networks (1D-CNN) [17], Bidirectional Gate Recurrent Unit (BiGRU) [18], and Bidirectional Long Short-Term Memory (BiLSTM) [19] have been proposed and applied to the fault diagnosis of electrical equipment. Temporal Convolutional Networks

[1] EHV Electric Power Research Institute of China Southern Power Grid, Guangzhou, Guangdong 510663, China.
[2] XJ Electric Flexible Transmission Company, Xuchang, Henan 461000, China.
*Corresponding Author: Taihu Ma.

(TCN) [20] are models based on Convolutional Neural Networks (CNN) that extract features and model time-series data through one-dimensional convolution operations. They are widely used in modeling and analyzing time-series data tasks. Compared to traditional Recurrent Neural Networks (RNN), TCN exhibits advantages in parallel computing, long-term dependency modeling, and insensitivity to sequence length, thus showing great potential in handling time-series data [21,22].

In conclusion, this paper proposes a fault diagnosis method for flexible DC transmission valve equipment based on EEMD and TCN. Initially, voltage signal data is extracted from the power submodule of the flexible DC transmission valve. EEMD is applied to extract frequency variations and fault characteristics from the voltage signal, strongly supporting subsequent fault diagnosis. TCN, on the other hand, learns the evolution patterns of voltage signals over time and constructs a fault diagnosis model for the equipment, effectively achieving an accurate diagnosis of multiple faults in flexible DC transmission valve equipment.

II. Theoretical Basis of EEMD and TCN

A. Theoretical Basis of Integrated EMD

EEMD is a signal processing method that decomposes nonlinear and non-stationary signals into a series of Intrinsic Mode Functions (IMFs) [23,24]. The basic principle of Ensemble Empirical Mode Decomposition is to obtain stable IMFs by reconstructing and averaging the signal multiple times.

The specific implementation steps of EEMD are as follows:

Step 1: Perform a first decomposition of the original signal to obtain the first IMF. The original signal sequence $X_n(t)$ can be represented as shown in Equation (1):

$$X_n(t) = \sum_{m=1}^{M-1} IMF_m^{(n)}(t) + r_m^{(n)}(t) \tag{1}$$

where m is the number of iterations of the sifting algorithm, t is the time point, $M-1$ represents the number of IMFs, and $r_m^{(n)}(t)$ represents the residual of extracting IMFs.

Step 2: Subtract the first IMF from the original signal to obtain a portion of the residual signal, and decompose the residual signal to obtain the second IMF.

Step 3: Repeat steps 2 and 3 until IMFs satisfying certain convergence conditions are obtained.

Step 4: Reconstruct and average each IMF to obtain the final IMFs, as shown in Equation (2).

$$IMF_m^{ave}(t) = \frac{1}{N}\sum_{n=1}^{N} IMF_m^{(n)}(t) \tag{2}$$

where $IMF_m^{ave}(t)$ is the average value of final IMFs, $IMF_m^{(n)}(t)$ denotes the nth IMFs.

The advantages of EEMD lie in its ability to effectively handle nonlinear and non-stationary signals while also exhibiting good noise suppression characteristics [9]. As illustrated in Figure 1, the original signal exhibits strong fluctuations and insignificant trends. However, after six iterations, the final IMFs represent the variations in the original signal.

In the fault diagnosis method of flexible HVDC valves, EEMD can be an effective tool for decomposing voltage signals and extracting features, which can be subsequently used to establish fault diagnosis models for the equipment.

B. Theory of TCN

TCN is a CNN-based model used for feature extraction and modeling of time-series data. They are widely employed in tasks involving the modeling and analyzing time-series data. Compared to other deep learning algorithms, key features of the TCN model include:

1) 1D convolution: is one of the core components of TCN. It operates by sliding in only one direction, like traditional two-dimensional convolution. As illustrated in Figure 2, for time-series data, 1D convolution can adjust the size of the window and the stride of movement by setting the size and stride of the convolution kernel. The computation formula for this convolution operation, as shown in Equation (3), involves element-wise multiplication of the convolution kernel with the input sequence, followed by summing the results to obtain an element of the output sequence. This process is repeated across the entire output sequence by sliding the convolution kernel. 1D convolution effectively captures local dependencies within the time series and extracts features at different time scales.

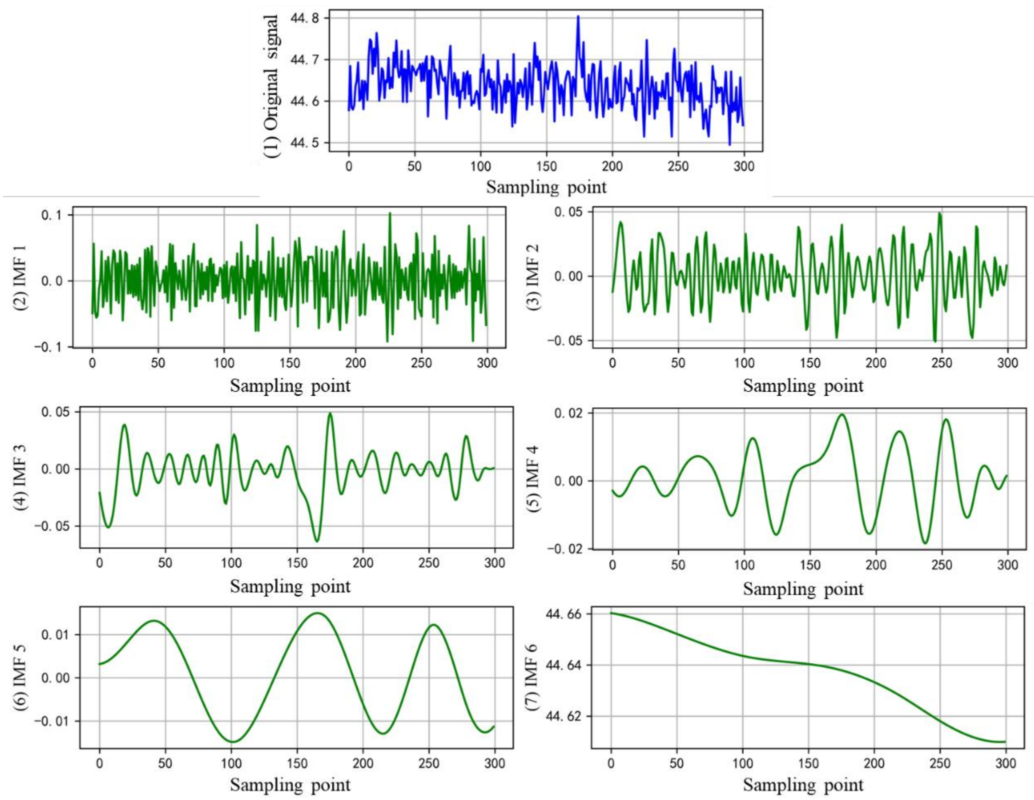

Figure 1. The variation trend of the original signal after IMED is accurately extracted

$$y(t) = \sum_{k=0}^{K-1} x[t-k] \cdot w(t) \tag{3}$$

where t represents the time step, x is the input sequence containing input elements up to time t, y is the output sequence, w is the weight of the convolution kernel, and k is the size of the convolution kernel, determining the number of time steps covered by each convolution.

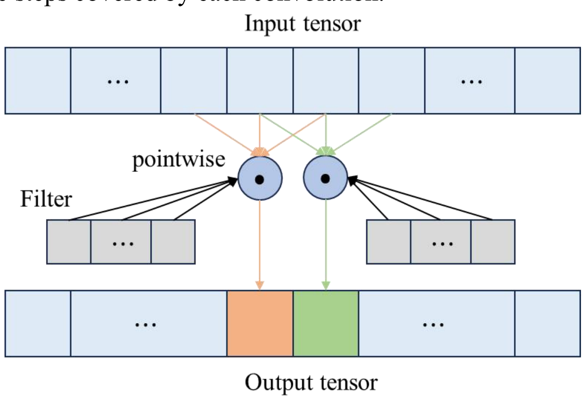

Figure 2. 1D convolution operations in TCN

2) Causal convolution: also known as autoregressive convolution, is a convolution operation within TCN. The computation formula for this convolution operation is shown in Equation (4). In causal convolution, zero-padding is applied only on the left side of the input tensor to ensure that the lengths of the input and output tensors are consistent.

$$y(t) = \sum_{k=0}^{K-1} x[t-k] \cdot w[k], \text{where } k \leq t \tag{4}$$

where $y(t)$ represents the element in the output sequence at time step t.

Unlike regular convolution, causal convolution restricts the convolution window to only move towards the past on the time axis. This ensures that each convolution operation at each time step only utilizes past observations without considering future data. Therefore, when using causal convolution for time series modeling, the process becomes more reasonable, aligns with real-world scenarios, and avoids interference from future data.

3) Dilated Convolution: is another convolution operation within TCN. It enlarges the receptive field by introducing fixed-step gaps between convolution kernels, as shown in Equation (5).

$$y(t) = \sum_{k=0}^{K-1} x[t - dk] \cdot w(k) \tag{5}$$

where d represents the dilation rate.

As shown in Figure 3, there are fixed gaps (i.e., dilation rate) between the weights within the convolution kernel of dilated convolution. Based on this, dilated convolution can capture a broader context without increasing the number of parameters. Dilated convolution is particularly useful for processing long sequence data, effectively capturing dependencies over longer distances within the sequence and extracting global features.

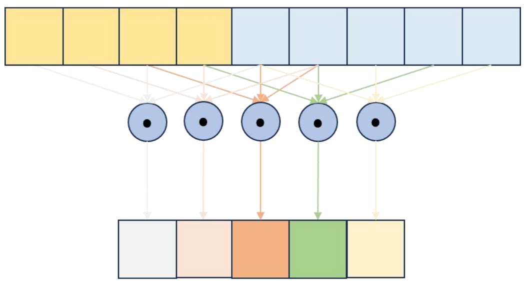

Figure 3. Dilation convolution involves input elements with subscript spacing of 2 when dilation rate is 2

TCN utilizes combinations of these convolution operations for deep feature learning. By stacking multiple one-dimensional convolutional layers, TCN can gradually learn higher-level abstract features and exhibit strong modeling capabilities. Compared to traditional recurrent neural networks, TCN possesses stronger parallel computing capabilities, enabling more efficient processing of long sequence data while mitigating issues, e.g., gradient vanishing and exploding.

In this paper, a temporal convolutional network is employed to diagnose various faults in flexible transmission system devices.

III. Fault Diagnosis Method based on EEMD and TCN

To enhance the accuracy and reliability of fault diagnosis in flexible transmission system devices, this paper proposes a fault diagnosis method based on EEMD and TCN. The flowchart of the proposed method is illustrated in Figure 4. The proposed method mainly consists of the following steps:

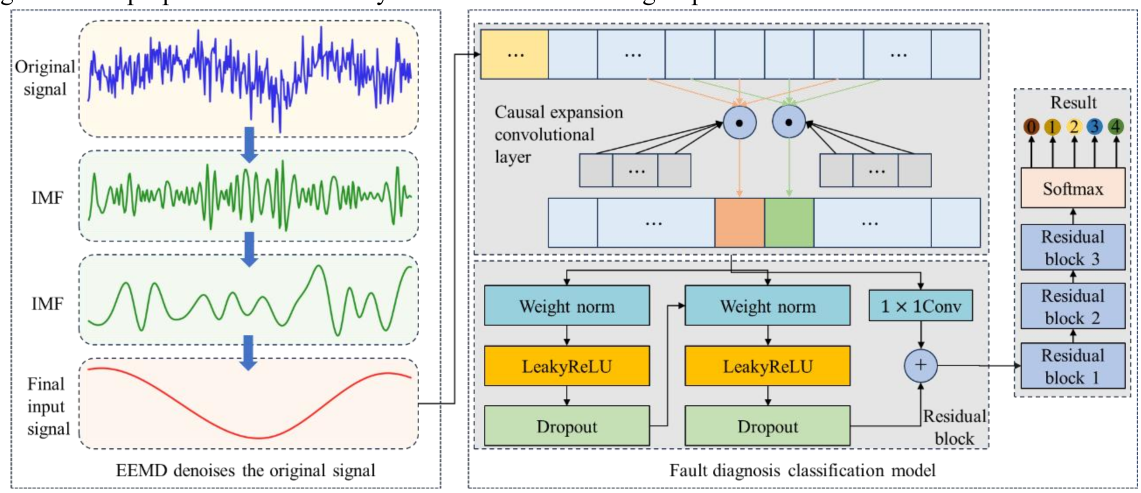

Figure 4. The proposed fault diagnosis method based on EEMD and TCN

1) The original voltage signals of the power submodule in flexible transmission system devices are decomposed using EEMD to obtain a series of IMFs. The filtered IMFs are then utilized as the final input signals for the fault diagnosis classification model.

2) Using the extracted IMFs as input, a temporal convolutional network is constructed for feature learning and fault diagnosis. The first step involves designing an appropriate temporal convolutional network structure. This paper employs a design with multiple convolutional layers and residual connections to enhance the network's expressive power and stability. Specifically, one-dimensional convolutional layers extract features from the input temporal data. Different feature information at different time scales can be captured by employing various kernel sizes and quantities. Following each convolutional layer, a LeakyReLU activation function is added (as computed in equation (6)) to enhance the network's non-linear representation capability. LeakyReLU is a modified version of the Rectified Linear Unit (ReLU) that does not fully truncate negative values to zero in the negative half-region but retains a small portion called the slope, which can increase the model's non-linearity.

$$\text{LeakyReLU} = \begin{cases} x, x \geq 0 \\ \alpha x, \ x < 0 \end{cases} \tag{6}$$

where α represents the slope, which is typically set to a small value, in this paper, it is set to 0.1. By introducing α, LeakyReLU can alleviate the issue of "dead neurons" associated with the ReLU function, thereby enhancing the model's robustness and generalization capability [25].

Furthermore, this paper introduces residual connections to mitigate the issues of vanishing or exploding gradients, where the convolutional layers add the input temporal data to the output of the feature [26]. This approach enables the network to learn residual information better, thereby improving the model's training effectiveness and generalization capability.

3) the fault diagnosis results for the flexible direct current converter valve equipment can be obtained by predicting the test data and comparing it with the actual fault labels.

IV. Experimental Verification

A. *Acquisition and Processing of Fault Data*

This paper utilizes the voltage signals of the flexible direct current converter valve power submodule to monitor the operation of the equipment. Through the data collected by these sensors, we can obtain the operational status of the flexible direct current converter valve under different operating conditions. The experimental equipment and environment are depicted in Figure 5, where the valve control core processing unit adopts the FCK611 control chassis, which includes boards such as the MC board (ZYNQ7030), recording board, LER (High Cloud) board, and SCE board (for networking).

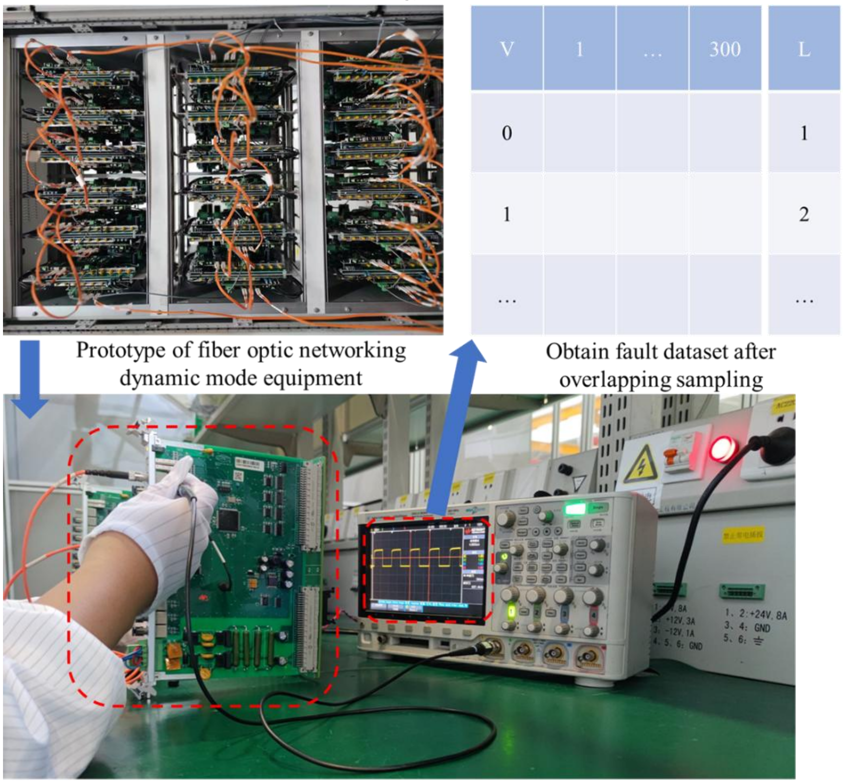

Figure 5. Setting the fault status of designed flexible converter valve equipment to obtain fault dataset

During actual operation, such equipment may encounter various faults due to aging or unexpected factors. Based on the recorded instances of actual faults, the faults of the flexible direct current converter valve can be categorized into the following four types:

1) Component faults of the flexible direct current converter valve equipment may arise from issues, e.g., controller malfunction, loose connections, poor welding, core short-circuiting, excessive valve vibration, and equipment overheating or smoking.

2) Fiber optic faults may include problems like loosening, detachment, breakage, interrupting signal transmission, or decreased signal quality. They may also suffer physical or environmental damage, such as excessive bending, breakage, or scratching, resulting in abnormal signal transmission and potentially causing component faults.

3) Power voltage drop faults could result from unstable power supply voltage, power line faults, or power overload, leading to voltage drops. Connecting too many load devices may exceed the power supply's capacity, causing voltage drops. Loose or damaged connections may impede current transmission, causing voltage drops. Faulty power filters may also contribute to voltage drops.

4) Anomalous flow injection faults may stem from hardware malfunctions like damaged network interfaces or processor failures. Misconfigurations or improper configurations could misdirect or inject anomalous flows. Network failures or malfunctioning network devices may cause data traffic in the network to exceed the device's processing capacity or network capacity.

In practical cases, the aforementioned faults may not occur in isolation. For instance, in a flexible direct current converter valve unit at a certain station in 2021, during stable operation, there was a depletion of redundant power modules, leading to a trip request from the valve controller and a tripping of the converter unit's three interlocks. Upon investigation, it was traced back that the B-phase upper bridge arm module experienced a fault in the charging process, and after completing the module fault reset, a fault in the uplink fiber optic of the B-phase upper bridge arm module was detected. Due to a logic problem in the current module comparison program, the B-phase upper bridge arm module erroneously passed the module comparison step, allowing the valve control system to unlock, making the bypass switch unable to close. With the uplink fiber optic fault, the valve control could not obtain the current capacitance-voltage of the module, rendering the overvoltage trip logic ineffective, leading to continuous charging of the module until the IGBT's withstand voltage value (3300V) was exceeded, causing component failure. Subsequently, the operating condition of the faulty device deteriorated, triggering a fire alarm. The continued heating and erosion of the faulty device caused nearby fiber optic damage, coolant pipe leakage, and inter-layer short circuits of the power module, leading to bypassing of adjacent module faults, depletion of redundant B-phase upper bridge arm, and ultimately resulting in system tripping.

Similarly, in another instance in 2018, a station experienced overvoltage faults in the bridge arm and power modules. Through on-site analysis, it was determined that the cause of the fault was a downlink fiber optic communication failure during the locking and charging period of the A-phase lower bridge arm module, causing the bypass switch to trigger. However, the energy storage capacitor in the loop did not reach the normal operating voltage level, preventing the execution of the bypass command and leading to an overvoltage trip of the module and subsequent DC system tripping. In another actual case, the cause of the DC system tripping was the unsuccessful bypass after the failure of the A-phase upper bridge arm module, leading to the overvoltage trip of the module due to the bypass switch refusal.

All the above practical fault cases resulted in obvious abnormal operating states of the equipment after the fault persisted, causing significant economic losses and extremely adverse effects on the stable operation of the power grid. Therefore, the fault diagnosis method proposed in this paper aims to promptly detect faults in the early stage of occurrence by monitoring the equipment's real-time operation status, thereby avoiding the adverse effects caused by faults.

To obtain early signals of faults, the above fault types were collected through artificially induced faults, with the collection process monitored using an oscilloscope, as shown in Figure 5.

Based on the aforementioned scenarios, there are five different fault types. Among them, the data sample length under the no-fault condition is 22,800, under component fault condition is 102,300, under fiber optic fault condition is 345,600, under voltage drop fault condition is 526,100, and under abnormal flow injection fault condition is 125,300. Each fault condition is subjected to overlapping sampling steps according to its sample length, generating 300 samples with 300 temporal data points. In total, 1,500 one-dimensional data samples of size 300×1 were obtained. Among these, 80% of the samples were used for training and 20% for testing. Within the training samples, 20% were used to validate the model iteration.

The proposed method runs on the TensorFlow 2.3 deep learning framework, simulated on the PC with Windows 11 system version, powered by a Core i7-1165G7 CPU running at 2.8GHz, and equipped with 16GB of RAM.

B. Result Discussion

In this paper, the TCN optimizer adopts Adam, the loss function is categorical cross-entropy, training is conducted using a mini-batch with a batch size of 16, the number of iterations is set to 100, and the learning rate is 0.001.

Early stopping and learning rate decay mechanisms are employed to enhance the model's generalization ability. The training dataset is divided into training and validation sets. By monitoring the loss value on the validation set, training is halted when the loss value does not decrease for several consecutive epochs to prevent overfitting. Additionally, a learning rate decay mechanism is utilized to gradually decrease the learning rate as training progresses, ensuring greater stability in the later stages of training.

The fault diagnosis model is first trained based on the set model hyperparameters. Figure 6 illustrates the change in the loss function indicator of the proposed method over 100 iterations. It can be observed that during the training process, the model's accuracy and loss function stabilize.

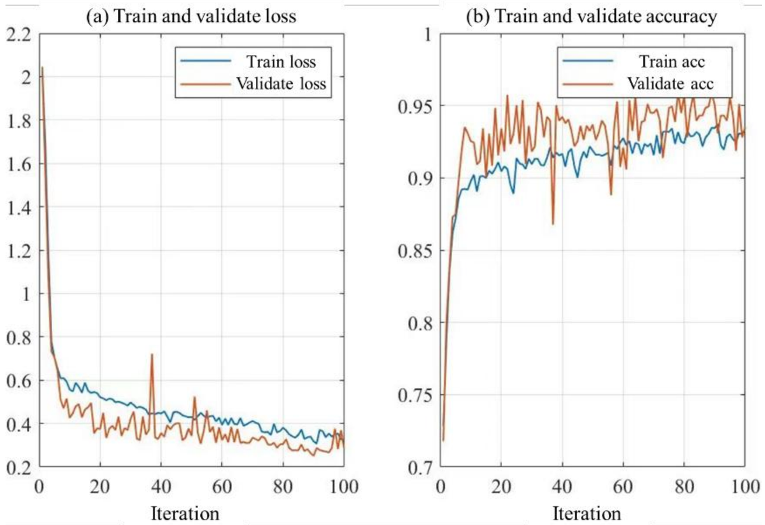

Figure 6. The loss function value and accuracy of the proposed method during the iteration process

Upon completion of training, the trained TCN is used to diagnose faults in the voltage signals of new flexible direct-current valve devices. Specifically, the temporal data to be diagnosed is input into the network, and through forward propagation, the network's output results are obtained. Based on the output results, faults in the device are determined, and appropriate maintenance and repair operations are further conducted.

To validate the advancement of the proposed method in this paper, the TCN fault diagnosis method is compared with common fault diagnosis methods for power equipment, including RF, LR, BPNN, 1D-CNN, BiGRU, and BiLSTM. Fault diagnosis experiments are conducted on the voltage signal dataset of flexible direct-current valve equipment, and the experimental results under various methods are shown in Figure 7. The results obtained by directly inputting the original signal into the fault diagnosis model are represented by blue bar charts. In contrast, those obtained by inputting the original signal after the yellow bar charts represent EEMD processing into the fault diagnosis model. The experimental results indicate that the fault diagnosis method proposed in this paper, based on EEMD and TCN, achieves higher accuracy in diagnosing faults in flexible direct-current valve equipment. Compared to other methods, the proposed method improves the F1-score (a metric used to measure the accuracy of multi-class classification models, balancing precision and recall, with values closer to 1 indicating higher classification accuracy) by at least 1.39% and the AUC (area under the curve, with values closer to 1 indicating higher classification accuracy) by at least 1.03% when EEMD processing is included. Without EEMD processing, the proposed method improves the F1-score by at least 1.67% and the AUC by at least 1.51%. Further analysis of the experimental results shows that after EEMD processing, the F1-score and AUC of the TCN model are improved by 2.05% and 1.23%, respectively, indicating that EEMD effectively reduces noise for diagnosing all proposed fault types. Compared to other methods, the proposed method better captures subtle changes in fault signals and demonstrates stronger robustness and generalization ability.

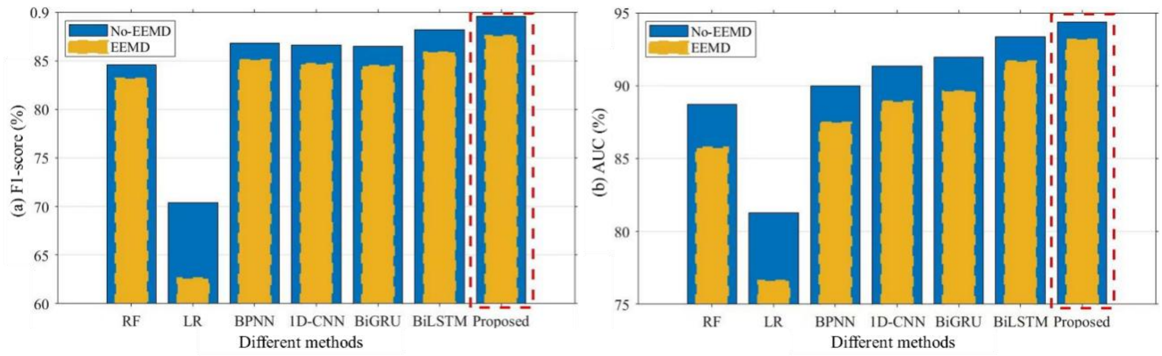

Figure 7. The average accuracy indicators of the proposed method compared to other methods

Furthermore, this paper compares the F1-score and AUC of different methods at Gaussian noise levels of 10%, 30%, and 50% (as shown in Figure 8). The results indicate that the proposed method achieves the highest accuracy metrics at all Gaussian noise levels compared to other methods. Although the accuracy metrics of all methods are affected as the Gaussian noise proportion increases, the proposed method exhibits less fluctuation in its accuracy metrics due to its signal decomposition of fault characteristics. This also demonstrates the strong tolerance of the proposed method to noise, maintaining high diagnostic accuracy even in the presence of data biases caused by aging or other factors.

The experimental results show that the proposed method performs well in diagnosing different types and degrees of faults, with high diagnostic accuracy and robustness.

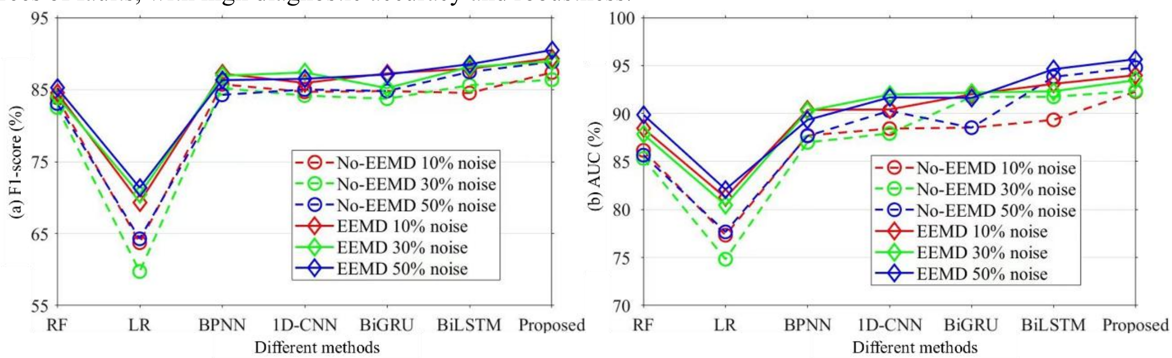

Figure 8. The accuracy indicators of the proposed method and other methods under different noise levels

V. CONCLUSION

This study focuses on fault diagnosis of flexible direct-current valve equipment and proposes a fault diagnosis method based on EEMD and TCN. Firstly, voltage signals of the equipment's power submodule are collected and analyzed. Utilizing EEMD, frequency variations and fault characteristics are extracted. Subsequently, a TCN-based fault diagnosis model is introduced to learn the temporal evolution patterns of voltage signals and accurately determine the equipment's operational status and fault types. Experimental results demonstrate the effectiveness of this method for fault diagnosis of flexible direct-current valve equipment.

Future research can be explored in several directions. Firstly, incorporating more types of equipment and fault samples could enhance fault diagnosis accuracy and generalization ability. Secondly, exploring additional feature extraction methods and model structures could further improve the effectiveness of fault diagnosis. Finally, applying the research findings to practical power systems for validation would provide more reliable and intelligent support for the operation and maintenance of power systems.

ACKNOWLEDGEMENT

This work was supported by Innovation Project of China Southern Power Grid Co., Ltd. (CGYKJXM20220059).

REFERENCES

[1] Cai, M., Lin, H., Liao, Q., Ma, G., Chen, B. (2019). Research on on-site test method for flexible HVDC converter valve power module. Southern Energy Construction, 6(02):70-76.

[2] Zhang, Y.Luo, W.Sun, X., Zheng, Q., Zhao, C. (2021). Multi-physical field coupling simulation analysis of flexible HVDC converter valve power module based on clamping IGBT element. High Voltage Apparatus, 57(11): 84-92.

[3] Ji, Y., Hou, T., He, Z., Li, Y. (2021). An accelerated aging test method of press pack IGBTs based power submodules for VSC-HVDC converter valve. Southern Power System Technology, 15(05): 1-11.

[4] Miao, Y., Zhang, B., Li, C., Lin, J., Zhang, D. (2022). Feature mode decomposition: New decomposition theory for rotating machinery fault diagnosis. IEEE Transactions on Industrial Electronics, 70(2), 1949-1960.

[5] Li, H., Ye, X., Fu, G. (2023). Review on the application of signal decomposition technology in power prediction of new energy power generation. Southern Power System Technology, 17(04): 3-15.

[6] Sun, Y., Li, S., Wang, X. (2021). Bearing fault diagnosis based on EMD and improved Chebyshev distance in SDP image. Measurement, 176, 109100.

[7] Li, P., Wang, Y., Lv, G., Xuan, J. (2021). Reliability research and improvement index analysis of converter valve. Power Electronics, 55(12): 55-59+68.

[8] Zhong, T., Qu, J., Fang, X., Li, H., Wang, Z. (2021). The intermittent fault diagnosis of analog circuits based on EEMD-DBN. Neurocomputing, 436, 74-91.

[9] Zhou, H., Chen, W., Shen, C., Cheng, L., Xia, M. (2023). Intelligent machine fault diagnosis with effective denoising using EEMD-ICA-FuzzyEn and CNN. International Journal of Production Research, 61(23), 8252-8264.

[10] Li, H., Liu, T., Wu, X., Li, S. (2021). Research on test bench bearing fault diagnosis of improved EEMD based on improved adaptive resonance technology. Measurement, 185, 109986.

[11] Jia, Y., Li, G., Dong, X., He, K. (2021). A novel denoising method for vibration signal of hob spindle based on EEMD and grey theory. Measurement, 169, 108490.

[12] Xu, M., Sun, J., Zhou, X., Tang, N., Shen, J., Wu, X. (2021). Research on nondestructive identification of grape varieties based on EEMD-DWT and hyperspectral image. Journal of Food Science, 86(5), 2011-2023.

[13] Ding, J., Deng, F., Liu, Q., Wang, J. (2023). Regional forecasting of significant wave height and mean wave period using EOF-EEMD-SCINet hybrid model. Applied Ocean Research, 136, 103582.

[14] Ye, Y., Zheng, J., Mei, F. (2019, June). Research on UPFC Fault Diagnosis Based on KFCM and Support Vector Machine. In 2019 14th IEEE Conference on Industrial Electronics and Applications (ICIEA) (pp. 650-655). IEEE.

[15] Mirsaeidi, S., Dong, X., Tzelepis, D., Said, D. M., Dyśko, A., Booth, C. (2018). A predictive control strategy for mitigation of commutation failure in LCC-based HVDC systems. IEEE Transactions on Power Electronics, 34(1), 160-172.

[16] Liu, S., Wang, S. (2023, May). Fault location of flexible DC system based on BP neural network. In Eighth International Symposium on Advances in Electrical, Electronics, and Computer Engineering (ISAEECE 2023) (Vol. 12704, pp. 640-645). SPIE.

[17] Wang, L., Zhao, Q., Liang, D. (2022, July). Fault Diagnosis of UHVDC Transmission Line Based on Deep Neural Network. In 2022 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia) (pp. 445-450). IEEE.

[18] Zang, X., Cao, Z., Xiao, M., Yang, X. (2023). Research on online monitoring of grid current transformer based on transformers and BiGRU. Journal of Computational Methods in Sciences and Engineering, (Preprint), 1-13.

[19] Wang, Q., Yu, Y., Ahmed, H. O., Darwish, M., Nandi, A. K. (2021). Open-circuit fault detection and classification of modular multilevel converters in high voltage direct current systems (MMC-HVDC) with long short-term memory (LSTM) method. Sensors, 21(12), 4159.

[20] Guo, Q., Zhang, X., Li, J., Li, G. (2022). Fault diagnosis of modular multilevel converter based on adaptive chirp mode decomposition and temporal convolutional network. Engineering Applications of Artificial Intelligence, 107, 104544.

[21] Bi, J., Zhang, X., Yuan, H., Zhang, J., Zhou, M. (2021). A hybrid prediction method for realistic network traffic with temporal convolutional network and LSTM. IEEE Transactions on Automation Science and Engineering, 19(3), 1869-1879.

[22] Chu, X., Bao, Z., Xu, L., Yan, Y. (2023). Fault line diagnosis scheme of active distribution system based on time-sequence con-volution residual network. Transactions of China Electrotechnical Society, 38(08): 2178-2190.

[23] Zhang, C., Qiu, B., Liu, J. (2022). Power system low frequency oscillation modal identification based on EFEMD-HT energy algorithm[J]. Southern Power System Technology, 16(03): 48-57.

[24] Zheng, H., Wang, C., Pan, S., Gao, W. (2020). Research on noise reduction method of magnetic memory signal based on EEMD and layered threshold[J]. Chinese Journal of Engineering Design, 27(04): 433-440.

[25] Xu, J., Li, Z., Du, B., Zhang, M., Liu, J. (2020, July). Reluplex made more practical: Leaky ReLU. In 2020 IEEE Symposium on Computers and communications (ISCC) (pp. 1-7). IEEE.

[26] Xu, Y., Yan, X., Sun, B., Zhai, J., Liu, Z. (2021). Multireceptive field denoising residual convolutional networks for fault diagnosis. IEEE Transactions on Industrial Electronics, 69(11), 11686-11696.