International Journal of Information Technologies and Systems Approach
Volume 16 • Issue 2

Research on Power Load Forecasting Using Deep Neural Network and Wavelet Transform

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ABSTRACT

In today's rapid economic development, industrial and civil electricity consumption is growing year by year, and how to guarantee stability of power system operation has become the focus of attention of the power sector in each country. Power load forecasting has been closely associated with the modernization of power system management and is a vital guarantee for the safe and stable operation and economic efficiency of the power system. In this article, the authors propose a recurrent neural network (RNN) decision fusion forecasting framework based on the wavelet transform to address the power load forecasting problem. The framework firstly performs the wavelet transform on the power load data and uses Daubechies wavelets to extract the high-frequency and low-frequency parts of the data; then the data with different frequencies are combined with the original data and fed into the RNN model separately, and the decision fusion is performed in the output layer; finally, the prediction results are obtained by superposition of two RNN networks. The results showed that the error of the predicted data in the last nine years decreased by 50%, compared with the traditional method of feeding the data into the RNN model for training, which provides a new idea for future power load forecasting.

KEYWORDS

Deep Learning, Power Load Prediction, Recurrent Neural Network, Wavelet Transform

INTRODUCTION

The development of the electric power industry is the basis of the industrial development of the whole country, which is related to national security, social stability, and people's livelihood, and is an indispensable pillar industry in modern society. As a special kind of energy, the production and

DOI: 10.4018/IJITSA.322411 *Corresponding Author

consumption of electricity are simultaneously completed, which makes it impossible to store. Thus, a dynamic balance between the production and consumption of electricity must be maintained at all times, which neither allows the supply to exceed the demand, which wastes energy resources and causes transmission blockage, nor allows the supply to exceed the demand, which cannot guarantee the users' demand for electricity and thus induces power shortage and large area blackout (Lin & Luan, 2020). To ensure the balance between supply and demand of electric energy, power load forecasting came into being. Through analyzing the historical load, predicting the future load situation of electricity, and formulating generation, transmission and power supply plans in advance based on the prediction results can achieve the balance of supply and demand in the power system to the greatest extent and ensure the stability and quality of power supply in the power system (Kosowski et al., 2019). Therefore, the prediction of regional load in a certain period or several periods of time is extremely significant for the development of regional power industry. Currently, the power data are growing exponentially, the scale of power grid is getting bigger and bigger, the complexity of power data is getting higher and higher, the factors affecting the load are becoming more and more diversified. Also, social, political, weather, and even economic factors have become the background of power load prediction, and the traditional means of power load prediction are hardly applicable to the prediction analysis in today's complex background (Kumar et al., 2022). A comprehensive and accurate load forecasting is the key for the power system to be able to operate safely and regulate flexibly, so it is particularly important to study an algorithm with high accuracy in load forecasting and that can take more external factors into account. Traditional statistical load forecasting models have a large data dependency, small-scale data cannot be trained perfectly, and large-scale data are time-consuming and labor-intensive to process. Therefore, how to build an algorithm that is fast, while taking into account the scale of the data, becomes an urgent problem (Meng et al., 2022).

The first step is to start from the data themselves, which have certain patterns, but it is difficult to distinguish the specific forms of different parts of the data from traditional regression and statistical theories alone. As a result, further decomposition of the data is needed. In this study, the authors took into account more information such as weather, economy, and service life, as predictors, but it is difficult to count such complex data for most regions, so starting the analysis from existing data is a vital way to enhance data performance (Deng et al., 2019). With the development of signal processing technology, modern signal processing methods such as wavelet variation and empirical modal decomposition have greatly enhanced the performance of the data in the frequency domain. Therefore, the selection of such methods for data denoising and frequency domain feature extraction can greatly enhance the data performance. As for the selection of prediction methods, machine learning type methods have become the main research object for power prediction when the computer performance has not been significantly improved (Rhif et al., 2019). Nowadays, the development of deep learning has greatly increased the interest of the academic community in the application of deep learning to prediction. Deep neural networks ensure the model accuracy and robustness through complex network structure, which greatly improves the prediction accuracy (Emmert-Streib et al., 2020). To enhance the signal performance and improve the result, the wavelet transform is also used to extract the frequency feature. Therefore, in this paper the authors use the combination of the wavelet transform and deep learning to complete the electric load prediction. The contributions of this paper are as follows:

1. The authors extracted the high-frequency and low-frequency characteristics of electric load data using wavelet variations to enhance data availability.
2. The authors established a decision-layer fusion method for power load forecasting, fed frequency domain data and raw data into two recurrent neural networks (RNNs) separately, and fused them at the decision layer to improve the model prediction accuracy; its prediction error decreased by 50%, compared with direct training.
3. The authors selected the data of the last five years from the corresponding regions for the actual prediction test; the results showed that the proposed method has certain generalization ability.

The remainder of this paper is organized as follows: The second section introduces related works for deep learning and electric load prediction; the third section introduces the model using the wavelet and RNN; the fourth section describes the experiment and result analysis of the prediction; the fifth section provides the authors' discussion of the experiment and result analysis of the prediction; the sixth section offers the conclusion.

RELATED WORKS

Power Load Forecasting Study

The global economy is developing rapidly, the demand for electricity is skyrocketing, and the research and application of power load forecasting has gradually become the focus of scholars. At present, the research on electric load can be divided into time series methods, regression analysis methods, Kalman filtering methods, and exponential smoothing methods (Alkesaiberi et al., 2022). Optimization through traditional mathematical derivation or machine learning methods has become the focus of current research. For the study of electric load forecasting, it is mainly divided into ultrashort-term forecasting, short-term forecasting, medium-term forecasting, and long-term forecasting (Zhao et al., 2021). Chen et al. (2017) generalized the time series model and changed the form to a model with transfer functions of multiple variables. The short-term load is decomposed into a cyclical component and an acyclical component, divided into two parts; it predicts both components, and the predictions are compared with the trend of big data. Besides, this method does not require a large amount of data and has a fast computational speed, which gives better prediction results when the system is less influenced by the external environment and is in a steady state. Wu Jun (2018) used the artificial clustering algorithm to optimize the weight coefficient of the background value of the traditional GM (1,1) model and improved the established grey model by minimizing the error, thus improving the accuracy of the prediction. However, the grey model is relatively closed, unable to reflect the characteristics of the periodic change of data, and, when the degree of data dispersion increases, the prediction effect will rapidly deteriorate. Therefore, it is generally used together with other methods. Vafamand et al. (2018) used the CPLS model to improve the uncertainty in electricity forecasting. In addition to using traditional mathematical methods for power forecasting, the continuous development of machine learning techniques has produced a gradual increase in power load forecasting using support vector machine and random forest, among others. Bo et al. (2020) used EMS to obtain load data online, and trained support vector machines reactive power forecasting models using historical data, thus improving the model and scope of power system forecasting. It can be seen that the current power load research is no longer limited to traditional load forecasting, but more specific and good research has been carried out to explain the underlying group factors of power load, so as to better improve the power load theory.

For the traditional time series and regression analysis methods, the data pattern is relatively single and the robustness after receiving disturbance is low. Thus, in recent years, the traditional research on power load forecasting has been gradually reduced and replaced by the deep learning forecasting research of neural network methods.

Prediction Study of the Deep Neural Network Method

As artificial intelligence and intelligent algorithm have developed drastically in these years, neural network methods with stronger computational power and robustness have been widely used. Dudek Grzegorz (2021) used patterns of time series to simplify the complex relationships between input and output, which makes the learning process more sensitive to the neighborhood. Based on the coder-decoder architecture inspired by WaveNet, researchers use extended causal convolution and hop connection to build a new model using long-term information (Dorado Rueda et al., 2021), which can learn from an input sequence to produce a prediction sequence in a one-time manner. The introduction of a day similarity metric model (Zoran et al., 2021) based on a multifiltering process produces optimal similar day selection even when it is not obvious. Considering that the parameters of the neural network have a significant impact on its performance, Shafiei et al. (2021) proposed a prediction method using neural network and the particle swarm optimization (PSO) algorithm. At the same time, they used a three-layer feedforward neural network trained by the back-propagation algorithm, next to the improved Gbest PSO algorithm, and defined the prediction error of the neural network as the cost function of the PSO. Eskandari et al. (2021) rearranged the electrical load and temperature time series into independent two-dimensional matrices and extracted the load and temperature features using convolutional neural network. Moradzadeh Arash et al. (2021) proposed a Bi-LSTM short-term electric load forecasting method for microgrids with great processing power for time series data based on reviewing various electric load forecasting techniques. Ahmad Ayaz et al. (2021) and Matrenin et al. (2020) took neural network forecasting as a starting point, respectively, from different training stages of the forecasting model for optimization of model parameters and appropriate selection of hyperparameters and training methods to significantly improve the accuracy and generalization performance of prediction models.

The above numerous studies related to neural networks evidence that the current improvement in power load forecasting is mainly started by increasing the accuracy of load forecasting, reducing the forecasting operation time, and incorporating more disturbing factors. Therefore, considering the error uncertainty of load data, enhancing the important information through modal decomposition, improving the neural network processing process, and considering more time factors are the easiest ways to deal with such problems. For this reason, in this study, the authors carried out research on power load prediction in both data and model and enhanced the accuracy of different components of the data by introducing the wavelet transform method to improve its anti interference ability. Meanwhile, in the model construction, they used the RNN method to improve the prediction accuracy and determined the decision and fusion strategy of the model data to reduce the prediction error.

ESTABLISHMENT OF RECURRENT NEURAL NETWORK POWER PREDICTION MODEL BASED ON THE WAVELET TRANSFORM OF LOAD DATA

Principle and Characteristics of the Wavelet Transform

Wavelet analysis technique is a recently proposed signal processing method, which is widely used in nonlinear and abrupt signal analysis. Compared with Fourier transform, wavelet analysis has adjustable time windows for the analysis of signals with different frequencies; at the same time, wavelet analysis can characterize the singularity of the signal and analyze the abrupt change characteristics of the signal (Jalayer et al., 2021). Wavelet analysis has a wider application in the direction of relay protection, harmonic analysis, fault location, power signal denoising, and power load prediction. Its specific definitions are as follows.

If the function $\psi\left(t\right)$ in the frequency domain satisfies Equation 1:

$$\int_0^\infty \frac{\left|\psi\left(\omega\right)\right|^2}{\omega}\, d\omega < \infty \tag{1}$$

or if, in the time domain, it satisfies Equation 2:

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0 \tag{2}$$

then the function $\psi\left(t\right)$ is a mother wavelet function. In Equation 1, $\psi\left(\omega\right)$ is obtained from the $\psi\left(t\right)$ Fourier transform; the translation and expansion of the mother wavelet function $\psi\left(t\right)$ can be obtained from Equation 3:

$$\psi_{a,b}\left(t\right) = \frac{1}{\sqrt{\left|a\right|}}\psi\left(\frac{t-b}{a}\right) \tag{3}$$

$\left\{\psi_{ab}\left(t\right)\right\}$ is called wavelet function, abbreviated as wavelet. a and b are real numbers; a is the scaling factor and b is the translation factor. The wavelet transform is mainly divided into continuous wavelet and discrete wavelet.

The Continuous Wavelet Transform

In analogy to the Fourier transform, the wavelet transform also includes the forward and inverse transforms, that is, by combining the signal $x\left(t\right)$ with the wavelets required by the loading properties $\psi_{abb}\left(t\right)$ by inner product. If the signal $x\left(t\right)$ is a productable real function, $\psi\left(t\right)$ is the mother wavelet function and is a real function, then $x\left(t\right)$ the continuous wavelet transform can be performed according to Equation 4:

$$CWT\left(a,b\right) = \frac{1}{\sqrt{\left|a\right|}}\int_{-\infty}^{+\infty} x(t)\psi\left(\frac{t-b}{a}\right)dt \tag{4}$$

The Discrete Wavelet Transform

In a practical wavelet transform application, when the signal and the wavelet in the stretching factor a and translation factor b. The continuous wavelet transform cannot be applied when there are discrete variables in the signal and wavelets, so the continuous wavelet transform should be discretized, which creates the discrete wavelet transform. Equation 5 shows the calculation procedure (Ghimire et al., 2019):

$$\begin{cases} a = a_0^m & a_0 > 0, m \in Z \\ b = nb_0 a_0^{m'} & b_0 > 0, n \in Z \end{cases} \tag{5}$$

The wavelet mother function can be expressed as Equation 6 after discretization:

$$\psi_{m,n}\left(t\right) = a_0 - \frac{n}{\psi}\psi\left(a_0^{-n1}t - nb_0\right) \tag{6}$$

The equation of discrete wavelet variation can be obtained by expanding the function of Equation 6, as Equation 7 shows:

$$DWT\left(a,b\right) = \int_R f(t)\mu_{m,n}(t)dt, m, n \in Z \tag{7}$$

For the wavelet transform, the selection of basis function has a significant impact on the result. In this paper, the authors selected Daubechies wavelet for data variation, which is usually abbreviated as dbN; N is the order of wavelet. The characteristics of Daubechies wavelet include finiteness, orthogonality, and tight branching set, which have the advantages of fast operation speed and high computational accuracy in mathematical operations. Daubechies wavelet has various forms, which is beneficial to decompose the components of historical load sequence with different frequency characteristics, so the authors conducted wavelet based on Daubechies wavelet analysis, in this study (Da Silva et al., 2019).

Recurrent Neural Network Power Prediction

Since power load forecasting often has a cyclical or longer-term trend of growth and decline, such characteristics need to be taken into account in the model selection process. Traditional back propagation neural networks have some predictive capabilities, but their performance in time series is generally slightly lower than that of RNN (Shi et al., 2022). RNN is established according to human cognition principles (Ahn et al., 2021). In contrast to the traditional deep neural networks, RNNs take into account the previous input, while the network can memory previous input, that is the current output of a sequence is also related to the previous output.

The RNN structure shown in Figure 1 can be represented by Equation 8:

$$O_t = g\left(V * f\left(U * x_t + W * S_{t-1}\right)\right) \tag{8}$$

In Equation 8, f, g is a nonlinear activation function, f It can be Tanh and other activation functions, g is usually Softmax, but it can be other functions, x_t indicates the current t is the input sample of the input layer at the current moment, S_{t-1} is the state information of the neurons in the hidden layer at the previous moment. According to Equation 8, it is easy to see that the output of the current moment has a certain relationship with the input of the current moment and the output of the previous moment, which has a very good time-series nature, and has certain advantages for the data with a more obvious temporal nature such as power load.

Model Prediction Based on the Wavelet Transform Power Load Optimization

To give full play to the data performance and the advantages of the wavelet transform, the authors used different forms of data trained separately in the final model prediction and the final nonlinear superposition to form the final prediction data, whose overall process is as follows (Figure 2).

Figure 1.
The structure of the RNN expanded

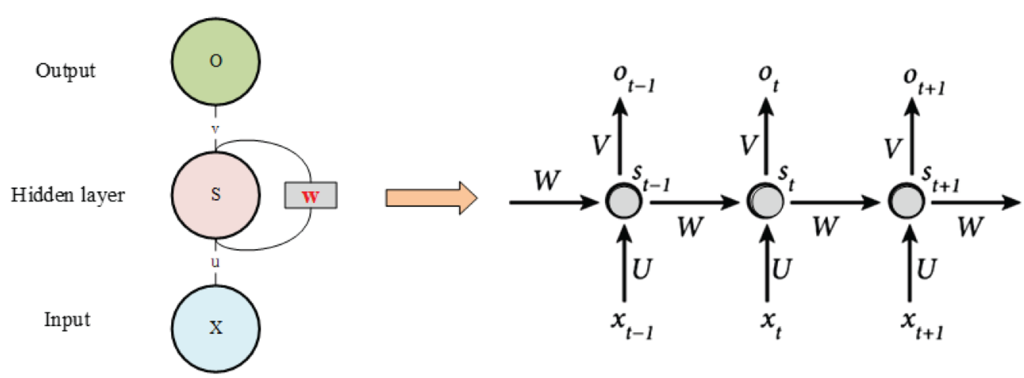
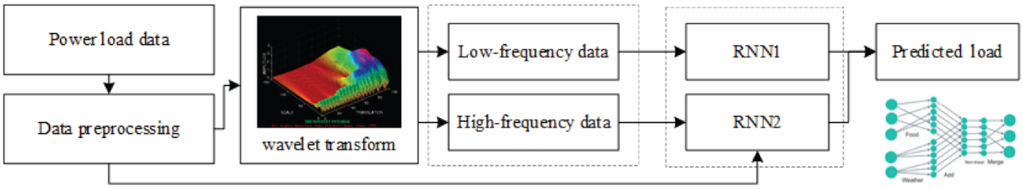


Figure 2.
The framework for the power load prediction using the wavelet transform and RNN



In this framework, the vital part is the decision fusion part that uses two independent RNNs. As the wavelet separated the data to high and low frequency part, it flourished the data performance. Since there is a certain amount of noise and indeed in the power load data, the authors selected smoothing filtering and low-pass filtering to remove the corresponding noise, and completed the subsequent model building on this basis. As Figure 2 shows, the processed historical load data notational wavelet changes, extracts its high-frequency and low-frequency parts, and sends the low-frequency data into RNN1 for calculation, while it sends the high-frequency data and the original data into RNN2 for calculation, and superimposes them in its decision layer, so as to get the final prediction data.

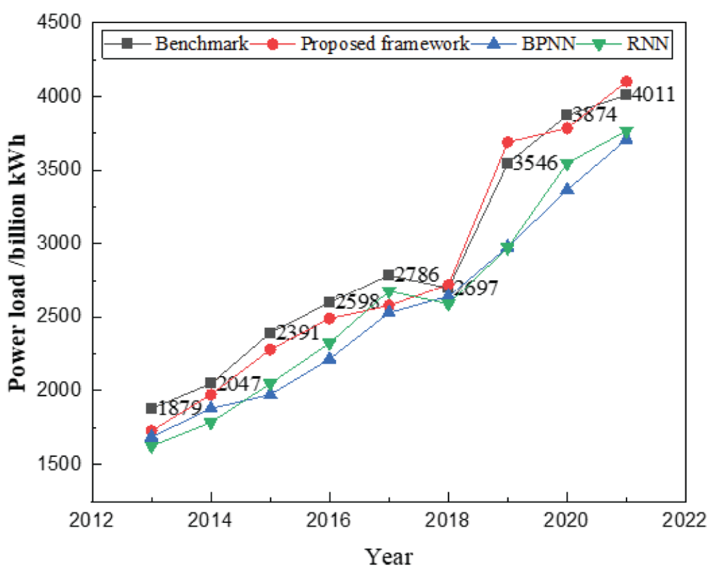
EXPERIMENT RESULTS AND ANALYSIS

Prediction Results and Method Comparison

According to the method framework proposed in the previous section, the authors analyzed and compared the results based on the power load provided by the power department in this region for the past nine years. For direct input, Figure 3 shows the predicted fitting results for different years.

In Figure 3, the actual data are indicated and labeled by the black part, and the framework proposed is indicated by the red line segment. By observing the effect of different methods in Figure

Figure 3.
The power load prediction in different years using different methods



3, it is possible to notice that the effect of the authors' proposed method is better, its trend is similar to the actual value, and the error control is better. In order to reflect the relationship between the three more intuitively, the authors chose the indicator of absolute error for comparative analysis. Figure 4 shows the absolute error of each method under different years.

Figure 4 highlights that the absolute errors of the proposed method are smaller than those of the back propagation neural network and RNN methods using unprocessed data in different years. At the same time, Figure 5 provides the sum of absolute errors of each method for the nine years of power forecasting, which shows that, after the wavelet transform and decision layer fusion, the errors of power forecasting decrease by more than 50%, compared with the traditional direct forecasting methods.

The combined results in Figures 3—5 show that the dual RNN overlay model based on the wavelet transform data augmentation and decision layer fusion the authors proposed has considerable advantages in power short-term forecasting, which greatly improves the accuracy of the direct input of the traditional model.

Model Test and Application

To verify the generalization performance of the model and the scope of application, the authors selected the electricity data of a region for the last five years, for prediction through online search based on the data state and characteristics described in the public dataset (https://github.com/weiyx15/short_term_load_forecasting). Figure 6 shows the prediction results.

Figure 6 allows to observe that the proposed framework has high accuracy for ultrashort-term data prediction, its prediction trend is the same as the actual data trend, the sum of the errors obtained by calculation for each year is 836, and the average error for each year is only 160. This is an acceptable and accurate result for ultrashort-term power forecasting. This data test proves that the proposed method has certain advantages in short-term and ultrashort-term power load forecasting, and the accuracy is improved by model optimization.

Figure 4.
The absolute error in different years using different methods

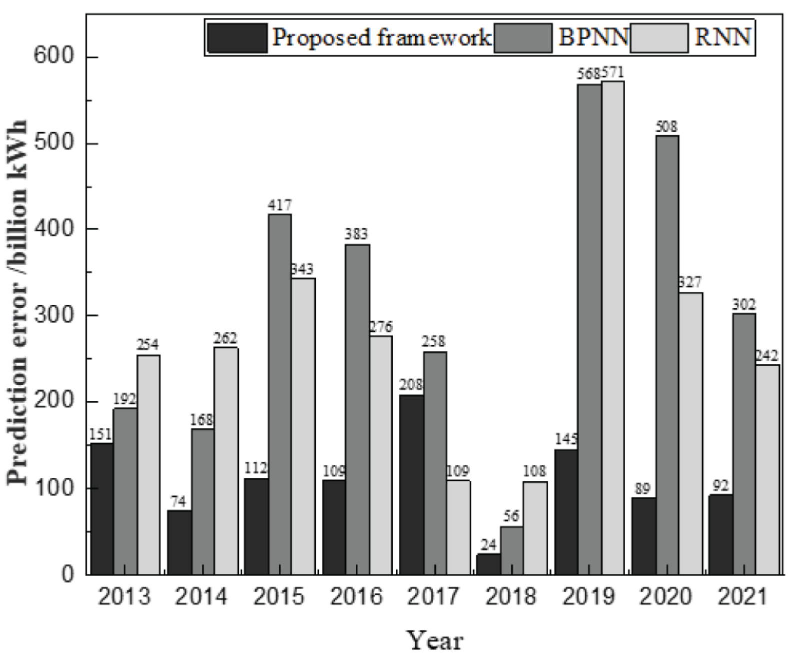


Figure 5.
Sum of the absolute error

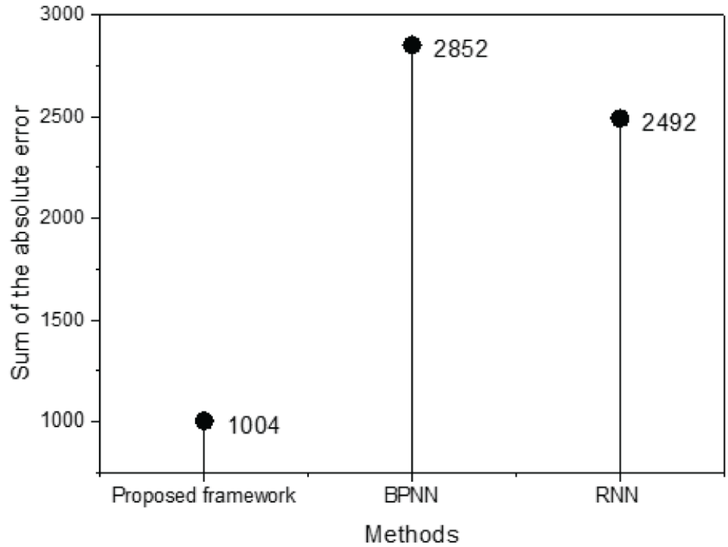
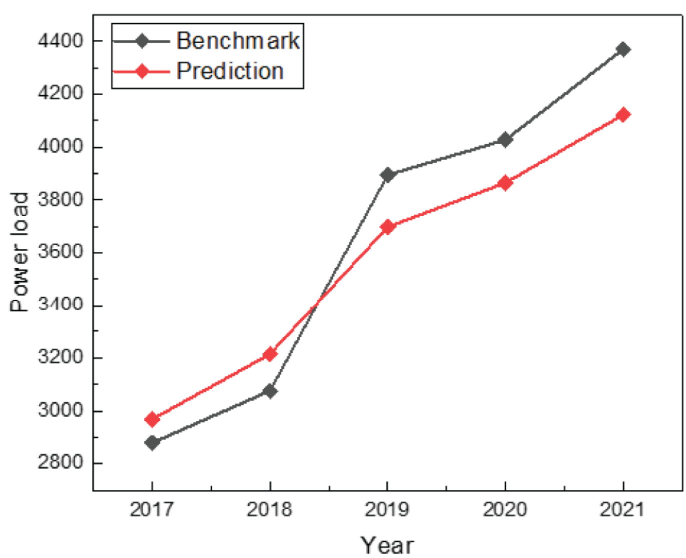


Figure 6.
Test result in the other region



DISCUSSION

Power load forecasting is the basic work for the electricity planning, safe operation, and economic dispatching. Accurate prediction of power load is helpful to reduce power loss, avoid transmission blockage, and ensure power supply. This is important to maintain the safety and stability of power system and enhance the reasonableness and economy of power system planning. In this study, the authors analyzed the differences of power forecasting results under wavelet analysis, RNN, and different layer fusion methods by combining the characteristics of power data and taking the annual power load of this region power as an example (Lee & Kim, 2019). RNN, as a widely used method in time series, has wide applications in power forecasting, by starting from the data themselves and using the memory characteristics of RNN to complete the long- and short-term power load. In this paper, the authors also considered the RNN structure to improve the prediction accuracy when they initially designed the model. However, the results were poor, so they optimized the data. For the mixed characteristics of high-frequency and low-frequency parts of the power data, the researchers employed the wavelet transform to separate them, and conducted separate training of different components of the data to improve the feature performance, so that the accuracy of the prediction results could be refined (Kumar et al., 2021). Therefore, in the study of long- and short-term prediction of electricity forecasting, in addition to the performance of the prediction model, the performance of the datashould also be given full play, and the data processing should be improved through time-frequency domain transformation and combination of features to finally achieve the improvement of the accuracy of electricity forecasting.

The reason why current power forecasting has become a hot spot for research is that, after completing more accurate power forecasting, the safety and stability of power system can be maintained in the first place, and the output of the power system at the generation end and the load at the user end should always be kept in a dynamic balance (Markovics & Mayer, 2022). When the supply exceeds the demand, the overall frequency of the power system rises, leading to a large amount of energy waste, and the power consumption of frequency-sensitive equipment at the user end increases, affecting the working life and quality of work and bringing security risks. When the supply exceeds the demand, the overall frequency of the power system decreases; this results in a drop in the system voltage, affects the motor speed, seriously endangers industrial production, and, in extreme cases, even induces a large area similar to the power crisis in California's, USA, blackout, causing extremely serious economic losses and endangering social stability (Duan et al., 2022). In addition, to improve the rationality of power system planning, the development of electricity demand is often accompanied by social and economic development, while the construction of the power system has a relative lag and the current demand for electricity to plan the power system under construction is obviously out of time. Power system planning must be forward-looking, and the power load forecast, especially the medium and long-term load forecast, can provide a solid and reliable basis for it. Based on long-term load forecasts for years or even decades to come, power system planning will be more rational and adaptable to socioeconomic development (Visser et al., 2022). Finally, to improve the economic efficiency, accurate power load forecasting can also coordinate the generation and consumption relationship between regions, realize efficient dispatching of power between regions, avoid transmission blockage to the greatest extent, optimize the supply and demand relationship of the power system, improve the profit of power generation, reduce transmission and substation losses, lower the cost of electricity consumption, and improve the economic efficiency of all segments of the power system. As the authors evidenced above, high-precision power forecasting is of great significance to the power industry itself as well as to the whole society.

CONCLUSION

In this paper, the authors proposed a multilevel fusion power forecasting framework based on the wavelet transform and RNN to study the current demand of power load forecasting. Daubechies wavelets are characterized by their finiteness, orthogonality, and tight support. They have the advantages of high computational speed and high computational accuracy in mathematical operations. The framework firstly uses the Daubechies wavelet in the wavelet transform to complete the data decomposition and obtain two parts of high frequency and low frequency data to realize the expansion of data features. In the construction of RNN prediction model, the auhtors improved the data availability by training the frequency domain data and the original time data separately, and finally completed the decision fusion of the two types of data to refine the prediction accuracy, compared with the traditional method. Its prediction error in the last nine years decreased by 50%.

Although in this study the authors achieved certain research results in short-term power load forecasting, there are still some problems, restricted to the data collection capability. Indeed, the authors could only predict the load according to the historical data, and not analyze the external factors affecting the load change. Therefore, expanding the data range and improving the model performance are the next focus of work.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers who have provided valuable comments on this paper.

CONFLICTS OF INTEREST

The authors of this publication declare there is no conflict of interest.

FUNDING AGENCY

This research was supported by the “Research and Development of New Smart Sensor Technology to Promote the Development of Green Energy” [No. 202104BN050011].

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