Convolutional neural network-based power system frequency security assessment

Changjiang Wang1  |  Benxin Li1  |  Chunxiao Liu2  |  Peng Li2

1Key Laboratory of Modern Power System Simulation and Control & Renewable Energy Technology, Ministry of Education, Northeast Electric Power University, Jilin, China
2Power Dispatching and Control Center, China Southern Power Grid, Guangzhou, China

Abstract
Weak inertia characteristics of power systems with high penetrations of renewables have become a prominent problem for frequency security. To solve this problem, a convolutional neural network (CNN)-based deep learning approach is applied to realize rapid frequency security assessment (FSA). First, the time series frequency security feature is autonomously mined from the wide-area measurement data to serve as the input data. By doing so, the complex construction process of frequency security feature quantity is avoided. A deep learning structure is then used to establish a non-linear mapping relationship between time series features and frequency security indicators to realize end-to-end power system frequency security prediction. Next, the evaluation accuracy of the proposed approach is optimized by tuning the key parameters in the CNN-based evaluation model. Through data measurement error analysis and a wind penetration sensitivity study, the anti-interference performance of the proposed evaluation model is demonstrated. Finally, the effectiveness of the CNN-based FSA is verified by case studies of a modified 16-machine 68-node system and the China Southern Power Grid.

1  |  INTRODUCTION

In China, with installations of large-scale renewable generators, DC transmission systems, and other power electronic equipment [1–3], the dynamic characteristics of power system frequency, voltage, and power angle are becoming increasingly complicated [4–8]. This seriously threatens the operating security of the power grid. As an important reference for evaluating the anti-interference ability of a system, the security of system frequency can be comprehensively evaluated according to the maximum frequency, rate of change of frequency, and quasi-steady state frequency when an active power disturbance occurs [9, 10]. However, since power electronic equipment can intensify the high-dimensional non-linear features of the system, it is usually difficult to obtain an accurate expression of system frequency after a disturbance. Thus, developing an accurate frequency security assessment (FSA) method is of great significance [11].

Currently, FSA methods can be divided mainly into two types: time-domain simulation [12, 13] and machine learning-based approaches [14–16]. Time-domain simulation obtains the system frequency curves by solving high-dimensional non-linear algebraic and differential equations after the active power disturbance. It then calculates the evaluation index to assess system frequency security. For example, the reference [12] uses time-domain simulation to calculate the quasi-steady state frequency of a power system and evaluate frequency security. However, power system frequency cannot be quantitatively described in this way. On the basis of analyzing the impacts of different frequency drop depths, the reference characterizes the accumulation area of different drop depths by weighting factors and then quantitatively describes the extent of the frequency response under the active power disturbance [13]. However, due to the highly non-linear features of the system (e.g. renewable generation output fluctuation, flexible DC system dynamic characteristics, and multitype disturbances), it is difficult to address the data combination explosion problem caused by multiple uncertainties using a time-domain simulation. In contrast, machine learning-based methods have the advantages of being model-free and highly accurate and thus are widely used in the areas of wind power prediction, information network security situation forecasting, and transient.
stability assessment. Reference [14] uses a single-layer extreme learning machine algorithm with one hidden layer for power system frequency security margin assessment. Reference [15] predicts the minimum frequency after a grid disturbance by a support vector machine regression model. The accuracy of the model is verified by the test system and the actual power grid. From the literature review, it is concluded that machine learning has higher accuracy and is promising for the online application of FSA.

Even though existing machine learning methods can effectively assess system frequency security, there are still problems, such as frequency security feature construction [16–17] and model construction [18–20], that need to be solved. In terms of feature construction, the ‘three-segment’ feature construction method [17] is generally used, which contains part of the time dimension information (the steady-state moment, initial moment of fault, and ultimate moment of fault). However, it is difficult to capture the overall time dimension information of the system operation, which restrict its potential to improve FSA accuracy. In terms of model construction, reference [18] proposes an artificial neural network (ANN)-based frequency dynamic assessment method to realize FSA effectively. Reference [19] first predicts a minimum frequency value through the linear frequency response model, then modifies it to improve the prediction accuracy by using a neural network. Reference [20] attempts to predict the maximum frequency after a disturbance in the islanding system by using a backpropagation neural network method to realize effective maximum frequency prediction. However, the above-mentioned single-layer learning approaches are restricted by data processing capabilities and generalization capabilities. They suffer from high dimensionality, low accuracy, and other problems in large-scale systems. As an important branch of the machine learning method, the convolutional neural network (CNN) [21–23], driven by wide-area measurement data, uses self-learning to learn the characteristics of wide-area measurement data during the whole process of a disturbance. It constructs a deep learning framework with a multiple-hidden-layers learning framework with multiple layers hidden by model training. The CNNs algorithm has been widely used in wind power forecasting [22], small-signal stability assessment [23], power transformer fault diagnosis [24, 25] etc. However, there is still a lack of research in CNN-based FSA. Given the advantages of self-learning and multilayer structured learning, the CNN provides a perfect alternative choice.

This paper considers self-learning and multi-layer structure learning model and CNN-based deep learning technique is applied to realize FSA. The main contributions of this paper are as follows:

(1) The time series frequency security feature is autonomously mined from the wide-area measurement data to serve as the input data to avoid the complex construction process of frequency security feature quantity.

(2) CNN is applied to realize end-to-end power system frequency security prediction, which significantly improves the evaluation accuracy of the proposed algorithm.

The remainder of this paper is organized as follows. Section 2 describes the principle of FSA. Section 3 develops the CNN based frequency security evaluation. Case studies with a modified 16-machine 68-node system and the China Southern Power Grid (CSG) are presented in Section 4 to demonstrate the effectiveness of the proposed method. Finally, the conclusions are drawn in Section 5.

2 PRINCIPLE OF FREQUENCY SECURITY EVALUATION

When an active power disturbance occurs during normal system operation, system frequency deviation can be described by the following first-order ODE [26]:

\[ 2H \frac{d\Delta f(t)}{dt} + DP^D \Delta f(t) = \sum_{g \in E, s} \Delta P_{g,s}(t) - \Delta P_L \]  

where \( H \) [MWs/Hz] is the inertia of the system after generation loss, \( \Delta f(t) \) is the frequency deviation of the system, \( D \) [1/Hz] is the damping coefficient of the load, \( P^D \) [MW] is the power system load level, and \( \Delta P_{g,s}(t) \) [MW] describes the additional power provided by the generator \( g \) or storage \( s \) following the generation loss \( \Delta P_L \) [MW]. Figure 1 shows the dynamic frequency–response curve.

As shown in Figure 1, \( f_{ex}, f_{ss}, \) and \( R_f \), are the extrema of frequency, quasi-steady state frequency, and rate of change of frequency. They can be used as three important indices to determine whether system frequency is secure after an active power disturbance.

Therefore, the system frequency security status is determined by whether \( f_{ex}, R_f, \) and \( f_{ss} \) would trigger the action of system frequency protection and cause cutting machine/load shedding. The details are explained as follows:

(1) The high-frequency cutting machine: if the maximum frequency is higher than the start-up frequency of the high-frequency cutting machine, system frequency is insecure.

(2) Under frequency load shedding: if the minimum frequency is lower than the start-up frequency under frequency load shedding, the system frequency is unsecured.

(3) Frequency change rate protection: if the absolute value of \( R_f \) exceeds the start-up frequency of the frequency change rate protection device, such as \( |R_f| > R_{F,max} \), the system frequency is insecure.

(4) Do not trigger frequency protection if the frequency is between \( f_{min} \) and \( f_{max} \), and \( |R_f| < R_{F,max} \), as the system frequency is secure.

The time-domain simulation is the most common method to determine system frequency security. It constructs a frequency–response model of a multimachine power system and simulates the frequency change curve under different active power disturbance circumstances. Because of
disadvantages of time-domain simulation, such as a large amount of calculation, long operational time etc., it is difficult to address the data combination explosion problem caused by multiple uncertainties.

3 | CNN-BASED FREQUENCY SECURITY EVALUATION

The CNN-based power system FSA is divided into three parts: input and output variables selection, offline training, and online evaluation.

3.1 | Input and output variable selection

Offline fault calculations are performed in the power system simulation software PSD-BPA under different load disturbance levels, generator outputs, wind penetration levels, and other circumstances. With the help of the system’s spatiotemporal big data properties, the time-series bus voltage magnitude, and phase angle, the active and reactive line power flows can be used as input variables with unit power regulation, inertia time constant, switch state, spinning reserve level, and damping coefficient taken as input variables. This gives the fault sample data both time and space properties to improve the evaluation accuracy rate. Based on the system frequency at the transient simulation, \( f_{es} \) and \( f_{sa} \) can be used as variable output and are shown in Table 1. The proposed CNN-based FSA method must read the measurement information within a short time after disturbance, so it is difficult for CNN to achieve \( R_f \) prediction. At the same time, the frequency protection device can calculate \( R_f \) based on the instantaneous data after the disturbance, so it is not used as variable output.

3.1.1 | Data normalization

The range and dimension of time-series data obtained from PSD-BPA (i.e. bus voltage magnitude and phase angle) are different. In the polar coordinate system formed by the voltage amplitude and phase angle, when the voltage vector rotates around the origin and passes the polar axis, the value of the voltage phase angle can jump from either 180° to −180° or from −180° to 180°, which will affect the measured results. For example, Figure 2 shows the bus voltage magnitude and phase angle in the modified 16-machine 68-node system when active power is suddenly reduced to 729 MW.

It is necessary to conduct a pretreatment for the original fault sample data based on the wide-area measurement. Currently, normalization and standardization are commonly used methods for preconditioning. However, it does not apply to time-series input data. Therefore, the bus voltage magnitude and phase angle are transformed into the form of real and imaginary voltage to normalize their dimensions and the value ranges in this work. This method can realize the normalization of measurement data, which the complete data of the system has reserved:

\[
\begin{align*}
U^R &= U \cos \theta \\
U^I &= U \sin \theta
\end{align*}
\]

(2)

where \( U \) and \( \theta \) are the respective voltage magnitude and phase angle, and \( U^R \) and \( U^I \) are the respective real and imaginary voltages. Once the real and imaginary parts of the voltage are converted by Equation (3), the influence of the initial state bias of the time series samples is avoided, so the input samples have the same distribution:

\[
\begin{align*}
U^{R, rv}(t) &= U^R(t) - U^R(0) \\
U^{I, rv}(t) &= U^I(t) - U^I(0) \\
P^{rv}(t) &= P(t) - P(0) \\
Q^{rv}(t) &= Q(t) - Q(0)
\end{align*}
\]

(3)

where \( U^R(0), U^I(0), P(0) \) and \( Q(0) \) are respectively the real and imaginary parts of the voltage, active power, and reactive power vector at the initial time, \( U^{R, rv}(t), U^{I, rv}(t), P(t) \) and \( Q(t) \) are respectively the real and imaginary parts of the voltage and the active and reactive power vector at time \( t \), \( U^{R, rv}(t), U^{I, rv}(t), \)
\[ X = [R, H, O, M, D, U_1, U_2, \ldots, U_L] \]

Suppose \( X_m n \) is the \( n \)-th sample of the \( m \)-th system operating state, and then from Equation (5), we further extend it to a multisystem operating state high-dimensional sample \( G \) containing the information of key busbars:

\[ G = [X_1^1, X_2^1, \ldots, X_N^1, \ldots, X_n^m, \ldots, X_N^M]^T \]

where \( m = 1, 2, \ldots, M, M \) is the sum of the system operating states, and \( n = 1, 2, \ldots, N, N \) is the sum of different load disturbances. The matrix dimension of \( G \) is \((N \times M)(5 + L \times 4T) = Z \times W\), where \( N \times M = Z \). To unify the input data format, the high-dimensional time sample matrix of the CNN needs to be reconstructed and imported as a colour picture. This work uses the extrema of frequency and quasi-steady-state frequency as output variables to obtain the output variable matrix \( Y_{Z \times k} \):

\[
Y = \begin{bmatrix}
y_1^1 & y_1^2 & \cdots & y_1^N & \cdots & y_m^1 & \cdots & y_m^N \\
y_2^1 & y_2^2 & \cdots & y_2^N & \cdots & y_{2m}^1 & \cdots & y_{2m}^N \\
\vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\
y_k^1 & y_k^2 & \cdots & y_k^N & \cdots & y_{km}^1 & \cdots & y_{km}^N \\
\end{bmatrix}^T
\]

where \( k = 2 \) is the number of output variables, representing there are two output variables and the number of channels is 2, \( y_m k \times n \) is the data corresponding to the \( m \times N + n \) row of the \( k \)-th output.

### 3.1.2 Data integration

According to the temporal characteristics of the system simulation curve, the high-dimensional fault sample matrix considering time distribution is constructed as the CNN input data. At time \( t \), the real and imaginary parts of the voltage of the \( l \)-th busbar are \( U_R l(t) \) and \( U_I l(t) \), respectively, and the active and reactive power are \( P_l(t) \) and \( Q_l(t) \), respectively, where \( t = 1, 2, \ldots, T \), and \( T \) is the length of the time window for data sampling, \( l = 1, 2, \ldots, L \), and \( L \) is the total number of busbars. Then the time-series feature of the \( l \)-th busbar is represented by

\[
U_l = \begin{bmatrix}
U_{1R}^{l}(1), U_{1I}^{l}(1), P_{l}^{1}(1), Q_{l}^{1}(1), \ldots, \\
U_{1R}^{l}(T), U_{1I}^{l}(T), P_{l}^{T}(T), Q_{l}^{T}(T)
\end{bmatrix}
\]

### 3.2 Training the CNN-based system frequency security evaluation model

The CNN is a deep learning network that focuses on convolution operations. The ‘end-to-end’ characteristic of CNN is the main difference with traditional machine learning methods. Users only need to input the system measurement data for frequency security prediction and there is no need to participate in feature extraction, dimension lifting, and other intermediate data processing. Therefore, it is more applicable for analyzing data with complex data structure or deep information which people cannot easily extract data features. CNN is composed of an input layer, a convolution layer, a pooling layer, and a fully connected layer. Figure 3 shows a typical CNN model.
3.2.1 | Input layer

The input layer is the matrix corresponding to the system frequency security prediction samples. Each row of the matrix represents the vector corresponding to a certain prediction sample of the frequency. The row and column are respectively the numbers of samples and sampling points, which can be used as the input layer. The number of the channel represents the number of the output variables.

3.2.2 | Convolution layer

The input feature is extracted by the convolution layer through a convolution operation and selects multiple convolution kernels based on actual conditions. Every convolution kernel performs a convolution operation with the input layer data of the upper layer to obtain the corresponding feature and is used as the input for the next layer. The convolutional method is a common processing method for image processing. The convolution kernel is a linear operation for two-dimensional input data. After the activation function is added, as shown in Equation (8):

\[ b_{ij} = f \left( \sum_{c=0}^{C-1} \sum_{d=0}^{D-1} G_{i+c,j+d} \varphi_{ad} + b \right) \]  

where \( b_{ij} \) is the \( j \)-th column and \( i \)-th row element of the output matrix, the matrix dimension is \( I \times J, i = 1, 2, \ldots, I; j = 1, 2, \ldots, J \), \( f \), \( \varphi_{ad} \) is the \( d \)-th column and \( c \)-th row element of the convolution kernel, and the matrix dimension is \( C \times D \). \( G_{i+c,j+d} \) is the \((j+d)\)-th column and \((i+c)\)-th row element of the input matrix, \( b \) and \( f \) are respectively the deviation variable and the activation function.

3.2.3 | Pooling layer

Since the convolution layer performs a convolution operation to the original input data, it contains a large number of features. However, these features cannot be directly used in the next layer due to the high computational burden. However, pooling the layers can enable the operation of polymerization statistics on features to realize data dimension reduction. Pooling is a down-sampling method, which divides the input into several non-overlapping areas, and takes the average of each area (average pooling), as calculated by

\[ E_{ab} = \frac{1}{S_1 \times S_2} \sum_{i=0}^{S_1-1} \sum_{j=0}^{S_2-1} b_{a S_1 + i, b S_2 + j} \]  

where \( S_1 \) and \( S_2 \) are respectively the row and column dimensions of the pooling area, \( E_{ab} \) is the \( a \)-th row, \( b \)-th
column element of the output matrix after pooling, and the dimension is $(I/S_1) (J/S_2)$, where $a = 0, 1, \ldots, I/S_1 - 1$, $b = 0, 1, \ldots, J/S_2 - 1$, $bS_a + bS_2 + j$ is the $aS_i + i$-th row and $bS_2 + j$-th column element of the output matrix. After pooling the output data obtained by the convolution operation, the matrix dimension is reduced to $1/(S_1S_2)$ of its original size, which significantly decreases the matrix dimension and the amount of calculation but improves the robustness of the model.

### 3.2.4 Fully connected layer

The fully connected layer expands the two-dimensional output data of the last layer into one-dimensional data. It maps learnt features onto the output. The fully connected layer is described as follows:

$$o = f \left( \sum_{i=1}^{n} \omega_i e_i + \mu \right)$$

(10)

where $e_i$ is $i$-th input variables, $\omega = [\omega_1, \omega_2, \ldots, \omega_n]$ is the connection weight, and $\mu$ and $o$ are respectively the deviation variable and output.

### 3.3 Process assessment of system frequency security

The flowchart of the CNN-based FSA is shown in Figure 4. It contains two parts: (1) offline system frequency security evaluation model training and (2) online system frequency security evaluation.

#### 3.3.1 Offline training

First, the big data sample set is constructed by the data from a historical database and offline transient simulation. Then the data sample set is randomly divided into two subsets for CNN-based FSA model training and testing. After setting reasonable convolutional kernel parameters and a convolution layer number, the FSA model is trained by the training set and then tested by the testing set.

#### 3.3.2 Online evaluation

System FSA or predicted power disturbance events can be determined according to grid operational characteristics. Once a disturbance happens, the measurement data is taken as the input and then normalized. An offline trained CNN model is used to operate system frequency security evaluation. Then, reverse normalization on the output data is conducted to obtain the frequency index value of the disturbance events. Finally, the frequency security of the disturbance events is comprehensively evaluated to determine whether the protection device should be activated.

### 3.4 FSA and prediction performance index

In this work, the mean absolute percentage error (MAPE) is used to evaluate the prediction accuracy of the system frequency, which is the MAPE of the actual and prediction value of the system frequency:

$$I_{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\%$$

(11)
where \( y_i \) and \( \hat{y}_i \) are respectively the frequency index actual value and prediction value of the \( i \)-th sample, and \( N \) is the number of test sample.

The frequency assessment accuracy rate, secure case evaluation accuracy rate, and insecure case evaluation accuracy rate are used to evaluate the FSA performance:

\[
E_{AC} = \frac{N_{TP} + N_{TN}}{N_{TP} + N_{FP} + N_{TN} + N_{FN}}
\]

\[
E_{AC1} = \frac{N_{TP}}{N_{TP} + N_{FP}}
\]

\[
E_{AC2} = \frac{N_{TN}}{N_{TN} + N_{FN}}
\]

where \( E_{AC} \) is the frequency assessment accuracy rate, \( E_{AC1} \) and \( E_{AC2} \) are respectively the secure and insecure case evaluation accuracy rates, \( N_{TP} \) and \( N_{FP} \) are respectively the number of power system frequency security samples that evaluated as secure and insecure, and \( N_{TN} \) and \( N_{FN} \) are respectively the number of power system frequency insecure samples that evaluated as secured and insecure samples.

4 | CASE STUDIES

In this section, the accuracy and effectiveness of the proposed method are tested in a modified 16-machine 68-node system and the CSG.

4.1 | The modified 16-machine 68-node system

This test system has five regions, where regions 1, 2, and 3 are equivalent systems and regions 4 and 5 are, respectively, the New York and New England systems, as shown in Figure 5. The modified system has 18 generators in total, including 16 synchronous generators and 2 wind farms. To simulate the impact of wind penetration on system frequency, the wind turbines are connected to nodes 66 and 68. Moreover, lines 41–42 are replaced by a VSC-HVDC line for power transmission between regions. The generator is a sixth-order model, and the excitation system model is IEEE-DC1. The load model is WECC, and the total load is 18,233 MW. The model and control parameters of wind power and VSC-HVDC can be referred to in the reference [27,28].

The power system simulation software PSD-BPA is used to conduct transient simulations under different load disturbances, generator power outputs, and wind penetration levels. The transient simulation generates 12,600 samples to form the sample set, including 6820 secure cases, 5737 insecure cases, and 43 critical cases. Among them, 8400 samples are randomly selected to train the FSA model, while the performance of the model is tested using the remaining samples. The activation criterion of the frequency protection device is \( f > f_{\text{max}}, f < f_{\text{min}} \)

\[|R_F| > R_{F,\text{max}} \text{ and } |R_F| < R_{F,\text{min}}\]. Otherwise, the protection device would not be activated where \( f_{\text{max}} = 51 \text{ Hz} \), \( f_{\text{min}} = 49 \text{ Hz} \), and \( R_{F,\text{max}} = 1 \text{ Hz/s} \).

4.1.1 | FSA accuracy analysis

The accuracy of the CNN-based FSA can be evaluated from the system frequency prediction error and the MAPE. The
number of CNN convolution layers is seven, and the wind penetration level is 5%. The sample distribution of CNN-based FSA is shown in Table 2.

As shown in Table 2, the sample proportion of the extrema of frequency and quasi-steady state frequency are respectively 92.76% and 95.63% under 0.05 Hz of frequency prediction error. The values of the MAPE are 0.0356% and 0.0392%, respectively. Therefore, it is concluded that the CNN-based FSA model has high prediction accuracy.

To further verify the accuracy of the CNN-based FSA, ANN, decision tree (DT), and kernel ridge regression (KRR) algorithms are also applied to evaluate frequency security using the same sample set. The MAPE and evaluation accuracies for the four artificial intelligence algorithms are shown in Table 3.

As shown in Table 3, the MAPE of the CNN-based FSA is the smallest. Compared with other prediction methods, CNN has a higher prediction accuracy. In contrast, the MAPE values of the ANN, DT, and KRR algorithms are respectively 9.32, 8.17, and 1.33 times that of CNN at the extremum of frequency. Meanwhile, the $E_{AC1}$ and $E_{AC2}$ of CNN are respectively 100% and 99.79% with seven convolution layers. Meanwhile, the $E_{AC}$ of CNN is 99.91%, which is higher than for the other three methods. The $E_{AC}$ of CNN has also been verified under quasi-steady state frequency. The main reason for this is that CNN constructs a deep learning framework with a multi-hidden-layer learning framework with multiple layers hidden by model training. It is applied to realize end-to-end FSA, which significantly improves accuracy. Therefore, it is summarized that the CNN-based FSA has a high system frequency prediction and assessment accuracy rate.

| TABLE 2 | The sample distribution of CNN-based FSA |
|---------------------|---------------------|---------------------|---------------------|---------------------|
| Error (Hz)          | >0.08               | 0.05~0.08           | 0.02~0.05           | <0.02               |
| $f_e$               | 1.36%               | 5.88%               | 24.36%              | 68.40%              |
| $f_s$               | 4.12%               | 0.88%               | 9.93%               | 85.7%               |

Abbreviations: CNN, convolutional neural network; FSA, frequency security assessment.

| TABLE 3 | MAPE and evaluation accuracy of the four artificial intelligence algorithms |
|---------------------|---------------------|---------------------|---------------------|---------------------|
| Model               | MAPE/%              | $E_{AC1}$/%          | $E_{AC2}$/%          | $E_{AC}$/%          |
| Extremum of frequency | ANN 0.331 7 | 98.59 | 95.01 | 97.00 |
|                     | DT 0.290 9 | 96.83 | 99.79 | 98.14 |
|                     | KRR 0.047 2 | 99.32 | 99.79 | 99.53 |
|                     | CNN 0.035 6 | 100 | 99.79 | 99.91 |
| Quasi-steady state frequency | ANN 0.365 7 | 99.12 | 91.71 | 96.14 |
|                     | DT 0.871 8 | 81.16 | 96.57 | 87.36 |
|                     | KRR 0.404 3 | 99.24 | 93.07 | 96.76 |
|                     | CNN 0.039 2 | 99.28 | 98.40 | 98.93 |

Abbreviations: ANN, artificial neural network; CNN, convolutional neural network; DT, decision tree; KRR, kernel ridge regression; MAPE, mean absolute percentage error.
layer. If the number of convolutional layers is increased to eight, the complexity of the convolutional layer will increase and cause an overfitting phenomenon, and the prediction accuracy will decrease. Therefore, the prediction and assessment accuracy rates are highest with seven convolutional layers. The convolution layers of CNN are reasonably selected, which can ensure the prediction accuracy rate of FSA.

With one and seven convolution layers, the CNN-based system frequency prediction errors are as shown in Figure 7.

As shown in Figure 7, the one-convolution layer power system frequency prediction error is centrally distributed in the range of 0–0.008 p.u. with poor frequency prediction accuracy. The power system frequency prediction error is centrally distributed in the range of 0–0.00249 p.u. when the number of convolution layers is increased to seven. At this time, the system frequency prediction accuracy can be effectively improved.

### 4.1.3 The impact of wind penetration on FSA

To investigate the impact of different wind penetration levels on frequency security evaluation, a comparative analysis of the MAPE and evaluation accuracy rate of the system frequency is conducted, covering the wind penetration levels of 0%, 5%, 10%, and 15% at the extremum of frequency, as shown in Table 5.

It can be observed from Table 5 that as the wind penetration level increases from 0% to 15%, the MAPE of the system frequency under different wind penetration levels remains small, and the secure and insecure system frequency case evaluation accuracy is higher than 99.24% and 99.34%, respectively. The main reason for this is that the time series frequency security feature at different wind penetration levels is autonomously mined from the wide-area measurement data to serve as the input data. Therefore, the CNN-based approach has good adaptability, and wind penetration has little influence on the FSA accuracy rate.

Further, the system frequency under different operating conditions is analyzed, as shown in Table 6. At this time, the active power disturbance is set to a sudden decrease of 1200 MW in load to observe system frequency index changes under different wind penetration ratios and system inertia.

From Table 6, it can be observed that as the wind penetration increases from 0% to 15%, the output power of thermal power generating units gradually decreases, and the system rotational inertia decreases from 18,408 MW/s to 15,468 MW/s. When the wind penetration ratio reaches 10% and higher, the low inertia characteristic of the power system becomes prominent, and the extremum of frequency higher than 51 Hz is obtained after the active power disturbance. The high-frequency cutting machine action is then triggered. Figure 8 shows different system frequency change curves. Under various wind power penetration rates and system inertia, it is observed that

### Table 4 MAPE and evaluation accuracy under different convolutional layers

| Convolutional layers | MAPE/% | E<sub>AC1</sub>/% | E<sub>AC2</sub>/% | E<sub>AC</sub>/% |
|---------------------|--------|-----------------|-----------------|-----------------|
| 1 layer             | 0.1114 | 99.61          | 98.07           | 98.93           |
| 2 layers            | 0.0461 | 99.91          | 99.03           | 99.52           |
| 3 layers            | 0.0442 | 99.96          | 98.61           | 99.36           |
| 4 layers            | 0.0375 | 100            | 99.03           | 99.57           |
| 5 layers            | 0.0392 | 99.83          | 98.98           | 99.45           |
| 6 layers            | 0.0381 | 100            | 99.36           | 99.72           |
| 7 layers            | 0.0356 | 100            | 99.79           | 99.91           |
| 8 layers            | 0.0404 | 100            | 98.98           | 99.55           |

**Abbreviation:** MAPE, mean absolute percentage error.

### Table 5 MAPE and evaluation accuracy under different wind penetration ratios

| Ratios | H/(MW*s) | MAPE/% | E<sub>AC1</sub>/% | E<sub>AC2</sub>/% | E<sub>AC</sub>/% |
|--------|----------|--------|-----------------|-----------------|-----------------|
| 0%     | 18408    | 0.0313 | 99.24           | 99.34           | 99.29           |
| 5%     | 17428    | 0.0366 | 100             | 99.79           | 99.91           |
| 10%    | 16488    | 0.0331 | 99.50           | 100             | 99.74           |
| 15%    | 15468    | 0.0362 | 99.67           | 99.85           | 99.76           |

**Abbreviation:** MAPE, mean absolute percentage error.
Multiple interference shown frequency data. When the signal, is mean measurement of the signal, interference measurement FSA 7 security accuracy is value that signals are. In section, values of the time performance proposed. Therefore, are 0.01, system of 8 val evaluation the prediction mined is the CNN system. When the frequency is 0.001 interference signal. ANN, artificial neural network; CNN, convolutional neural network.

### Anti-interference of frequency security evaluation

In this section, interference signals are added to the input data to simulate the measurement error of wide-area measurement data. When there is no interference signal, the system frequency prediction accuracy of the CNN and the ANN are as shown in Figure 9.

The anti-interference ability of the CNN for system frequency security evaluation is analyzed when the mean values of interference signals are 0.0001, 0.001, and 0.01, respectively. Multiple system frequency security evaluations are performed to obtain the mean value of the MAPE and evaluation accuracy rate, as shown in Tables 7 and 8.

From Table 7, it is observed that when the mean value of the interference signals is 0.0001, the mean value of MAPE for the CNN-based FSA is 0.04076%. In contrast, the mean value of the MAPE for the ANN-based FSA is 9.47 times that of the CNN-based FSA. When the mean values of the interference signals are 0.001 and 0.01, the prediction performance of the CNN is still better than that of ANN because the time series frequency security feature is autonomously mined from the wide-area measurement data to serve as the input data to avoid complex construction process of frequency security feature quantity. Therefore, the proposed CNN-based FSA method is robust towards interference signals. As shown in Table 8, when the mean value of the interference signal is 0.0001, the mean value of the CNN system frequency $F_{\text{acc}}$ is 99.56%. Meanwhile, the $F_{\text{acc}}$ of the ANN is higher than that of the CNN. When the mean value of the interference signals is 0.001 and 0.01, the evaluation accuracy of the CNN-based FSA is still better than that of the ANN-based FSA. This indicates that under different interference signals, the evaluation accuracy rate of the CNN-based FSA is better than it is for the ANN-based FSA. In conclusion, the CNN-based FSA has better anti-interference ability than the ANN-based FSA.

### Table 6: Accuracy of power system FSA under different operating modes

| Ratios                        | $H/(\text{MW} \cdot \text{s})$ | TDS/Hz | CNN/Hz   | Error/Hz |
|-------------------------------|-------------------------------|--------|----------|----------|
| Extremum of frequency         |                               |        |          |          |
| 0%                            | 18 408                        | 50.911 | 50.914   | 0.003    |
| 5%                            | 17 428                        | 50.954 | 50.956   | 0.001    |
| 10%                           | 16 488                        | 51.001 | 51.016   | 0.015    |
| 15%                           | 15 468                        | 51.048 | 51.040   | −0.008   |
| Quasi-steady state frequency  |                               |        |          |          |
| 0%                            | 18 408                        | 50.365 | 50.366   | 0.001    |
| 5%                            | 17 428                        | 50.335 | 50.331   | −0.004   |
| 10%                           | 16 488                        | 50.365 | 50.352   | −0.009   |
| 15%                           | 15 468                        | 50.421 | 50.418   | −0.003   |

Abbreviations: CNN, convolutional neural network; FSA, frequency security assessment.
4.2 CSG system

The CSG system contains 4933 over 110 kV transformer substations, 9950 transformers, 12,740 transmission lines, 19 converter stations, and 92 converter transformers, as shown in Figure 10. To verify the effectiveness of the proposed CNN-based FSA in the CSG system, PSD-BPA is used for fault calculation. A total of 13,824 samples, including 9132 secure samples, 4632 insecure samples, and 62 critical samples, are used for model training and validation. The 9206 samples and 4618 samples are randomly selected as the training and testing samples.

The accuracy rates of the extrema of frequency and quasi-steady state frequency are shown in Figure 11.

It can be observed from Figure 11 that the system $E_{AC}$ of the extremum of frequency is 99.16%, which is less than the $E_{AC}$ values of the quasi-steady state frequency. The $E_{AC2}$ rate of the extremum of frequency is 97.51%, which is an improvement of 0.64% compared with the case of quasi-steady-state frequency. The $E_{AC2}$ of the extremum of frequency is 100%, which is a 0.42% improvement over the cases of the quasi-steady state frequency. Therefore, the CNN-based approach maintains a high evaluation accuracy rate in a practical grid.

Further, we conduct a comparative analysis of the frequency evaluation accuracy of the ANN, DT, KRR, and CNN at the extremum of frequency. The number of convolution layers is seven, as shown in Table 9.

Since the data dimension of the actual system is too large for the ANN to conduct security evaluation, only results of the CNN, DT, and KRR are provided in this work. Table 9 shows that the $E_{AC1}$ of CNN at the extremum of frequency is 100%, which is the same as that of DT and KRR. The $E_{AC2}$ of the CNN is 97.51%, which is improved by 7.51% and 5.31% compared with DT and KRR. Meanwhile, the $E_{AC}$ of the CNN is 99.16%, which is still higher than the DT and KRR classifiers. Therefore, the effectiveness and accuracy of the proposed method in CSG system frequency security evaluation are validated.

**TABLE 7 MAPE of CNN with different interfering signals**

| Mean | 0.0001 | 0.001 | 0.01 |
|------|--------|-------|------|
| MAPE% | CNN 0.040 76 | 0.048 74 | 0.053 70 |
| ANN 0.385 82 | 0.417 78 | 0.484 12 |

**Table 8 Accuracy of CNN with different interference signals**

| Mean | 0.0001 | 0.001 | 0.01 |
|------|--------|-------|------|
| $E_{AC}$% | CNN 99.56 | 99.39 | 99.33 |
| ANN 94.82 | 95.82 | 92.51 |

Abbreviations: ANN, artificial neural network; CNN, convolutional neural network; MAPE, mean absolute percentage error.

**FIGURE 10** The China Southern Power Grid system
5 | CONCLUSION

A CNN-based deep learning approach is proposed to realize rapid FSA. Compared with existing machine learning methods, such as the ANN, DT, and KRR, the CNN can self-extract features from wide-area measurement data and avoid the feature-construction difficulties of traditional machine learning methods with a higher frequency prediction and evaluation accuracy rate. From the accuracy analysis of CNN, it is concluded that the CNN has a higher evaluation accuracy when the convolutional kernel size is 5 × 5 and the number of convolution layers is seven, and wind penetration has little influence on the FSA accuracy rate.

Further, the CNN-based FSA has better anti-interference ability than traditional classifiers, such as ANN, so it can provide a more reliable reference. In this regard, the output of CNN-based FSA could be used as an input signal for a frequency security control system that protects and controls the power system under emergency conditions. The validity of the CNN-based FSA is verified in a CSG system.

ACKNOWLEDGEMENT

The authors acknowledge the support of the China Southern Power Grid Research and Development Programme (No. ZDKJXM20180151).

ORCID

Benxin Li https://orcid.org/0000-0003-2573-9357

REFERENCES

1. Mochamad, R.F., Preece, R.: Assessing the impact of VSC-HVDC on the interdependence of power system dynamic performance in uncertain mixed AC/DC systems. IEEE Trans. Power Syst. 35(1), 63–74 (2020)
2. Li, Z., et al.: Hybrid control strategy for AC voltage stabilisation in bipolar VSC-MTDC. IEEE Trans. Power Syst. 34(1), 129–139 (2019)
3. Luo, Y., et al.: Coordinated control strategy of large-scale wind power generation sending system under mono-polar block fault. Trans. China Electrotech. Soc. 34(19), 4108–4118 (2019)
4. Dong, X., et al.: Research and application of frequency emergency coordination and control technology in hybrid AC/DC power grids. Power Syst. Protect. Contr. 46(18), 59–66 (2018)
5. Das, K., et al.: Frequency stability of power system with large share of wind power under storm conditions. J. Mod. Power Syst. Clean Energy. 8(2), 219–228 (2020)
6. Su, A., et al.: Identification of power system low frequency oscillation mode based on multivariate empirical mode decomposition. Power Syst. Protect. Contr. 47(22), 113–125 (2019)
7. Yang, W., Zhu, Y., Liu, Y.: Fast assessment of transient voltage stability based on convolutional neural network. Autom. Electr. Power Syst. 43(22), 46–52 + 139 (2019)
8. Chen, H., et al.: Transient stability assessment in hybrid AC/DC systems with VSC-HVDC via port energy. Trans. China Electrotech. Soc. 33(03), 498–511 (2018)
9. Wen, Y., et al.: Frequency dynamics constrained unit commitment with battery energy storage. IEEE Trans Power Syst. 31(6), 5115–5125 (2016)
10. Obaid, Z.A., et al.: Frequency control of future power systems: reviewing and evaluating challenges and new control methods. J. Mod. Power Syst. Clean Energy. 7(1), 9–25 (2019)
11. Chang, Y., et al.: A new method for frequency control performance assessment on operation security. Trans. China Electrotech. Soc. 34(06), 1218–1229 (2019)
12. Cai, Z., Xu, Z., Shen, H.: Direct method for frequency stability analysis of power system. In: Proceedings of the EPSA, (Z1), pp. 13–17. Tianjin University, Tianjin (1999)
13. Tan, F.: Study on Frequency Stability Control for Sending-end Power System with Large-scale Wind Powers. North China Electric Power University, Beijing (2016)
14. Xu, Y., et al.: Extreme learning machine-based predictor for real-time frequency stability assessment of electric power systems. Neural Comput. Appl. 22(3–4), 501–508 (2013)
15. Bo, Q., Wang, X., Liu, K.: Minimum frequency prediction based on v-SVR for post-disturbance power system. Electr. Power Autom. Equip. 35(7), 83–88 (2015)
16. Zhang, Y., et al.: A method of frequency curve prediction based on deep belief network of post-disturbance power system. Proc. CSEE. 39(17), 5095–5104+5200 (2019)
17. Mitchell, M.A., et al.: Using a neural network to predict the dynamic frequency response of a power system to an under-frequency load shedding scenario. In: Proceedings of the Power Engineering Society Summer Meeting, pp. 346–351, Seattle (2000)
18. Djukanovic, M.B., et al.: Prediction of power system frequency response after generator outages using neural nets. IEEE Proc. C Gener. Transm. Distrib. 140(5), 389–398 (1993)
19. Aguero, E.D., Colome, D.G., Granda, N.V.: Adjustment of frequency transient response with reserve deficit using artificial neural network. In: Proceedings of the 2016 IEEE PES Transmission & Distribution Conference and Exposition-Latin America (PES T&D-LA), pp. 1–6. Morelia (2016)
20. Wu, Y.-K.: Frequency stability for an island power system: developing an intelligent preventive-corrective control mechanism for an offshore location. IEEE Ind. Appl. Mag. 23(2), 74–87 (2017)
21. Gao, K., et al.: Transient stability assessment for power system based on one-dimensional convolutional neural network. Autom. Electr. Power Syst. 43(12), 18–26 (2019)
22. Niu, Z., et al.: Short-term wind power forecasting model based on deep gated recurrent unit neural network. Electr. Power Autom. Equip. 38(5), 36–42 (2018)
23. Li, Y., et al.: Small signal stability assessment of power system based on convolutional neural network. Autom Electr Power Syst. 43(2), 59–59 (2019)

FIGURE 11 Comprehensive evaluation results

TABLE 9 Frequency evaluation accuracy of the four artificial intelligence algorithms

| Model | E_{AC1}/% | E_{AC2}/% | E_{AC}/% |
|-------|-----------|-----------|----------|
| ANN   | -         | -         | -        |
| DT    | 100       | 90.01     | 96.68    |
| KRR   | 100       | 92.20     | 97.40    |
| CNN   | 100       | 97.51     | 99.16    |

Abbreviations: ANN, artificial neural network; CNN, convolutional neural network; DT, decision tree; KRR, kernel ridge regression.
24. Huang, X., et al.: Fault diagnosis of high-voltage circuit breaker based on convolution neural network. Electr. Power Autom. Equip. 38(5), 136–140+147 (2018)

25. Xu, S., et al.: A deep learning approach for fault type identification of transmission line. Proc. CSEE. 39(1), 65–74, 321 (2019)

26. Teng, F., Trovato, V., Strbac, G.: Stochastic scheduling with inertia-dependent fast frequency response requirements. IEEE Trans. Power Syst. 31(2), 1557–1566 (2016)

27. Li, S., et al.: Optimal and direct-current vector control of direct-driven PMSG wind turbines. IEEE Trans. Power Electron. 27(5), 2325–2337 (2012)

28. Wang, Y., et al.: A novel supplementary frequency-based damping control for VSC-HVDC station connected to a weak AC grid. Proc. CSEE. 38(10), 2989–2998+3149 (2018)

How to cite this article: Wang C, Li B, Liu C, Li P. Convolutional neural network-based power system frequency security assessment. IET Energy Syst. Integr. 2021;1–13. https://doi.org/10.1049/esi2.12021