Power Quality Prediction of Active Distribution Network Based on CNN-LSTM Deep Learning Model

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Abstract. Aiming at the sequential and non-linear characteristics of power quality data over a long time span, a set of PQ evaluation and early warning system with DG distribution network based on deep learning is proposed. The intelligent power distribution network power quality monitoring and early warning system aims to realize the monitoring and forecasting and early warning functions of multiple indicators of power quality in the distribution network. First, use the sliding window to convert the power quality data into a number of square graphs with time as the scale; second, use the feature extraction advantages of the (Convolutional Neural Network, CNN) to extract the features of each square graph sample and extract it The characteristic information of is transformed into the input of (Long Short Term Memory, LSTM) in a time series sequence; Finally, according to the output of CNN, LSTM is used to complete the power quality data prediction of the active distribution network. Through an IEEE-13 node active distribution network simulation example with distributed power sources, this method decouples the feature extraction analysis and prediction tasks of power quality data, and simplifies the prediction work. Compared with the selected control model, it is significantly Improve the prediction accuracy.

Keywords: Deep learning · Convolutional neural network (CNN) · Long-term and short-term memory network (LSTM)

1 Introduction

A complete power quality (PQ) information prediction and early warning system is the key to timely discovering power quality problems in distribution networks and improving power quality. Countries around the world are actively seeking to use environmentally friendly and renewable energy sources. Among them, distributed new energy sources represented mainly by wind power and photovoltaic power generation are attracting more and more attention. A distribution network with the ability to combine control of various DGs, energy storage, controllable loads, etc.-Active Distribution Network (ADN) has become one of the most important development models of smart distribution networks in the future [1]. However, due to the wide access of DGs and the flexible operating characteristics of the active distribution network, each node of the active distribution

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network will inevitably face severe power quality problems such as voltage fluctuations and flicker, harmonic distortion, and over voltage [2]. The grid connection of a large number of distributed power sources will bring a more severe test to power quality. The realization of high-performance power quality situation prediction, evaluation and early warning is a prerequisite for effective power quality active control.

Regarding the problem of power quality prediction, although experts at home and abroad have carried out active explorations, systematic in-depth research and consensus results have been few. So far, there are relatively few research literatures on power quality prediction. Literature [3] proposed a combined forecasting model based on linear regression method (LR), random time series method (RTA) and gray model (GM), which improved the prediction accuracy of a single method, but improved the weight determination and modeling The difficulty. Literature [4] combined autoregressive moving average (ARIMA) model and BP neural network to predict power quality indicators, using their respective good performance in handling non-stationary series and high-dimensional nonlinear problems, but their time-dependent data time correlation The ignorance of this will significantly reduce the accuracy of medium and long-term forecasts. Literature [5] uses a combination of discrete Fourier decomposition and time series autoregressive (AR) to predict. Because it removes part of the frequency domain components, there is a defect that the prediction results are lacking as a whole. Literature [6] proposed a prediction method based on dynamic time warping (DTW) and MonteCarlo algorithm. This method introduces clustering ideas to effectively improve the prediction performance, but the randomness introduced by the Monte Carlo algorithm will lead to a certain degree of power quality prediction results. Uncertainty. Literature [7] proposed a random forest model (RF) prediction method with better prediction effect by quantifying the relationship between power quality indicators and temperature, energy storage battery status, but because it needs to consider specific lines, equipment parameters and operation Information is only applicable to certain specific occasions. Literature [8] puts forward a power quality prediction method based on improved KPCA and GA-BP neural network by taking environmental factors, load and historical power quality data as input. Although this method has good prediction results, the method used the algorithm tools are complicated, and the prediction accuracy of BP neural network is limited, which is not suitable for high-complexity target prediction. Literature [9] first reconstructed the phase space of the power quality data by using the chaos theory, and then used the particle swarm algorithm to optimize the prediction parameters of the least square support vector machine, so that the prediction model has a faster convergence speed. And higher prediction accuracy, but considering that support vector machines are generally only suitable for small data volume predictions, they have certain limitations in use. The methods proposed in the above documents have their own characteristics, but under the background of the active distribution network with high DG penetration in the future, they face the high-dimensional and non-linear correlation characteristics between the multiple influencing factors of system power quality and the data of various indicators of power quality. How to better achieve the prediction performance of power quality index items in a longer period of time is still very challenging.

In recent years, in order to solve traditional load clustering methods that require manual setting of load characteristic indicators and the inability to consider load timing characteristics, multiple deep learning models such as recurrent neural network (RNN), convolutional neural network (CNN) and deep confidence network (DBN) and other artificial intelligence models have been vigorously developed and applied in the field of power quality forecasting [10], especially the Long Short-Term Memory (LSTM) model in load forecasting and other time series forecasting applications. Get the attention of the industry. Literature [11] proposed a load forecasting method based on the CNN-LSTM hybrid neural network model. First, a convolutional neural network (CNN) is used to extract feature vectors from a continuous feature map constructed by load influencing factors, and then use the previously extracted feature vectors Establish the LSTM model, and finally carry out the corresponding load forecast [12]. LSTM deep learning has unique network characteristics and its powerful memory function. It can not only realize good memory but also deeply mine the time correlation of massive multi-dimensional time series data in a long time span [13, 14]. The time series prediction function is very strong.

This paper proposes a method for predicting steady-state power quality indicators of active distribution networks based on convolutional neural networks (CNN) and LSTM network deep learning models. First, the structure of the CNN-LSTM model is introduced. Secondly, the obtained data set is preprocessed and segmented according to the model requirements, and load and power quality data are selected as the prediction target to establish a load training and test set that meets the deep learning model. Power quality training and test set; then, use the training set and test set obtained by data segmentation to train and test the respective CNN-LSTM models of load and power quality, and optimize the parameters of CNN and LSTM to select training The model with the best effect; then, use the selected optimal model to complete the forecast of the electricity load in the future period; then, according to the environmental variables in the future period and the predicted load, complete the forecast of the power quality in the future period; finally, pass The IEEE-13 node simulation example of an active distribution network with distributed power sources analyzes and verifies the effectiveness and advancement of the proposed method for predicting the steady-state index of active distribution network power quality (Fig. 1).

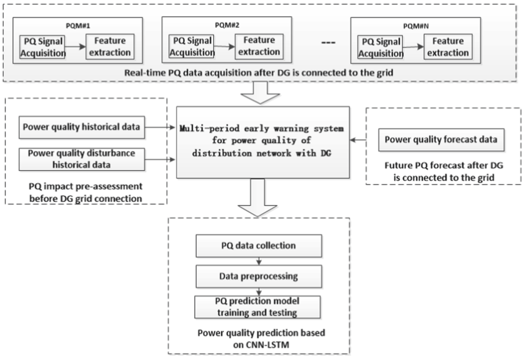

Fig. 1. System framework of PQ prediction based on clustering and LSTM model

2 The Overall Framework of the Hybrid Deep Learning Predictive Model

The system framework of the power quality prediction model of DG active distribution network based on convolutional neural network (CNN) and LSTM deep learning network model, mainly including PQ data set preparation, PQ data preprocessing, CNN-LSTM model training and testing, PQ Data prediction has four functional modules.

The main tasks of each functional module:

1) PQ data set preparation: According to the forecast demand of power quality steady-state index data, arrange environmental variable monitoring devices, load monitors, and load monitors at suitable locations in the active distribution network with three distributed energy sources including photovoltaics, wind power, and fuel cells. Intelligent instruments such as power quality monitors can obtain system light intensity, temperature and other environmental factor data, load data, and corresponding power quality common steady-state indicator data in a long time span, and associate and save them based on the same time mark. As a data source for predictive model training and performance evaluation.
2) PQ data preprocessing; preprocessing and segmenting the acquired data set according to model requirements. And select the load and power quality data as the prediction target to establish the load forecasting training and testing set and the power quality forecasting training and testing set that meet the deep learning model.
3) CNN-LSTM model training and testing: build a CNN-LSTM deep learning network model, use the training set and test set obtained by data segmentation to train and test the respective CNN-LSTM models of load and power quality, and test CNN and LSTM The parameters are tuned to select the model with the best training effect; then, the selected optimal model is used to complete the forecast of electricity load in the future period.
4) PQ data prediction: Obtain the environmental factor forecast data and load forecast data of the target power grid in a certain period in the future, and implement clustering to determine its category; use it as input data, and call the CNN-LSTM network of the corresponding category that has been trained The model makes predictions, and the output of the model is the predicted data of the target grid power quality steady-state index items to be obtained.

3 CNN-LSTM Hybrid Depth Model

3.1 Convolutional Neural Network (CNN) Model

Convolution Neural Network (CNN), as a feedforward neural network, is one of the most popular and widely used models in the field of deep learning in recent years [15–19]. It consists of one or more convolutional layers and pooling layers, as well as associated weights and a fully connected layer at the top. Through the convolutional layer and pooling layer in its structure, CNN can make full use of the two-dimensional characteristics of the original data, and can automatically extract the local features of the original data and make effective representations in the form of a combination of a single convolutional layer and a single pooling layer. At the same time, through the information transfer between each combined layer, CNN can establish a condensed and complete feature vector for the top fully connected layer. Therefore, this paper uses this superior feature of CNN to extract features of the data. For the input, the characteristic information format transfer is shown in Fig. 2. In the figure, N is the abbreviation of Node, and (N, 32, 32) is the node matrix.

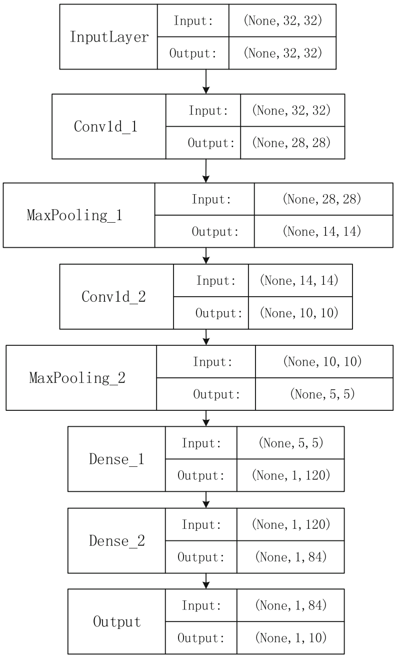

Fig. 2. Convolutional neural network information transfer format

3.2 Long Short-Term Memory (LSTM) Neural Network

LSTM neural network is an improved deep learning algorithm based on time recurrent neural network (RNN). Because of its unique design structure, LSTM is particularly suitable for processing tasks with very long time intervals and delays. As a nonlinear model, LSTM is very suitable for constructing larger deep neural networks.

LSTM has a form structure of a chain of repeated modules of a neural network [20]. Compared with a single neural network layer of (RNN), LSTM has four layers that interact in a very special way. The repeating module chain of LSTM neural network is also called LSTM cell unit, as shown in Fig. 3. In the entire LSTM network structure, the cell state of the LSTM unit is the most critical. They are like a conveyor belt on the production line, which transmits information from the previous cell unit to the next cell unit. The linear correlation with the elements in the current cell unit is low, and the efficiency of information transmission is low. Very high. The LSTM network deletes information or adds information to the unit state through a structure called "gate" [18]. "Gate" is a structure that controls the selective passage of information. It is composed of an output value in the [0, 1] interval to activate the function Sigmoid and pointwise multiplication operations. Each LSTM cell unit contains a forget gate, an input gate, and an output gate. The forget gate is responsible for deciding to keep part of the unit state from the previous moment to the unit state at the current moment; the input gate is responsible for deciding to keep the proportion of the unit state from the current moment input to the current moment; the output gate is responsible for deciding the proportion of the unit state output at the current moment.

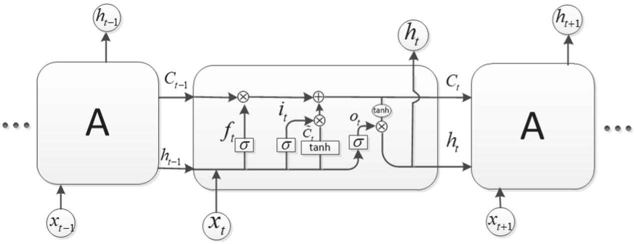

Fig. 3. Structure of LSTM cell

The first step of the LSTM neural network needs to solve the problem of discarding part of the information in the cell state. This function is realized by the forget gate. The forget gate is a Sigmoid function with the output of the previous cell unit and the input of this cell unit as input. It generates a value in [0, 1] for each item in it to control the state of the previous cell unit the degree of being forgotten. In Fig. 3, f_t is the output sequence of the Sigmoid function:

$$f_t = \sigma\left(W_f \cdot \left[h_{t-1}, x_t\right] + b_f\right) \tag{1}$$

Where σ is the Sigmoid activation function, W_f is the weight coefficient matrix, and b_f is the bias term.

The input gate and a hyperbolic tangent function tanh cooperate to update the control information. The activation function creates a new candidate value vector $\tilde{C}_t$, and the input gate $\tilde{C}_t$ generates a value in [0, 1] for each item, determines how much new information is added, and updates the state of the unit:

$$i_t = \sigma\left(W_i \cdot \left[h_{t-1}, x_t\right] + b_i\right) \tag{2}$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{3}$$

$$\tilde{C}_t = \tanh\left(W_c \cdot \left[h_{t-1}, x_t\right] + b_c\right) \tag{4}$$

The output gate is used to determine the last part of the information output. First, the Sigmoid activation function is used to determine which part of the cell state will be output to the next unit, and then we process the cell state through the tanh function to generate a value in [0, 1] for each item, and compare it with the Sigmoid function The output results are multiplied, and finally, the degree to which the control unit status is filtered:

$$o_t = \sigma\left(W_o \cdot \left[h_{t-1}, x_t\right] + b_o\right) \tag{5}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{6}$$

Where i_t, $\tilde{C}_t$, o_t and f_t have the same form, but their respective weight coefficient matrices $\{W_\mathrm{i}, W_\mathrm{c}, W_\mathrm{o}\}$ and bias terms $\{\mathrm{b_i}, \mathrm{b_c}, \mathrm{b_o}\}$ are completely different from each other; Sigmoid and functions are used to "compress" the input continuous real value to where is a certain range between [0, 1] and [−1, 1].

3.3 CNN-LSTM Network Model

For the regression prediction of time series, when faced with a large-scale data set with multiple features, it is often difficult for a simple LSTM model to achieve high-precision prediction results. The main reason is that its temporal structural characteristics make it difficult to extract Go to the global feature information. However, for CNN, one of its characteristics is that it can extract the local features of the input data and generate high-level features through layer-by-layer combination abstraction. This feature completes the high-level mapping of the global features of the input data and solves the feature extraction of the LSTM model. Of inadequacy. Therefore, through the combination of CNN and LSTM network models, adding the CNN feature extraction layer before the LSTM model, on the one hand, it can decouple the two tasks of feature extraction and time series prediction that a separate LSTM model needs to do. First, use CNN for data set The feature extraction and flattening the extracted feature information as the input of the LSTM model, and then use LSTM to complete the time series prediction. On the other hand, it can also reduce the complexity of the single LSTM model and effectively improve the prediction accuracy of the model. For complex data The regression prediction of the set is of great significance. The CNN-LSTM network model is shown in Fig. 4.

In order to evaluate the prediction performance of the model, select the Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (Mean Absolute Percentage Error) in the evaluation indicators of the regression prediction algorithm. MAPE) is used as an evaluation index item. For the MAPE index, if there is 0 item in the true value of the data, then the index is no longer suitable as an evaluation item.

The calculation formula of each index is as (7)–(9):

$$\varepsilon_{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{7}$$

$$\varepsilon_{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[y_i - \hat{y}_i\right]^2} \tag{8}$$

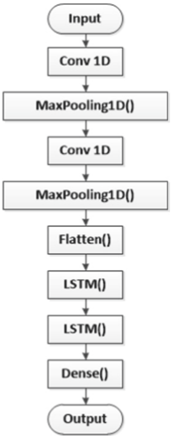

Fig. 4. CNN-LSTM network model structure

$$\varepsilon_{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{9}$$

In the formula: y_i and $\hat{y}_i$ are the true value and predicted value of the time data respectively; n are the total number of predictions.

4 Power Quality Prediction Model Based on CNN-LSTM

4.1 PQ Influencing Factors and Data Set Construction

For the Active Distribution Network (ADN), it often contains a variety of distributed power (DG), including wind power (WP), photovoltaic power (Photovoltaic power, PV), fuel cell (FC), biomass power (Biomass power, BP), etc., among which wind power, photovoltaic power and fuel cells are the most commonly used. For DG, the principle is nothing more than converting a certain form of energy into electrical energy through corresponding devices. Common methods include wind energy to electrical energy, light energy to electrical energy, and biochemical energy to electrical energy. Therefore, environmental factors affect DG. Working status is very important. When the DG is connected to the ADN, the working status of each DG is closely integrated with the working status of the active distribution network. When external environmental factors affect the work of the DG, it will also indirectly affect the ADN. The power quality of the ADN is bound to be Will be affected, so environmental factors are one of the influencing factors of ADN power quality. In the active distribution network, in addition to a large number of DGs, a large number of different types of electrical loads will definitely be connected. These loads play the role of power consumption in the ADN. Therefore, when the load fluctuates, its fluctuations It will also become one of the influencing factors of ADN power quality changes. At the same time, in addition to the above two ADN power quality influencing factors, by adding appropriate prior knowledge in the training of the neural network model, that is, predicting the data at the current time of the target, using single-step or multi-step historical target data as Entering one of the characteristic variables can effectively improve the performance of the model. Therefore, the ADN power quality data itself is also an influencing factor of ADN power quality changes [14]. The influencing factors of ADN power quality changes are shown in Table 1.

Table 1. Summary of factors affecting power quality.

Influencing factors	Characteristic variable	Unit
Envirnmental factor	**Temperature**	/°C
Envirnmental factor	**Light intensity**	W/m
Envirnmental factor	**Wind speed**	m/s
The fuel cell	**Fuel cell capacity**	/AH
Load factor	**Load type curve**	/W
Historical data	*Voltage deviation*	/
Historical data	*Frequency deviation*	/
Historical data	*Voltage three-phase unbalance*	/

According to the influencing factors of power quality, the input of deep learning model training can be constructed, in the form of a two-dimensional vector containing multiple features, the ordinate represents the feature vector, and the abscissa represents the time span of this input.

Thereafter, in order to evaluate the power quality prediction performance of the obtained LSTM model, a considerable amount of specific historical data is also required for testing and evaluation. Therefore, after selecting the historical data set used to determine the power quality LSTM prediction model, it needs to be data segmented. Based on general principles, this article divides the used power quality historical data set into training set and test set in chronological order, and their magnitudes account for about 70% and 30% of the total historical data set, respectively. In this way, it can not only ensure that the LSTM prediction model can fully learn the relevance and regularity of the input variables and output index items in the historical data set, but also can fully guarantee the effectiveness of the obtained prediction model performance evaluation.

4.2 Data Preprocessing

1) Abnormal data processing
   There are many factors influencing power quality prediction. In the process of acquiring and counting power quality data, load data and environmental data, there will be abnormal data due to model operation errors and negligence. Their existence will affect the training model to a certain extent. Accuracy, so you need to exclude them. There are 4 common outlier processing methods, which are to delete the records

containing outliers; to treat the abnormal values as missing values and hand them over to the missing value processing methods; use the average value to correct them; not to process them. The above several methods can be selected and used according to the actual situation to improve the data set.

2) Data standardization
Considering that each characteristic variable that affects power quality has different dimensions, and each characteristic variable has a large numerical span within each dimension, in addition, analyze the input and output range of the nonlinear activation function in the cell unit in the LSTM deep learning model, In order to prevent the neurons in the LSTM model from falling into a saturated state, and to ensure that all variables can equally affect the change prediction of power quality, it is necessary to standardize all variables and power quality indicators.
Characteristic variables such as temperature, light, wind speed, electricity load, fuel cell capacity, historical power quality, etc. are all standardized, and they are linearly converted to [0, 1] using formula (10). Correspondingly, the predicted data of the power quality index items obtained by the LSTM model are also standardized data. In order to obtain the power quality data with actual physical significance, it needs to be de-standardized using formula (11):

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

$$x = x' * (x_{\max} - x_{\min}) + x_{\min} \tag{11}$$

In the formula, x, x' respectively represent the value of the variable or index item before and after normalization; $x_{\max}$, $x_{\min}$ select the maximum and minimum limits of each variable or index item in the historical data set.

3) Data set segmentation
For a given data set, in order to obtain a CNN-LSTM deep learning model that can realize the power quality prediction function, it is first necessary to determine the input object and output target according to the data set to form a supervised learning sequence, and secondly, a large amount of specific input variable historical data and Output power quality target historical data for supervised learning training to obtain the internal parameters of the CNN-LSTM network model. Finally, in order to evaluate the power quality prediction performance of the obtained CNN-LSTM model, a proper amount of specific historical data is required for testing and evaluation. Therefore, based on general principles, the data set containing characteristic variables and power quality target data is divided into training set and test set in chronological order, and their magnitudes account for approximately 70% and 30% of the total data set, respectively. In this way, it can not only ensure that the CNN-LSTM prediction model can fully learn the relevance and regularity of each input variable and output target item in the historical data set, but also can fully guarantee the effectiveness of the obtained prediction model performance.

4) Set the input step size of the training and test sets
As the feature extraction part of the CNN-LSTM model, CNN has one of the advantages of its application in that it can directly extract feature information from the numerical matrix. Therefore, after the data is divided, it is necessary to specify the

step size n_steps (single step corresponding to a time point) of the single input data when training and testing the model, and then form the input matrix. In addition, the selection of n_steps can refer to the value of the feature variable. In general, its value should be selected as the number of feature variables to form a square matrix with the same rows and columns to facilitate subsequent CNN feature extraction.

4.3 Power Quality Prediction Based on CNN-LSTM

After the data is preprocessed, the power quality prediction model based on CNN-LSTM can be trained and tested according to historical power quality data and power quality influencing factor data. Then, by using the load forecast in the future period completed in 3.4, the complete power quality influencing factor data in the future period can be obtained, and finally the power quality forecast data in the future period can be obtained according to the input of the influencing factors.

5 Power Quality Prediction Results and Comparative Analysis

In order to verify the superiority of the CNN-LSTM prediction model proposed in this article, the typical methods of time series prediction are selected as references, mainly including differential autoregressive movement translation (ARIMA) model, BP neural network, CNN and LSTM.

For the prediction of power quality in the future, use CNN-LSTM to model the PQ training set and use the test set for testing, and select Voltage Deviation (VD) as a case. The test results are shown in Table 2. At the same time, using the predicted load of the next two days to predict the power quality of the next two days, and compare with the reference model, the results are as follows (Fig. 5).

Table 2. Comparison of MAE, RMSE, MAPE prediction results of each model.

VD	ARIMA	BP	CNN	LSTM	CNN-LSTM
MAE	2.08	0.92	0.53	0.53	0.38
RMSE	2.91	1.60	0.67	0.89	0.50
MAPE	187.1%	27.4%	10.4%	10.5%	7.6%

Through the observation and analysis of Table 2, Fig. 7, and Fig. 8, we can know that in terms of MAE and RMSE indicators, BP, ARIMA, LSTM, CNN, and CNN-LSTM are in a decreasing state, and the CNN-LSTM model corresponds to the smallest value. It shows that the actual situation of the error between the predicted value and the actual value of the CNN-LSTM model on the test set is the best. It also shows that the deviation between the predicted value and the actual value on the test set is the smallest, and the model prediction is the most stable; just MAPE In terms of indicators, ARIMA, BP, LSTM, CNN, and CNN-LSTM are in a decreasing state. The minimum MAPE index of

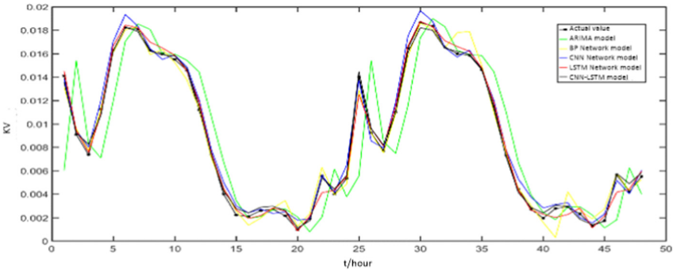

Fig. 5. Comparison of VD prediction curves and actual curves of each model in the next two days

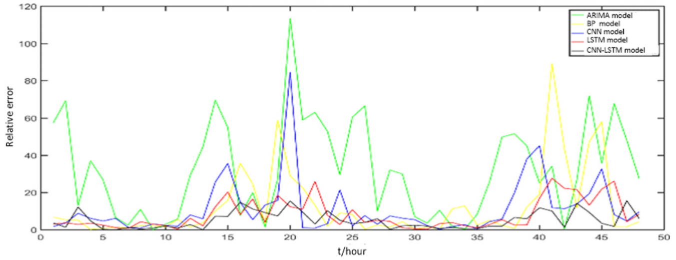

Fig. 6. Comparison of relative errors of VD prediction results of each model in the next two days

the CNN-LSTM model is only 1.8%, which is the closest to 0, indicating the predicted value of the CNN-LSTM model on the test set. The relative error with the actual value is the smallest, and the model's prediction accuracy is the highest; for the load forecast in the next two days, the CNN-LSTM model has the smallest forecast fluctuation, and the relative error is kept within 6%, which fits the actual value as a whole; CNN, LSTM model The overall volatility is good, but the LSTM model fluctuates too much at individual points; BP performs the worst, with nearly half of the points exceeding 4%. Although the performance of ARIMA is much better than BP, the prediction effect is still poor. The main reason for the above situation is that the BP neural network uses the fully connected layer as the hidden layer, and the feature extraction ability under multivariate is weak, and it does not have the ability to learn sequence dependence on a long time span. Therefore, the data forecast for future periods will fluctuate greatly.; The ARIMA model is complicated in order and is not suitable for large-volume data prediction. In essence, it can only capture linear relationships. In addition, it uses time as the only variable to target prediction, so that its predictive indicators MAE and RMSE are better, but it does not have time. The learning ability of the sequence dependence relationship fluctuates greatly at some prediction points, and the index MAPE is correspondingly large; the CNN model has a better feature extraction ability, but it is difficult to learn the dependence relationship of the target sequence over a long time span; LSTM model It can well memorize the dependence of the target sequence in a long time span, but for multi-feature variable data sets, the feature extraction ability is poor; the CNN-LSTM model makes full use of the advantages of the CNN and LSTM models. For multiple features, generally It can give full play to its advantages and has the best prediction performance. From a comprehensive analysis point of view, the optimal model for load forecasting is CNN-LSTM.

In addition to the voltage deviation indicators, frequency deviation and harmonics are selected as the prediction objects. The comparison of the indicators for the next two days and the results of the prediction curve and the time curve are as follows (Fig. 8).

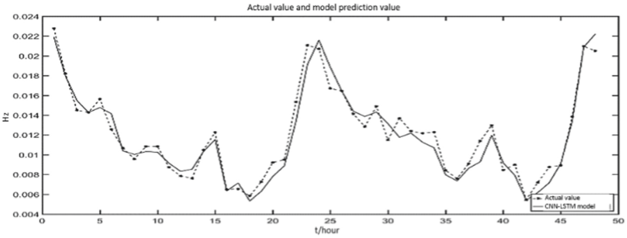

Fig. 7. Comparison of frequency deviation prediction curve and actual curve of CNN-LSTM model in the next two days

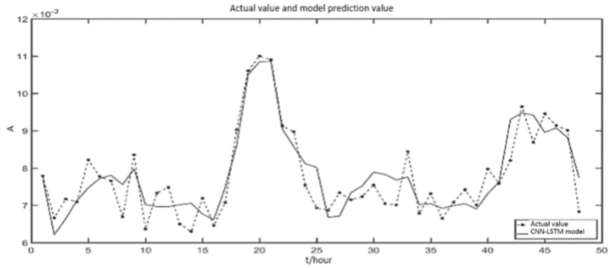

Fig. 8. Comparison of harmonic prediction curves and actual curves of CNN-LSTM model in the next two days

For the two indicators of frequency deviation and harmonics, analyze the prediction of the two steady-state indicators. From above figures, it can be seen that the MAPE indicator of the CNN-LSTM prediction model is similar to that of the voltage deviation prediction, and the predicted value is According to the actual value change curve, the CNN-LSTM model has performed a good fit to the power quality indicators. Overall, the CNN-LSTM deep learning model is the best choice for power quality prediction in active distribution networks.

6 Conclusion

In response to the increasing demand for power quality situational awareness in future DG-containing active distribution networks and considering the limitations of traditional prediction algorithms, this paper proposes a power quality prediction method based on the CNN-LSTM deep learning model. This method takes advantage of the two deep learning models of convolutional neural network and long-short-term memory network.

It not only solves the problem of difficult extraction of massive and complex power quality data features, but also solves the lack of correlation information for time series in traditional forecasting algorithms. Considerations. Finally, the comparison of calculation examples shows that the prediction model of the early warning system has good accuracy and is suitable for the power quality data prediction of today's active distribution network with DG.

In subsequent work, it is necessary to use more effective algorithm tools to further improve the data cleaning and processing tasks, and at the same time add more factors to the power quality influencing factors, such as seasonal changes, holidays, and emergencies, so as to further improve the performance. Improve the universality and accuracy of prediction models.

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