Recognition Method of Voltage Sag Sources Based on RMT-CNN Model

Li-Zhen Wu*, Lang-Chao He, Wei Chen, Xiao-Hong Hao

Abstract-**The precise recognition of the sources of voltage sag is the basis and key to formulating a voltage sag governance plan and clarifying responsibility for an accident. Due to the complexity of grid devices and the identification of the mode of power consumption, the conventional approach to identifying voltage sags faces a new challenge. Due to the dependence on accurate voltage sag models, the traditional methods are inadequate for complex problems with multiple uncertainty factors. The random matrix theory based on a data-driven method analyzes data correlation using single characteristic statistics, which is not suitable for the dimensional change of the matrix. It is obvious that this method is not applicable to the position of the source of the voltage sag due to random sags. Therefore, this paper proposes a voltage sag source recognition method based on the combination of random matrix theory (RMT) and a convolutional neural network (CNN). In this method, the CNN optimizes the characteristic statistics of RMT and constructs new characteristic statistics such as the correlation analysis index of the voltage sag source recognition model to avoid the error caused by a single characteristic statistic. First, random matrix theory is used to extract characteristics from historical data, and characteristic statistics under different faults and different data dimension matrices are obtained and then, are used as the input characteristic sets of the CNN. Then, through training extraction, the optimized characteristic statistics that can be applied to a variety of conditions are obtained. Furthermore, a voltage sag source recognition model based on random matrix theory is constructed by using optimized characteristic statistics. The correlation analysis index is obtained to recognize voltage sag sources under different data conditions. Finally, examples are given to verify the feasibility and effectiveness of the proposed method.**

Index Terms-**Voltage sag, Random matrix theory (RMT), Convolution neural network (CNN), Fault location, Characteristic statistics**

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I. Introduction

To reach the goal of carbon neutrality and peak carbon emissions, China will build a modern power system with modern energy as the main component based on a smart grid. The new power system will have many key characteristics, such as green and low carbon, flexibility and efficiency, diversified interaction, and high marketization, which are mainly promoted by informatization and digitalization [1], [2], [3]. To ensure the accuracy of information communication and control instructions, it is necessary to measure and test high sensitivity equipment to ensure the accuracy and reliability of all kinds of communication equipment, which has made it more demanding to ensure power quality. To guarantee the precision of message transmission and command, we need to use highly sensitive measurement devices to guarantee the precision and reliability of various telecommunication devices, so that we can improve the performance of the system. However, in power systems, approximately 70% of power quality problems are caused by voltage sags, which are unavoidable and harmful [4]. Voltage sag is a phenomenon of transient disturbance in which the mean root value of the square voltage drops to 90%~10% of the amplitude of the rated voltage instantaneously and recovers to normal after 0.5~30 cycles [5]. Voltage sag has caused production interruptions in precision processing industries such as microelectronics and intelligent control, causing massive economic losses for users, and has become the most common power quality problem. Accurate identification of the type of voltage sag event and determination of the main cause of the sag event is the basis for solving the voltage sag problem.

Voltage sags can be divided into two types: random voltage sags and planned voltage sags. Random voltage sags are sags caused by short-circuit faults. A short-circuit fault is the main cause of voltage sag in the power grid that can have a wide range of effects and can cause the most serious economic loss. Planned drop is caused by human operation, and includes the start of large induction motors and the switching on and off of transformers[6], [7].

Many studies on the recognition and location of voltage sags have been carried out. The traditional method for locating voltage sag sources is mainly based on analyzing the characteristics of the voltage sag data to determine the fault source, which is related to the location of the power quality monitoring device. Currently, research on voltage sag source recognition methods is mainly based on physical characteristics, including characteristic extraction and pattern recognition. Characteristics extraction transforms and reconstructs voltage sag signals through signal processing and mathematical statistics, including recognition wavelet transform [8], [9] Fourier transform [10], Hilbert Huang transform [11], and S transform [12]. Pattern recognition is the use of a classifier to determine to which type of voltage sag source the interference signal belongs. The main methods commonly used are neural networks [13], support vector machines [14], etc. However, in a complex power grid, the timing of its operation process is very complex, and it is difficult to establish an accurate and universal model for it. In the process of characteristic extraction, the drawbacks of existing algorithms also become increasingly obvious due to the loss of information data and overly complex classification models. The position of the voltage sag source relative to the power quality monitoring device can be determined by using the characteristic information of the voltage sag, but the specific position cannot be determined. Traditional voltage sag source recognition is achieved mainly by detecting the change in voltage and current phase angles to accommodate the change in reactive power polarity for the sag source, such as the disturbed power method and the disturbed energy method. However, there are some problems, such as low reliability, complex models, and long analysis times [15-19]. Therefore, many scholars have proposed a feature extraction-based method for identifying voltage sag sources. It uses a wavelet transform and empirical mode decomposition to extract the characteristic signal and combines the extracted fault characteristic signal with a neural network to locate the voltage fault source [20-22]. Nevertheless, the above fault source location method is limited by the structure of the power grid and is difficult to apply to modern digital power systems.

In recent years, the power system has contained a high proportion of intermittent renewable energy, the system operation has become more complex, and big data technology has also been widely used in system operation control and maintenance [23]. Electric power companies have built power quality monitoring platforms, that can monitor and record voltage sag data and characteristics, and massive monitoring records provide basic data for voltage sag prevention and management. As a big data technology, random matrix theory does not rely on the simplification and assumption of the system model, and can mine effective information from the data of complex systems. However, random matrix theory has made some achievements in power system fault location [24], [25] and power grid operation state evaluation [26]. However, different power grid structures have different data dimensions. According to the same linear characteristic statistic (mean spectral radius) of the RMT, the statistical information of all state data matrices cannot be accurately expressed; that is, the average spectral radius cannot be applied to matrices of all dimensional. It is often necessary to formulate the characteristic statistic according to the dimension of the matrix. The deep learning method is proposed for characteristic recognition and classification. The support vector machine (SVM) has been proposed to classify voltage sag sources [27]. D. Li et al. proposed a self-supervised voltage sag source identification method based on a convolutional neural network (CNN) [28]. However, as a nonparametric model, the convolutional neural network relies too much on training data and is prone to generalization problems.

Therefore, to better recognize the voltage sag source caused by random sag in the grid, this paper proposes a voltage sag source identification method based on RMT and CNN integration. First, the system is identified by random matrix theory to determine whether a fault occurs, and the augmented matrix is established by considering the number of states and influence factors. To avoid the problem of the mean spectral radius not being suitable for multidimensional matrices, the characteristic statistics of RMT are optimized through the CNN to construct new characteristic statistics. Additionally, characteristic statistics are used to identify the source of voltage sags. This method can train and learn the different characteristic statistics of RMT through CNN, and obtain optimized characteristic statistics, instead of the original single linear characteristic statistics, so that the statistics have better applicability and effectiveness.

The contributions of this paper can be summarized as follows:

i. The state data matrix and influence factor matrix are used to establish the augmented matrix.

ii. A voltage sag source recognition model based on RMT-CNN is proposed.

iii. A new characteristic statistics index is constructed and used to identify voltage sag sources.

The rest of this paper is organized as follows: Section II discusses random matrix theory and convolutional neural networks. The voltage sag source recognition method based on RMT-CNN, including CNN structure design and statistical indicators. is presented in Section III. Section IV includes simulation results, and Section V concludes the paper.

II. Random Matrix Theory and Convolutional Neural Network

A. Random matrix theory

1. Empirical spectral distribution function

The empirical spectral distribution function is a relatively general concept in random matrix theory and is often used to describe the distribution of the eigenvalues of a random matrix. For $p \times p$ order matrix A, the ESD function can be expressed as (1) [29]:

$$F^{A}(x)=\frac{1}{p}\sum_{i=1}^{p} I(\lambda_i \le x) \tag{1}$$

where, $I(\cdot \le \cdot)$ is the indicative function. In some special cases, the empirical spectral distribution function will follow some special laws.

2. Single Ring Law

Assume that $X=\{x_{i,j}\}$ is a random matrix of $p \times n$ order consisting of independent variables where $E(x_{i,j})$=0 , $\delta^2(x_{i,j})$=1 . The matrix $Z=\{z_{i,j}\}$ is obtained by quadrature of O the random matrix X , and then normalized to obtain. the matrix $\overline{Z}=\{\overline{z}_{i,j}\}$. Each element satisfies the mean $E(z_{i,j})$=0 and the variance $\delta^2(z_{i,j})$=$1/N$. As $p,n \to \infty$ with ratio $y=p/n \in (0,1]$, the probability density function of $\overline{Z}$ is defined as (2) [30]:

$$f_{ESD}(\lambda)=\begin{cases}\dfrac{1}{\pi yO}|\lambda_i|^{\frac{O}{2}-2}, & (1-y)^{\frac{O}{2}}\le|\lambda_i|\le 1\\ 0, & \text{others},\end{cases} \tag{2}$$

where, λ_i is the eigenvalue of the matrix $\overline{Z}$. According to the characteristics of the single ring law, when the system is in a stable state, the eigenvalues of the matrix $\overline{Z}$ are roughly distributed in the ring with an outer ring radius of 1 and inner ring radius of $(1-y)^{L/2}$, as shown in Fig. 1.

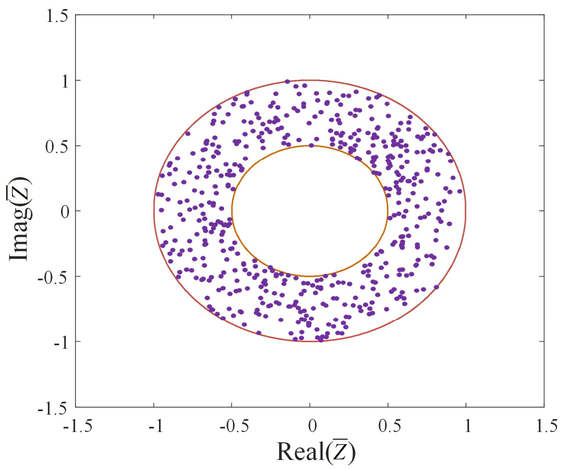


Fig. 1. Single-ring law.

3. Mean Spectral Radius

The mean Spectral Radius (MSR) is a method of reflecting the eigenvalue distribution by the distance between the eigenvalue and the origin in the complex number plane. It is often used as a linear eigenvalue statistic in the single-ring law and defined as (3) [31]:

$$L_{MSR}=\frac{1}{p}\sum_{i=1}^{p}|\lambda_i| \tag{3}$$

where, λ_i is the eigenvalue of the matrix. Comparing L_{MSR} to its spectral radius limit under conventional conditions gives an indication of the operation of the system. MSR is obtained by solving the trace of the whole random matrix, so it can better reflect the characteristic statistics of the random matrix.

B. Data Preprocessing

Suppose that there are n buses in the power grid, all the buses are equipped with power quality monitoring devices, and each monitoring device measures m state variables. At the sampling time t_i, the measured data can form a column vector as shown in Equation (4).

$$X(t_i)=[x_{1,i},\dots,x_{m,i},\dots,x_{(n\times m),i}]^T \tag{4}$$

The measurement data at each sampling moment are arranged in a time series as a state data matrix which can be calculated as:

$$X=[x(t_1),x(t_2),\dots x(t_i),\dots] \tag{5}$$

The raw data matrix X is truncated from the data matrix $\hat{X}$. After each sampling, the separation window moves back one time point, thus carrying out the monitoring of the dynamic process of state variables.

Since the monitored data do not meet the data requirements of the single ring law, it is necessary to perform data processing on the raw data matrix $N\times T$ to obtain a non-Hermitian standard matrix $\overline{X}$:

$$\overline{x}_{i,j}=\frac{\delta(\overline{x}_i)}{\delta(\hat{x}_i)}[\hat{x}_{i,j}-E(\hat{x}_i)]+E(\overline{x}_i) \tag{6}$$

where, i=1,2,…,N, j=1,2,…T, and $\hat{x}_i=(\hat{x}_{i,1},\hat{x}_{i,2},\dots\hat{x}_{i,t})$; $\delta(\overline{x}_i)$=1, $E(\overline{x}_i)$=0;

The matrix $\overline{X}_u$ is introduced as the singular value equivalent of $\overline{X}$ by:

$$\overline{X}_u=U\sqrt{\overline{X}\overline{X}^T} \tag{7}$$

where, U is a Haar unitary matrix, and $\overline{X}_u\overline{X}_u{}^T=\overline{X}\overline{X}^T$.

After the above processing of arbitrary $\hat{X}$, O-independent standard non-Hermitian matrices $\overline{X}_{u,i}(i=1,2,\dots O)$ can be obtained, and their matrix product is shown in Equation (8):

$$Z=\prod_{i=1}^{L}\overline{X}_{u,i} \tag{8}$$

The Z matrix is standardized according to Equation (8) to obtain the matrix $\overline{Z}$:

$$\overline{z}_i=\frac{z_i}{\delta(z_i)\sqrt{N}} \tag{9}$$

where, $z_i=(z_{i,1},z_{i,2},\dots,z_{i,N})$ and $\overline{z}_i=(\overline{z}_{i,1},\overline{z}_{i,2},\dots,\overline{z}_{i,N})$. $\delta(z_i)$ is the standard deviation of the matrix z_i.

C. Convolutional Neural Networks

The convolutional neural network is a variant of a multilayer perceptron and a feedforward neural network. CNN was proposed by computer scientist Yann LeCun et al. in 1998 and quickly became one of the representative neural networks in the field of deep learning research. Due to its excellent extraction capability and analysis effect, the CNN has gradually attracted great attention in many research fields, such as face recognition, large image processing, target tracking and detection, and fault diagnosis. Fig. 2 shows the structure diagram of a convolutional neural network, including the convolutional layer, the pooling layer, and the connection layer.

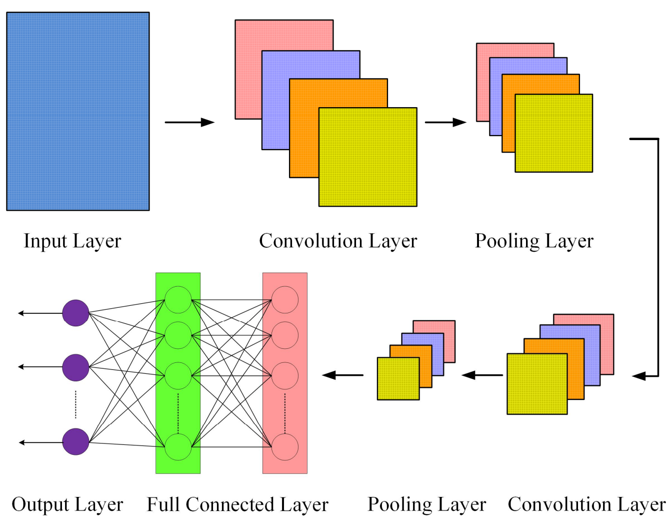


Fig. 2 Structure diagram of the convolutional neural network.

1. Convolution layer

The convolutional layer is the essential component of CNN. The convolutional kernel is used to scan the input matrix and extract the corresponding characteristics. The structure diagram of the convolutional layer is shown in Fig. 3.

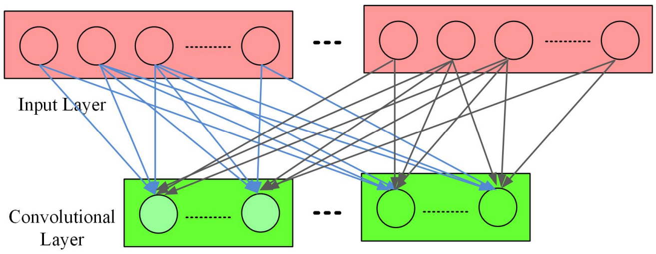


Fig. 3. Schematic diagram of the structure of the convolutional layer.

Fig. 3 depicts that the convolutional layer takes each element of the input layer as a characteristic point, and uses the convolutional kernel to perform convolution operations to extract different characteristics of the input layer to form the output layer matrix. Convolution operations can enhance the characteristic attributes of the original input matrix and reduce noise. As the number of convolutional layers increases, the characteristics that can be extracted become more complex.

The convolution operation is given by:

$$\boldsymbol{C}(o,p)=\sum_{v}\sum_{w}\boldsymbol{R}(o+v,p+w)\boldsymbol{K}(v,w) \tag{10}$$

where, $\boldsymbol{C}(o,p)$ is the output matrix of order $o\times p$ obtained by the convolution operation in the input layer; $\boldsymbol{R}(o+v,p+w)$ is the input matrix, the matrix size is $(o+v)\times(p+w)$ order; and $\boldsymbol{K}(v,w)$ is the $v\times w$ order convolution kernel matrix. A schematic diagram of the convolution operation, is depicted in Fig. 4.

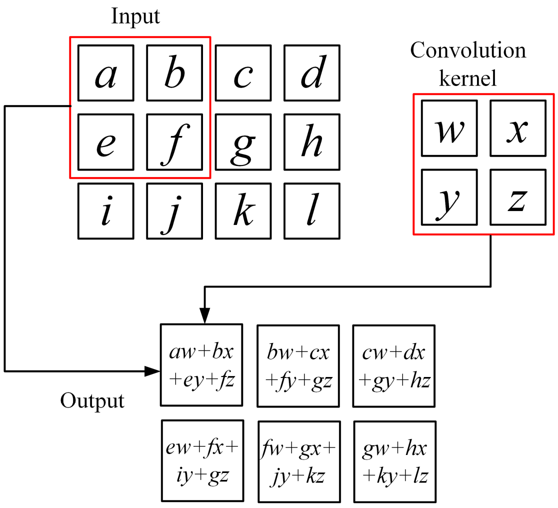


Fig. 4. Convolution operation diagram.

As the convolution operation is performed, it is necessary to ensure that the input matrix and the output matrix are identical in depth. Therefore, this method uses the all-zero filling method to process the input matrix. The all-zero filling method adds false elements with a value of 0 to all edges of the original input matrix. By using the method of full 0 fillings, the peripheral elements of the original input matrix can be placed in the center of the convolution kernel during the convolutional operation while extending to the false elements outside the edge to ensure unity of the depth of the input matrix and output matrix.

In CNNs, as the depth of the matrices deepens, the number of features subsequently increases, and the feature space that the network can characterize becomes larger and the deeper the learning capacity becomes. However, it will also result in more complex neural network calculations and overfitting phenomena. In practical application, parameters such as the number of characteristics and the size of the convolutional kernel should be appropriately selected to obtain a better effect from the required model.

2. Pooling layer

The pooling layer is mainly performed by aggregating similar characteristics in a matrix and then merging them. Thus, reducing the number of characteristics and the size of input data can speed up the network calculation and prevent the interference of overfitting problems. The pooling process is similar to the convolution process in that a filter structure of appropriate step size is slid onto the input matrix, but the adopted method is different from that of convolution [32]. Since the characteristics obtained by the maximum pooling method are more sensitive to the characterization of the characteristic information of the original matrix texture, the method presented in this paper utilizes the maximum pooling method to process the output matrix of the convolutional layer. The calculation formula for the maximum pooling method is shown in Equation (11).

$$\boldsymbol{P}(v,w)=Max\{a(v,w)\} \tag{11}$$

where, $\boldsymbol{P}(v,w)$ is the output matrix after pooling and $a(v,w)$ is the region to be pooled for the output matrix of the convolution layer. The maximum pooling operation process is shown in Figure 5.

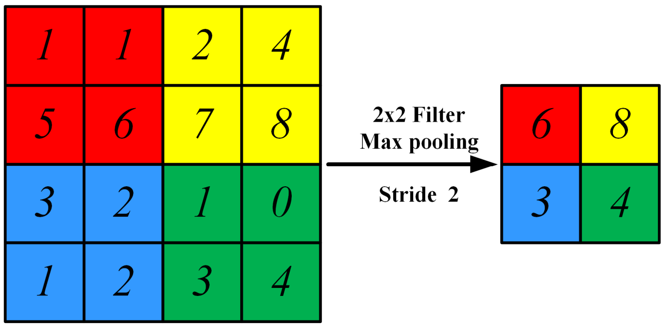


Fig. 5. Maximum pooling operation.

3. Fully connected layer

After the initial input matrix is processed by the convolution pool several times, the final output matrix is connected to the fully connected layer which is considered a “classifier” for the entire CNN, synthesizing the previously extracted characteristics [33]. The fully connected layer is not essential in CNNs and can generally be realized through convolutional operation, that is, the convolution layer of the convolutional kernel with size 1*1 is used instead.

III. Voltage Sag Source Recognition Based on the RMT-CNN Model

A. RMT-CNN model

Under different matrix dimensions, RMT applied to the recognition of voltage sag sources still has excellent results. By constructing an augmented matrix, the high-order characteristic is extracted from the bottom measurement data of the power grid as input. With the characteristic extraction capability of the one-dimensional convolution and pooling operation, the nonlinear mapping relationship between the input characteristic and the results of the voltage stability evaluation is fully exploited. By optimizing the feature statistics of the RMT through CNN and constructing the correlation analysis index of the new voltage sag source recognition model, the mapping effect of the feature statistics can be effectively improved, and the error caused by a single statistic can be avoided. Fig. 6 shows the structure diagram of voltage sag source recognition based on RMT-CNN.

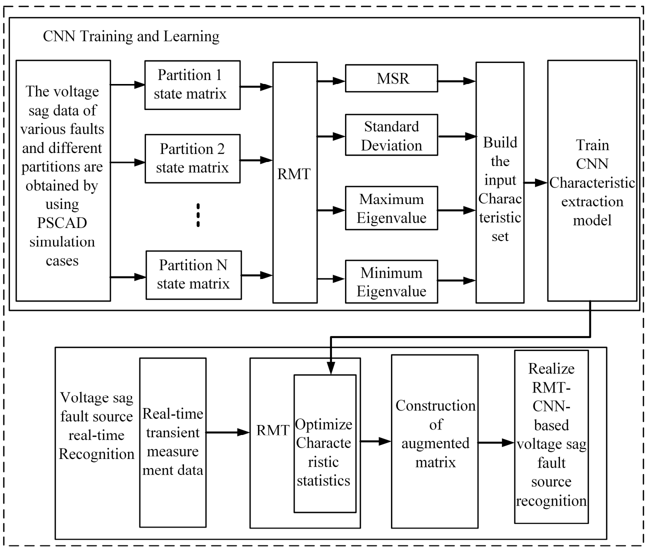


Fig. 6. Voltage sag source recognition based on RMT-CNN.

As can be seen from Fig. 6, when the simulation case data are used for preliminary calculation, various types of faults should be designed to simulate different voltage sag events, and different grid partitions should be simulated to obtain the state data matrix with different dimensions under various fault conditions. The grid partition method based on the community structure proposed in [34] is adopted to perform grid partitioning for a complex power grid. Based on the voltage data of all nodes in N partitions, a data matrix is established to analyze the correlation between the data in each partition. Through the RMT, N kinds of characteristic statistics are obtained from each state data matrix, and the input characteristic set is constructed. Then, it input into the two-layer CNN characteristic extraction model, and optimized characteristic statistics are obtained through a neural grid.

1. Construction of augmented matrix

The state matrix is built using the operation status data of the power grid, and the influence factor data of each bus are taken as the augmented part to construct the augmented state matrix. By analyzing the augmented matrix through RMT, the characteristics of the augmented matrix are used to explore the intrinsic connection between the influencing factors of each monitoring point and the grid operation status. The degree of influence of the voltage sag source on each monitoring point is judged by the correspondence between the influencing factor data and the operating state data. Based on this result, the position of the voltage sag source and the monitoring point is closer to be judged, to recognize the position of the voltage sag source.

The operating status data of the power grid can be composed of various power grid status data, such as bus voltage; injected active, reactive power; and current of each line. Influencing factor data include distributed power output, bus load, etc. Since the location of the source of voltage sag must be recognized, the data selected for the influence factor matrix are the characteristic data related to voltage sag, such as voltage and current at each bus.

It is assumed that m buses exist in the data detected by the power grid, m_c state variables are selected for each bus, and m_f influencing factors are selected. After collecting T times in the real-time sliding separation window, the state matrix $D_c \in C^{((m\times m_c)\times T)}$ and the factor matrix $D_f \in C^{((m\times m_f)\times T)}$ are obtained.

To reduce the impact of repeated data on the factor matrix, random noise needs to be added to the factor matrix, formulated by

$$M_f = D_f + m\times M \tag{12}$$

where, m is the magnitude of the random noise.

The augmented matrix is shown in Equation (13).

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{D}_{\mathrm{c}} \\ \boldsymbol{M}_{\mathrm{f}} \end{bmatrix} = \begin{bmatrix} D_{1,1} & D_{1,2} & \cdots & D_{1,T} \\ \vdots & \vdots & \vdots & \vdots \\ D_{m,1} & D_{m,2} & \cdots & D_{m,T} \\ D_{m+1,1} & D_{m+1,2} & \cdots & D_{m+1,T} \\ \vdots & \vdots & \vdots & \vdots \\ D_{m\times m_c,1} & D_{m\times m_c,2} & \cdots & D_{m\times m_c,T} \\ M_{\mathrm{f}1,1} & M_{\mathrm{f}1,2} & \cdots & M_{\mathrm{f}1,T} \\ \vdots & \vdots & \vdots & \vdots \\ M_{\mathrm{f}m,1} & M_{\mathrm{f}m,2} & \cdots & M_{\mathrm{f}m,T} \\ \vdots & \vdots & \vdots & \vdots \\ M_{\mathrm{f}m\times m_f,1} & M_{\mathrm{f}m\times m_f,2} & \cdots & M_{\mathrm{f}m\times m_f,T} \end{bmatrix} \tag{13}$$

In addition, to eliminate the correlation between the data, the reference augmentation matrix is constructed using the state matrix and the random noise matrix and is differenced, formulated by

$$\tilde{\boldsymbol{A}} = \begin{bmatrix} \boldsymbol{D}_{\mathrm{c}} \\ \boldsymbol{M} \end{bmatrix} = \begin{bmatrix} D_{1,1} & D_{1,2} & \cdots & D_{1,T} \\ \vdots & \vdots & \vdots & \vdots \\ D_{m,1} & D_{m,2} & \cdots & D_{m,T} \\ D_{m+1,1} & D_{m+1,2} & \cdots & D_{m+1,T} \\ \vdots & \vdots & \vdots & \vdots \\ D_{m\times m_c,1} & D_{m\times m_c,2} & \cdots & D_{m\times m_c,T} \\ M_{1,1} & M_{1,2} & \cdots & M_{1,T} \\ \vdots & \vdots & \vdots & \vdots \\ M_{m,1} & M_{m,2} & \cdots & M_{m,T} \\ \vdots & \vdots & \vdots & \vdots \\ M_{m\times m_f,1} & M_{m\times m_f,2} & \cdots & M_{m\times m_f,T} \end{bmatrix} \tag{14}$$

The integral over the real-time sliding window time scale is defined for the mean spectral radius difference as the correlation index, and its calculation formula is:

$$Q_{MSR}(t)=\int_{t_0}^{t}(L_{MSR.A}(t)-L_{MSR.\tilde{A}}(t))dt \tag{15}$$

where, t_0 and t are the sampling start and end times of the real-time sliding window, respectively. $L_{MSR.A}(t)$ and $L_{MSR.\tilde{A}}(t)$ are the average spectral radius values of $\boldsymbol{A}$ and $\tilde{\boldsymbol{A}}$, respectively.

$Q_{MSR}(t)$ can be used to express the magnitude of the correlation between different influences and the state of the power grid during this sampling period. The higher the value of $Q_{MSR}(t)$ is, the greater the influence of the influencing factors of the bus on the system status in the sampling period. Moreover, the region where the bus is located is more likely to be the region where the fault disturbance source is located. The $Q_{MSR}(t)$ obtained in each sub grid is sorted, and then the specific recognition of the fault disturbance source is determined according to the recognition results of each sub grid.

2. Construction of input characteristic sets

The rationality of the construction of the input characteristic set will affect the accuracy of the RMT-CNN voltage sag source identification model. The extraction of characteristic information from the state matrix of the system using CNN directly comes with some problems, such as a large amount of data and lengthy computing time, and the characteristic effect of the state data matrix is not very obvious. In the method presented in this paper, the CNN optimizes the characteristic statistics of the RMT, new characteristic statistics are constructed, and optimized characteristic statistics are used to recognize the source of the voltage sag source. Therefore, in the case of different voltage sag events, the single-ring law and the M-P law of the RMT can be used to calculate the mean spectral radius, standard deviation of the eigenvalue, maximum eigenvalue and minimum eigenvalue of the system state data matrix as the input matrix of the CNN, which can effectively combine the RMT and CNN. In this way, RMT and CNN are combined to fully utilize the advantages of each to obtain more appropriate characteristic statistics.

3. Design of the CNN Structure

To extract characteristic statistics values from input characteristic sets more effectively, a two-layer CNN model is established, and its characteristic extraction model is shown in Fig. 7 [35].

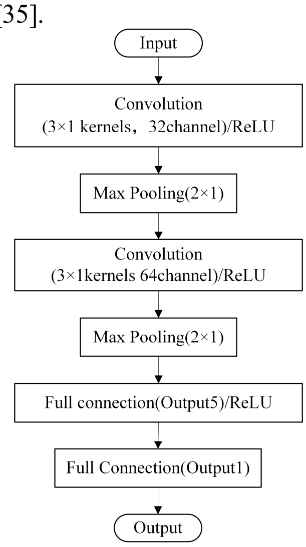


Fig. 7. Two-layer CNN characteristic extraction model.

As shown in Fig. 7, the CNN model includes two convolution layers, two maximum pooling layers, two full connection layers, and one output layer. ReLU activation functions are added to all the convolutional layers and full connected layers, and the Adam algorithm is used to optimize the parameters during training.

4. Statistical indicators

Most of the existing voltage sag source recognition models are mainly realized by analyzing the correlation of data among the system's augmented state matrix through the mean spectral radius of linear characteristic statistics. The main purpose of the RMT-CNN voltage sag source recognition method is to extract an optimized characteristic index to avoid the problem of the MSR being unable to be applied effectively in different data dimensions. Therefore, the integral value of the difference in the average spectral radius obtained from the full matrix analysis can be used as a standard to verify whether the optimized characteristic statistics are more effective. To measure the effect of different characteristic statistics on the recognition of voltage sag sources, the following indicators are defined for evaluation.

The correlation proportion error (CPE) is defined as :

$$\mathrm{CPE}=\left(\frac{\sum_{i=1}^{3}\max\{Q_{\mathrm{MSR}}\}}{\sum_{i=1}^{n}Q_{\mathrm{MSR}}}-\frac{\sum_{i=1}^{3}\max\{Q_{\mathrm{LSE}}\}}{\sum_{i=1}^{n}Q_{\mathrm{LSE}}}\right)\times 100\% \tag{16}$$

where, Q_{MSR} refers to the integral value of the difference between the mean spectral radius of $\boldsymbol{A}$; Q_{LSE} refers to the integral value of the difference of the characteristic statistics obtained by using other characteristic statistics; and n is the number of monitoring locations. Note that the solution of Q_{MSR} is obtained after the analysis of the nonpartition situation of the power grid and the composition of different partitions according to the demand. In the research process, it is found that the buses represented by the three values with larger difference integral values of characteristic statistics are most likely to be close to the recognition of the voltage sag source, and a larger the value indicates a higher degree of influence and a higher percentage.

Recognition accuracy C [36], recognition error rate W [37], and recognition missing rate L [38] are shown in Equation (17):

$$\begin{cases} C=\dfrac{S_{00}+S_{10}}{S_{00}+S_{01}+S_{10}+S_{11}+A_{00}+A_{11}} \\ W=\dfrac{S_{01}+S_{11}}{S_{00}+S_{01}+S_{10}+S_{11}+A_{00}+A_{11}} \\ L=\dfrac{A_{00}+A_{11}}{S_{00}+S_{01}+S_{10}+S_{11}+A_{00}+A_{11}} \end{cases} \tag{17}$$

where, S_{00} , S_{01} denotes the number of correctly and incorrectly identified samples without partitioning of the grid; S_{10} , S_{11} denotes the number of correctly and incorrectly identified samples with the partitioning of the grid; A_{00} , A_{11} denotes the number of samples identifying missed judgments in the grid with and without partitioning.

IV. Simulation Experiment Analysis

On the PSCAD simulation platform, the corresponding short-circuit fault simulated voltage sags were set up based on the IEEE-39 bus system. The IEEE-39 bus system is divided into four zones using the community structure grid partition method, in which each zone corresponds to four characteristic statistics, and the CNN is used to train characteristic statistics. Its partitions are shown in Fig. 8, and the number of buses is presented in TABLE I.

TABLE I
THE NUMBER OF BUSES IN EACH PARTITION

Subnet name	Zone1	Zone2	Zone3	Zone4
Bus number	8	11	7	13

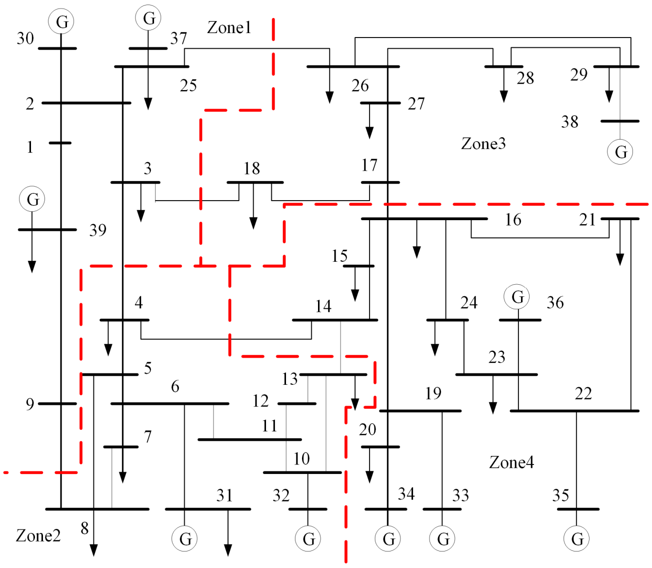
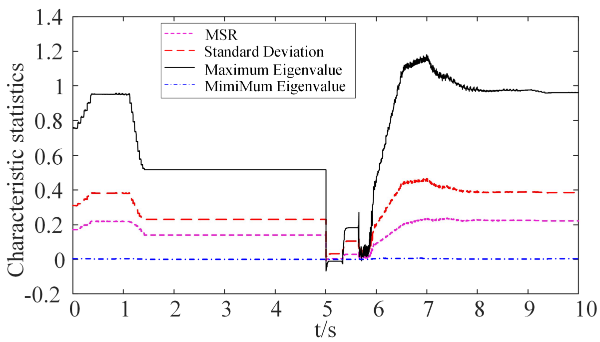


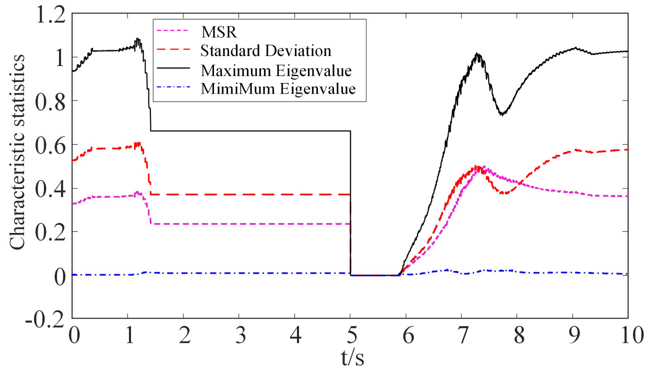
Fig. 8. IEEE-39 bus system with partition.

A. *Analysis of the effect of grid partitioning and different characteristic statistics on RMT*

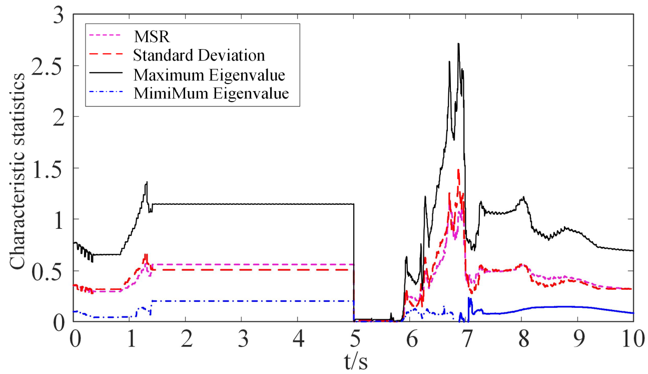
In the IEEE-39 bus system between buses 26-27, a three-phase short-circuit fault is set, which is close to bus 26. When $t = 5$ s, a short-circuit fault occurs; when $t = 5.5$ s, the fault is eliminated. The mean spectral radius, the standard deviation of the eigenvalues, the maximum eigenvalue, and the minimum eigenvalue are obtained by using the single ring law and the M-P law of RMT to calculate and analyze the voltage sag data in the partitioned and unpartitioned cases. Its influence on the analytical effect of the RMT is shown in Figs. 9 and 10.



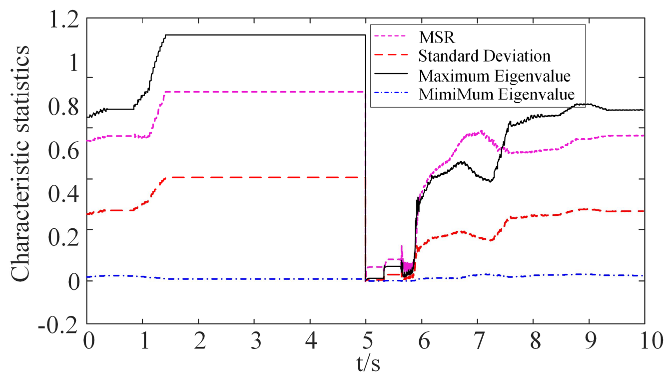
(a) Each characteristic statistic of Zone 1.



(b) Each characteristic statistic of Zone 2.



(c) Each characteristic statistic of Zone 3.



(d) Each characteristic statistic of Zone 4.

Fig. 9. Comparison of each characteristic statistic with partition

Fig. 9 shows that the higher the dimension of the state data matrix is, the better the effect of the characteristic statistics, as shown in Fig. 9(d). As the dimension of the state data matrix declines, the effect of the characteristic statistics worsens, as depicted in Fig. 9(c). Fig. 9(c) indicates that the data dimension is too small, the characteristic statistics show a drastic waveform after 6 s, and the random change cannot be predicted. Therefore, the feature statistics used in the text will gradually lose their statistical effect as the data dimension becomes progressively smaller. From Fig. 10, it can be seen that the characteristic statistics can reflect the overall condition of the state matrix very well when the dimensionality of the state data matrix is sufficiently large, and the effect is better as the dimensionality increases.

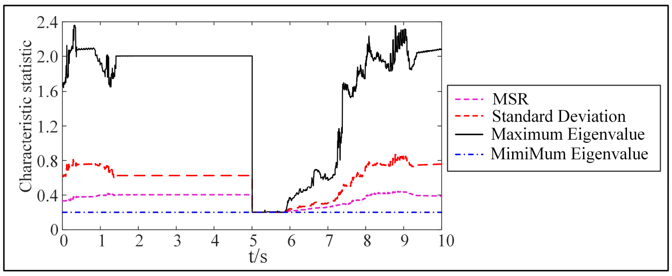


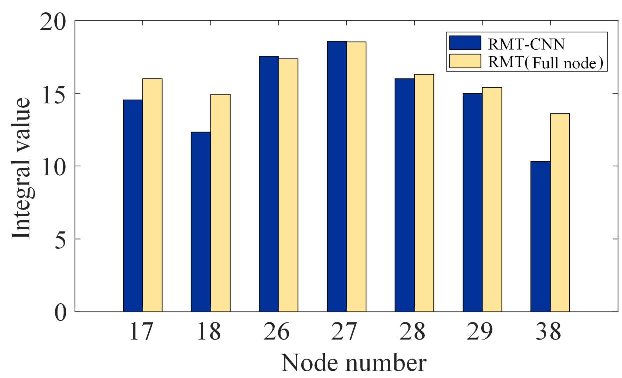
Fig. 10. Comparison of each characteristic statistic without partitioning.

According to Figs. 9 and 10, the state data matrix has different dimension sizes and presents different analyses with different characteristic statistics. Of the four characteristic statistics indices used in this study, the MSR and the standard deviation have a flatter effect and the best results. The change curve corresponding to the maximum eigenvalue jitters more dramatically, and its result is the second most effective. The minimum eigenvalue changes insignificantly, and its statistics are the worst.

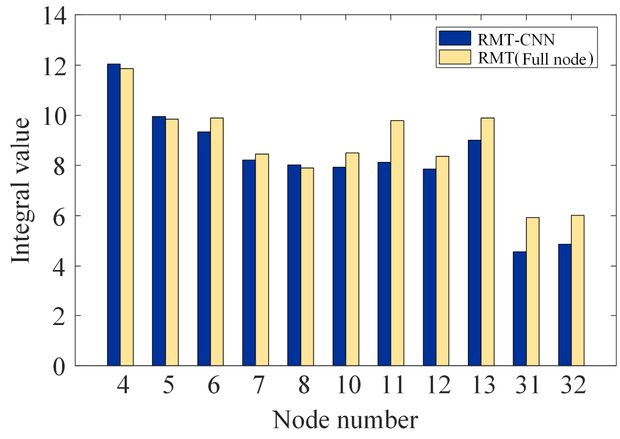
B. Verification of a voltage sag source recognition method based on RMT-CNN

A total of 60 simulation cases are set up in the IEEE-39 bus system between Lines 1-2, 3-4, 4-5, 11-12, 17-18 and 26-27 for a three-phase short circuit fault, two-phase short circuit fault, two-phase grounded short circuit fault and single-phase short circuit fault, respectively. All faults are set to a short-circuit fault at t = 5 s and eliminated at t = 5.5 s. The simulation of the three-phase short-circuit fault at Lines 26-27 is taken as a validation example, and the other simulations are taken as historical cases of CNN training. According to the partitioning and nonpartitioning conditions, the single ring law and M-P law of the RMT were used to analyze historical cases of voltage sag data to obtain four characteristic variables, including the mean spectral radius, the standard deviation of the eigenvalue, maximum eigenvalue and minimum eigenvalue, which were used as the input characteristic set of the CNN.

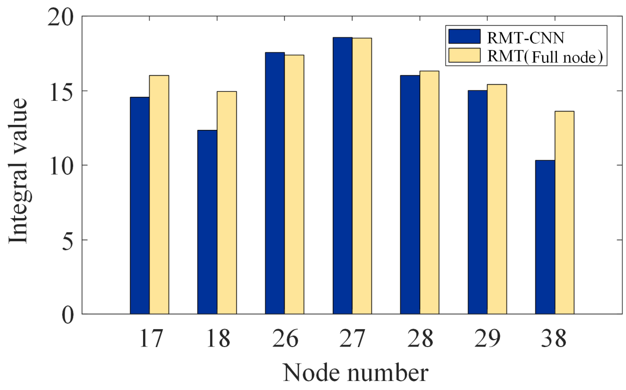
The optimization characteristic statistics obtained by the CNN training are substituted into the simulation analysis of the three-phase short-circuit fault at Lines 26-27. Figs.11 and 12 show the comparison distribution of the integral of the difference between the optimized characteristic statistics and the difference between the mean spectral radius obtained by the voltage sag source identification model under the two conditions of partition and nonpartition.



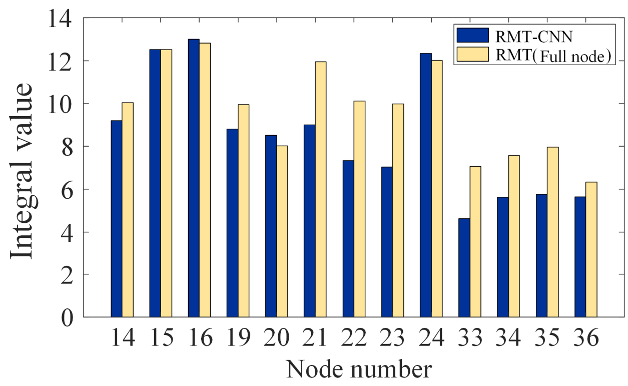
(a) Comparative distribution map of optimized Q_{LSE} and Q_{MSR} .



(b) Comparative distribution map of optimized Q_{LSE} and Q_{MSR} .



(c) Comparative distribution map of optimized Q_{LSE} and Q_{MSR} .



(d) Comparative distribution map of optimized Q_{LSE} and Q_{MSR} .

Fig. 11. Comparative distribution map of optimized Q_{LSE} and Q_{MSR} with partitioning.

It can be seen from Fig. 11 that in the four zones, different integral values of characteristic statistics corresponding to buses 26, 27, and 28 are significantly larger than those of other buses. Thus, the voltage sag source should be recognized within the region of buses 26, 27 and 28. Moreover, buses 26 and 27 should be closer to the voltage sag source point. The results of the simulation are the same as those obtained by setting the fault. The results show that the optimized characteristic statistics extracted by using RMT-CNN can effectively recognize voltage sag sources even under conditions of few dimensions. In Figs. 11(a)

-11(d), the differences between the results of the full matrix analysis with MSR as an index and the results obtained by the RMT-CNN-based voltage sag source recognition method in the case of partitioning are small, indicating that the obtained optimized characteristic statistic can effectively analyze different-dimensional state data matrices in different partitions, and the obtained results do not differ much from the results of the full matrix analysis with MSR as an index. Therefore, the optimized characteristic statistics have good applicability and can overcome the problem of MSR is not being fully applicable in data matrices of different-dimension.

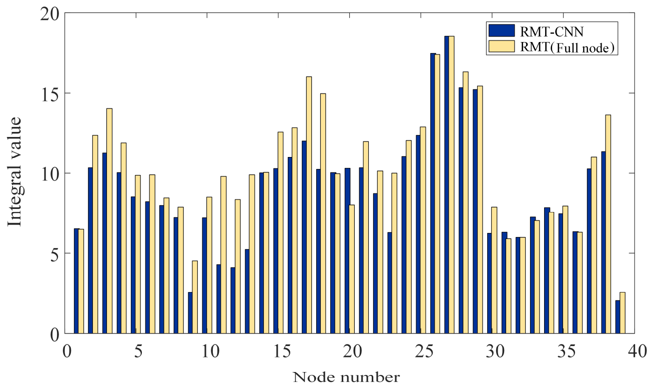


Fig. 12. Comparative distribution map of optimized Q_{LSE} and Q_{MSR} without partition.

As can be seen in Fig. 12, the Q_{LSE} values of buses 26, 27, and 28 are much higher than the other nodes in the results of the RMT-CNN-based recognition method. However, in the RMT-based positioning method, in addition to the large values corresponding to buses 26, 27, and 28, there are also large values for buses 16 and 17, which have interference items. Thus, the RMT-CNN-based recognition method to recognize the source of voltage sag can effectively eliminate the interference of other nodes in the system and has better recognition results compared with the fault recognition results using RMT alone. The proportion error of the correlation between partitions and nonpartitions is given in TABLE II.

TABLE II
COMPARISON OF CORRELATION RATIO ERROR RESULTS

CPE	Grid Partition				Nonpartitioned (Full bus)
	Zone1	Zone2	Zone3	Zone4	
	7.006	2.081	1.123	5.022	1.664

TABLE II reflects the outcome that full matrix analysis based on MSR can be achieved by using optimized characteristic quantity under different matrix dimensions regardless of there being a partition or no partition, and the gap of CPE is small and within the normal range. It shows that compared with MSR, the optimized characteristic quantity has a higher applicability and a better effect.

In conclusion, the positioning effect obtained by using the optimized characteristic statistics extracted by RMT-CNN is not different from that obtained by using the full matrix analysis of the MSR index, and other interference items can be excluded, resulting in good positioning results.

V. DISCUSSION

To verify the positioning effect of the optimized characteristic statistics extracted by RMT-CNN under different faults and different partitions, the simulation data were combined with the IEEE-39 bus system structure to set partitions of different sizes to obtain state data matrices of different dimensions. Ten groups of partition forms were set to obtain a total of 600 groups of state data matrices. The optimized characteristic statistics obtained by the above methods were analyzed. The results of the method proposed in this paper are compared with the results of the recognition of voltage sag sources based on MSR, maximum eigenvalue, improved maximum eigenvalue, and RMT-PCA-based models and evaluated according to the recognition accuracy (C), recognition error rate (W) and recognition missing rate law (L). The evaluation results for each model are given in TABLE III.

TABLE III
EVALUATION RESULTS OF DIFFERENT MODELS

Model	C	W	L
MSR	95.68	2.53	1.79
Maximum eigenvalue	94.92	3.26	1.72
Improved maximum eigenvalue	95.73	2.59	1.68
RMT-PCA	96.27	2.48	1.25
RMT-CNN	97.39	1.84	0.77

As seen in Table 3, after extracting the system characteristics of the system with RMT, CNN, and RMT-PCA, the optimal characteristic statistics greatly improve the precision of the recognition of the voltage sag source. The W and L obtained by using single characteristic statistics are relatively high, such as the maximum eigenvalue. It shows that the recognition method that combines RMT and other deep learning algorithms has more accurate recognition results compared to the RMT method alone. The accuracy of RMT-PCA is higher than that of a single characteristic, but its misjudgment rate is still higher. Compared with the RMT-CNN method, the accuracy is 1.12% lower, the recognition error rate is 0.64% higher, and the recognition missing rate is 0.48% higher. The above analysis illustrates the greater advantage of using CNN in extracting data features and the ability to obtain optimized feature volumes with better perceptual effects.

VI. CONCLUSIONS

The modern power system is a complex system that integrates digitalization and information technology. The factors causing voltage sag are complicated and complex, which makes it difficult to recognize voltage sag sources. To solve the problem of the characteristic statistics of random matrix theory not being completely applicable to the correlation analysis of state data matrices of different dimensions, the CNN can train and learn different characteristic statistics of RMT to obtain optimized characteristic statistics, which can replace the original single linear characteristic statistics and cause the statistics to have better applicability and effectiveness. In this paper, a voltage sag source recognition method based on the RMT-CNN model was proposed. First, RMT was used to analyze the training data, and four characteristic statistics, including the mean spectral radius, and the standard deviation of the characteristic eigenvalue, maximum eigenvalue, and minimum eigenvalue, were obtained. These characteristic quantities were then used to construct the CNN input characteristic set. The CNN was used to train and extract these characteristic statistics so that the optimized characteristic statistics could be well applied to data analysis and processing in different dimensions and under different fault conditions. Furthermore, the optimized characteristic values were used in the voltage sag source recognition model. Finally, examples were given to verify the applicability of the proposed method in voltage sag source recognition research, and compared with several current characteristic statistics extraction models, the RMT-CNN voltage sag source method is better.

On the basis of the study presented in this article, we can conduct in-depth research on the following aspects in the future. For example, for the combination of random matrix theory and deep learning methods, deep neural networks can be used to optimize the coefficients of the test function to determine the coefficients of the test function and the mapping effect. Then, we can find the relationship between the coefficients of the test function and the mapping effect to obtain the optimal characteristic statistics under different dimension matrices.

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