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Power Load Prediction Algorithm Based on Wavelet Transform

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To address the environmental impact, low efficiency, and poor accuracy of existing power load prediction methods, this study innovatively proposes a power load prediction system that combines wavelet transform with digital twin technology. Compared with similar power load prediction methods, the proposed method achieved the highest power load prediction accuracy rate of 97.26%, with the lowest MAPE and RMSE being only 3.96% each. Our proposed method has good noise resistance and overcomes the disadvantage of traditional power load prediction methods that are easily affected by the environment. Moreover, the false detection rate of the load information data obtained from the power system in the Fuxin area from 2022 to 2023 was less than 5%, further verifying the reliability of the proposed method. This achievement is attributed to the powerful signal processing capabilities of the discrete wavelet transform, advanced pattern recognition and prediction capabilities of these three deep learning network algorithms, and the intelligence of digital twin technology. The combination of these three elements has brought new technological breakthroughs to the field of power load prediction.

ACM CCS (2012) Classification: Applied computing → Physical sciences and engineering → Electronics

Keywords: wavelet transform, ensemble learning, deep learning networks, power, load prediction

1. Introduction

With the development of digital and intelligent distribution networks, accurate and effective power load prediction has become particularly important [1]. Timely power load supply can ensure stable social development. Accurate prediction results can achieve supply-demand balance in the power system [2-3]. Therefore, in recent years, many scholars both domestically and internationally have conducted research on power load prediction. Xue M *et al.* aimed to effectively balance the peak valley difference caused by power dispatching, improve the power supply utilization rate of power grid dispatching, and reduce the power supply pressure of line transformers. Therefore, a power load prediction method combining Extreme Gradient Boosting (XGBoost) and Long Short Term Memory (LSTM) was proposed. The experimental results indicated that the method could support regional load prediction for penetration electric vehicles, further successfully optimizing the current power dispatch method [4]. Kalhori M R N *et al.* developed a data-driven power load prediction system for long-term trend related macroeconomic factors and short-term temperature factors in power generation-transmission expansion planning. The designed system performed significantly better than other systems in residential, commercial, and agricultural electricity loads [5]. Tao Y *et al.* designed a hybrid energy consumption prediction framework by combining the LSTM with the encoder-decoder unit to address the shortcomings of historical power load data. Several commonly used algorithms were extensively experimented on integrated cross-domain datasets. The experimental results showed that the designed framework outperformed existing methods [6]. Agga F A *et al.* developed a power load prediction model based on deep learning networks to address the power outages or overproduction in photovoltaic power plants under unstable weather conditions. The experimental results showed that when the number of hidden layers in deep learning networks changed at different configurations, the model performance also varied, but the change in the number of hidden layers did not affect the accuracy of its power load prediction [7].

Wavelet Transform (WT) is an excellent load prediction method that can project various sequence components onto different scales and obtain complete results through wavelet reconstruction. It has been widely applied in the field of electricity [8]. Ylmaz A *et al.* built a feature extraction method based on WT to classify power quality interference. An experimental Distributed Generation (DG) system was constructed in the LabVIEW environment. This method had excellent noise sensitivity in noise environments of 25dB, 30dB, and 40dB [9]. Wang Y *et al.* proposed a short-term power load prediction strategy by combining WT and Recurrent Neural Network (RNN) to improve the accuracy and reliability of power load prediction. The Mean Absolute Error (MAE) of the proposed method was 7.77, and the Root Mean Square Error (RMSE) was 17.41 [10]. Ruiz M *et al.* proposed a WT-based power quality signal compression rate algorithm to manage the large amount of data obtained by telecommunications networks and avoid the cost increase caused by a large number of data storage devices. The optimal compression rate of the algorithm was 99.80%, the RTE was 99.95%, the Normalized Mean Square Error (NMSE) was 0.000434, and the Cross-Correlation was 0.999925 [11].

In summary, existing power load prediction methods still have significant shortcomings, especially in dealing with the limitations when processing massive data sources and identifying prediction issues in complex environments. Some studies attempt to improve the accuracy of power prediction by integrating deep learning models, such as RNN and LSTM, and using WT to perform frequency decomposition on load sequences to achieve model generalization. However, they still cannot accurately grasp the impact of load change patterns and environmental factors, resulting in low overall performance and difficulty in adapting to the power load characteristics of different regions or time periods. In response to these limitations, this study innovatively utilizes the power digital twin application framework and a deep learning network algorithm to propose a WT-based power load prediction algorithm and a power digital twin application framework combined with load prediction. The WT-based power load prediction algorithm utilizes ensemble learning theory and integrates various deep learning networks to solve the long-term dependence on information loss and noise interference in traditional WT algorithms. This ensemble method not only improves the ability to grasp the load change patterns, but also enhances the system's robustness to environmental factor changes. The digital twin application framework for power load prediction creates a virtual replica of the power system, which can simulate and predict the system's behavior under different conditions, providing support for real-time monitoring and decision-making of the power system. The application of digital twin technology makes the prediction model more flexible to adapt to different operating conditions, improving the model's universality and generalization ability. By innovatively integrating various deep learning networks, digital twin technology, and WT, advanced technical support has been provided for the field of power load prediction, promoting technological progress in this field. This study is divided into four parts. The first part is the research analysis and summary of various researchers. The second part introduces the improved power load prediction algorithm and the application framework of power digital twin. The third part tests the designed method. Finally, the last part summarizes the article.

2. Methods and Materials

In order to better remove noise interference from the original power load data and address the problems in power load prediction, this study introduces the Discrete Wavelet Transform (DWT) method. Then the DWT method is optimized by ensemble learning. Secondly, the application framework of digital twin is designed having five dimensions, combined with an improved power load prediction algorithm. Finally, a novel power load prediction system combining DWT and digital twin is proposed, aiming to improve the accuracy and detection efficiency of power load prediction and ensure timely power load supply in the distribution network.

2.1. Construction of Power Load Prediction Algorithm Based on Wavelet Transform

Power load prediction algorithms directly affect the accuracy of power load prediction results. The current intelligent power load prediction methods usually combine WT for feature extraction to smoothly classify Power Quality Disturbance (PQD) [12–13]. WT is a mathematical transformation method that can decompose a signal into wavelet functions to analyze the local characteristics of the signal. This transformation is widely applied in the fields of signal processing, image processing, data compression, and other areas. The common WT methods can be divided into three types, namely Continuous Wavelet Transform (CWT), DWT, and Wavelet Transform Reconstruction (WTR) [14]. DWT can transform continuous wavelets into discrete sequences, minimizing redundancy to the greatest extent possible [15]. Therefore, in order to better remove the noise from the original power load data, the DWT method is adopted in the study, as displayed in Figure 1.

In Figure 1, DTW generally contains two stages, namely the wavelet decomposition and the wavelet reconstruction [16]. Firstly, in the wavelet decomposition stage, load data are subjected to WT and single branch reconstruction to obtain low-frequency and high-frequency coefficients. Secondly, in the wavelet reconstruction stage, the low-frequency and high-frequency coefficients obtained in the wavelet decomposition stage are subjected to wavelet reconstruction to obtain low-frequency and high-frequency signals. Finally, load prediction is performed on signals with different frequencies to obtain the prediction results. The coefficient matrix $V_x(j, k)$ of wavelet decomposition is shown in equation (1).

$$V_x(j,k) = a_0^{-\frac{j}{2}} \int_{-\infty}^{+\infty} f(t)\sqrt{\Psi(a_0^{-j}t-k)dt} \tag{1}$$

In equation (1), $a_0^{-\frac{j}{2}}$ represents the scale factor. and represent basic functions and wavelet basis functions, respectively. $a_0^{-j}t$ represents the time shift factor. j and k represent constants. The low-frequency coefficient $A_1(n)$ of DTW is shown in equation (2).

$$A_1(n) = f(k) \cdot h(k-n) \tag{2}$$

In equation (2), $f(k)$ represents the discrete. $h(k-n)$ represents the low-pass coefficient of the wavelet analysis filter. The high-frequency coefficient of DTW is shown in equation (3).

$$D_1(n) = f(k) \cdot g(k-n) \tag{3}$$

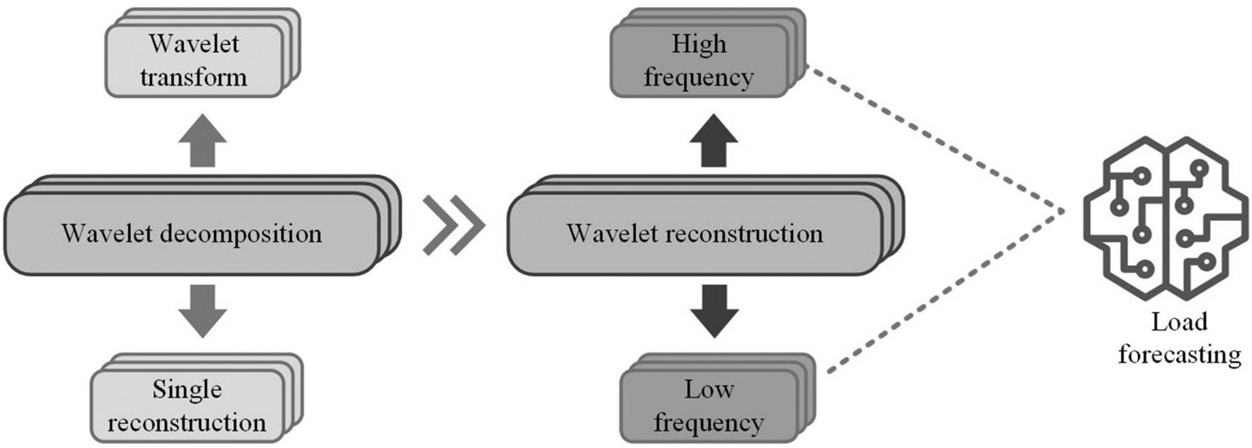


Figure 1. Structure of the DWT.

In equation (3), $g(k-n)$ represents the high-pass coefficient of the wavelet analysis filter. However, a simple DWT method cannot meet the requirements of current power load prediction. Ensemble learning constructs multiple individual learners and by combining them using specific combination strategies it is possible to produce a more powerful learner [17]. A significant improvement in data prediction performance can be achieved, making the algorithm more fault-tolerant and disturbance resistant [18–19]. Multiple learners are independent of each other, and the prediction accuracy of each learner itself should not be less than 50%. The Deep Belief Network (DBN), LSTM, and Multi-layer Perceptron (MLP) deep learning algorithms precisely meet this requirement. Furthermore, DBN constructs a deep network by stacking multiple Restricted Boltzmann Machines (RBMs), which can automatically extract advanced features from data and enhance the model's generalization ability. LSTM can avoid gradient vanishing in traditional RNNs and effectively capture long-term dependencies in time series through its gating mechanism. MLP can learn the nonlinear mapping relationships between input features and outputs. Therefore, the study combines these three deep learning network algorithms through ensemble learning to construct an ensemble deep learning algorithm, namely DBN-LSTM-MLP algorithm. The process framework of this algorithm is shown in Figure 2.

As shown in Figure 2, the study uses a simple averaging method to combine these three deep learning algorithms. Firstly, these raw load data are preprocessed and divided into training and testing sets. Secondly, the dataset is subjected to WT using DBN, LSTM, and MLP, respectively, to obtain three different prediction results. Finally, the predicted values are subjected to inverse normalization, and the final load prediction result is obtained by taking the average. The prediction error is calculated based on the prediction result. The output of DBN is shown in equation (4).

$$y_{DBN}(x_i) = f_{DBN}(x_i, \theta_{DBN}) \tag{4}$$

In equation (4), $y_{DBN}(x_i)$ represents the explanatory variable vector. f_{DBN} represents the function that maps the control variable vector to the explanatory variable vector. x_i and θ_{DBN} represent the control variable vector and the parameters of the trained DBN, respectively. The DBN loss function $L(x, x^*)$ is displayed in equation (5).

$$L(x, x^*) = \| x - x^* \|_2^2 \tag{2}$$

In equation (5), x and x^* represent the input data vector and the reconstructed data vector, respectively. The output of LSTM is shown in equation (6).

$$y_{LSTM}(x_l) = f_{LSTM}(x_l, \theta_{LSTM}) \tag{6}$$

In equation (6), $y_{LSTM}(x_l)$ represents the output corresponding to the input data vector x_l in LSTM. f_{LSTM} represents the corresponding relationship of LSTM network mapping. θ_{LSTM} represents the parameter value within LSTM. The output of MLP is shown in equation (7).

$$y_{MLP}(x_t) = f_{MLP}(x_t, \theta_{MLP}) \tag{7}$$

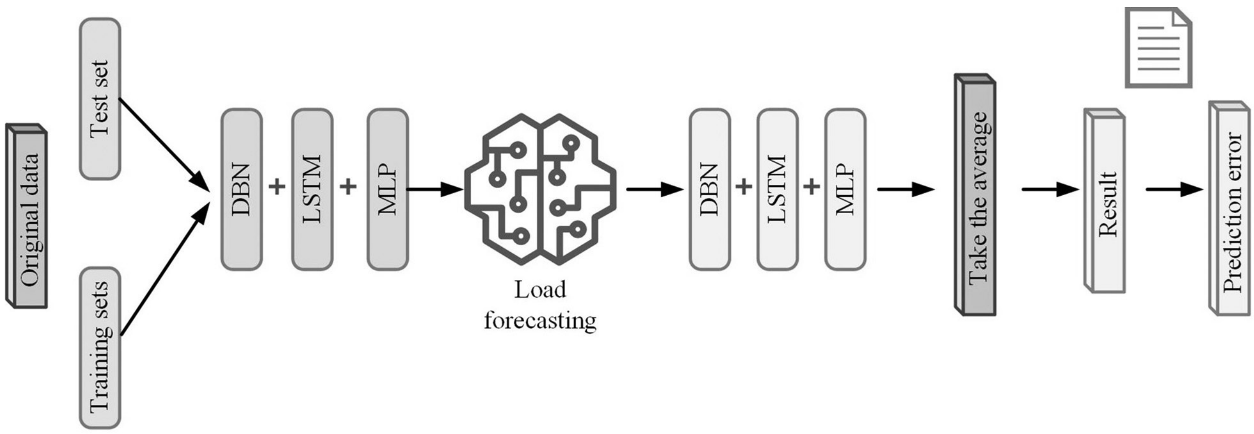


Figure 2. Process framework diagram of DBN-LSTM-MLP algorithm.

In equation (7), $y_{MLP}(x_t)$ represents the output value of MLP. f_{MLP} represents the mapping of the trained MLP with respect to input and output. x_t and θ_{MLP} represent the input vector and the parameter of the trained MLP, respectively. The output value x_{ij} of each neuron in the MLP feedforward process is shown in equation (8).

$$x_{ij} = \sigma(w_i x_{i-1} + b_{i-1}) \tag{8}$$

In equation (8), σ and w_i represent the Sigmoid activation function and weight vector, respectively. x_{i-1} and b_{i-1} represent the input vector of layer $i-1$ and the bias of layer , respectively. The feature normalization calculation is shown in equation (9).

$$X_{norm} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \tag{9}$$

In equation (9), X_{norm} represents the normalized value. X, $X_{\max}$ and $X_{\min}$ represent the initial data, the maximum value of the initial data, and the minimum value of the initial data, respectively. Based on the above improvements, the DBN-LSTM-MLP algorithm is combined with DTW to propose a power load prediction algorithm, namely DTW-DBN-LSTM-MLP algorithm. The framework flow of the DTW-DBN-LSTM-MLP algorithm is shown in Figure 3.

A shown in Figure 3, the study first uses the DTW method to decompose the experimental data into multiple wavelet components and predicts components of different frequencies separately to improve prediction accuracy. Then, WT and single branch reconstruction are performed on these load data to obtain low-frequency and high-frequency coefficients. Wavelet reconstruction is performed on each frequency component to obtain low-frequency and high-frequency signals. Finally, the DBN-LSTM-MLP prediction algorithm for each wavelet component is trained using these data from the training set. The trained prediction algorithm is used to predict each wavelet component in the testing set. Finally, the prediction results and prediction errors are obtained. The prediction value of the DTW-DBN-LSTM-MLP algorithm is shown in equation (10).

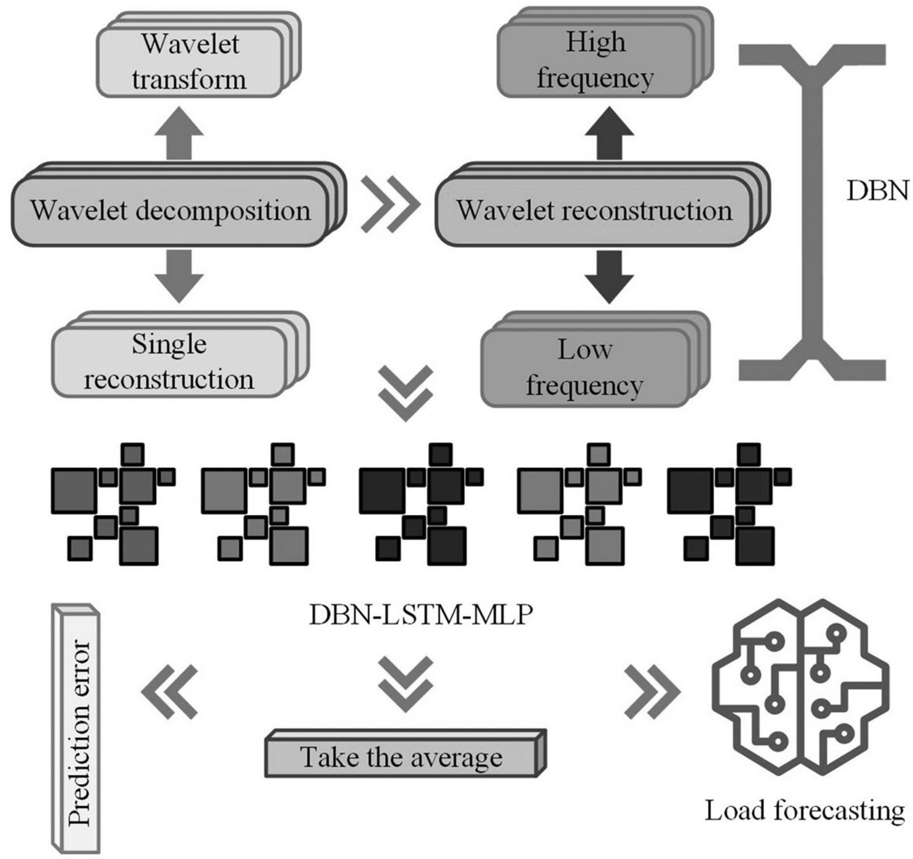


Figure 3. Framework flow of DTW-DBN-LSTM-MLP algorithm.

$$y^* = \sum_{i}^{n} y_{D,j} + y_A \tag{10}$$

In equation (10), y^* represents the prediction result vector of the DTW-DBN-LSTM-MLP algorithm. $y_{D,j}$ and y_A represent the prediction results of the high-frequency and low-frequency components using the DTW-DBN-LSTM-MLP algorithm, respectively.

2.2. Construction of Power Load Prediction System Combining Wavelet Transform and Digital Twin

As a bridge between the physical world and the digital world, digital twin technology can simulate and predict the behavior of physical entities under different conditions by creating virtual replicas. In power systems, digital twin can construct virtual models of electrical equipment to monitor and predict the state and performance of the power system in real time. A power load prediction system that combines WT and digital twin technology can fully leverage the advantages of both to achieve more accurate predictions. To promote the better application of digital twin technology in power load prediction systems, a basic application framework is established to provide architectural support for subsequent applications. The commonly used digital twin technologies at present mainly include five parts: physical entities, virtual entities, twin data, connections, and services [20]. However, the digital twin technology at home and abroad is still in the exploratory stage, and existing technologies cannot meet the effective prediction of power load in the power system. The basic process of power load prediction is shown in Figure 4.

In Figure 4, the power load prediction has two stages, namely the data preparation and the model construction. The former collects real and reliable electricity load data. Then, the collected power load data is preprocessed and divided into training, validation, and testing sets. Secondly, during the model construction phase, the model is continuously improved and adjusted to its optimal state through evaluation and testing in the validation set. Finally, the testing set is input into the model and adjusted to the optimal state to obtain the final prediction results. However, the process of power load prediction is influenced by many different factors. Therefore, to avoid the influence of multiple factors, the digital twin application framework is designed utilizing five dimensions [21]. The structure of the power digital twin application framework is shown in Figure 5.

As shown in Figure 5, the designed power digital twin application framework mainly consists of five parts: the data center, digital distribution network, transmission connection, physical

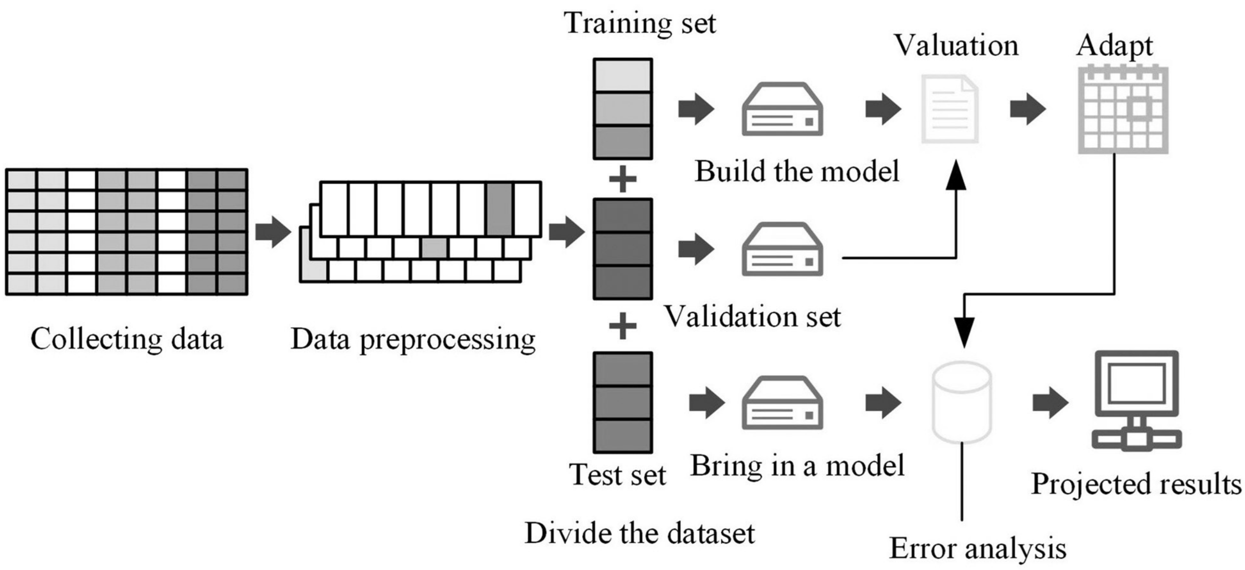


Figure 4. Electricity load prediction process flow.

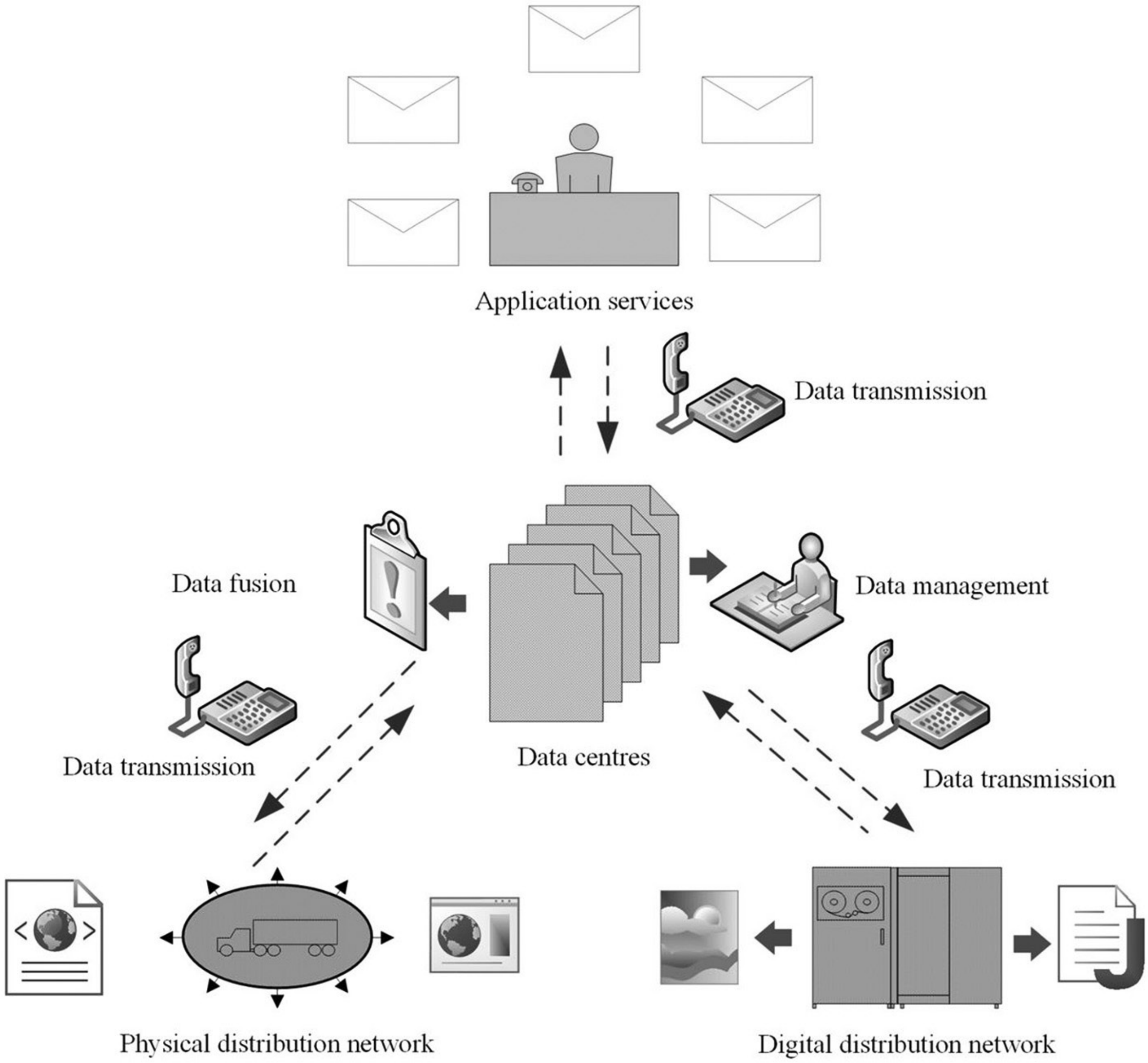


Figure 5. Power digital twin application framework architecture diagram.

distribution network, and application services. The physical distribution network is mainly composed of physical entities, such as distribution network infrastructure, sensors, communication equipment, edge computing devices, jointly responsible for the precise perception, collection, and real-time stable transmission of data on the status, electrical, physical, sound, environment, and other aspects of each link [22–23]. The digital distribution network is a complete mapping of physical entities in the digital space, providing intelligent and digital support for physical entities. The transmission connection section is responsible for stable, reliable, and efficient communication transmission connections between various links. The data center is responsible for data management and virtual real integration. The application services mainly serve scenarios such as optimized scheduling, coordinated control, monitoring and analysis, data prediction, and state estimation. Finally, based on the proposed digital twin application framework and the DTW-DBN-LSTM-MLP algorithm, a power load prediction system combining the DTW-DBN-LSTM-MLP load prediction algorithm and digital twin is proposed. The flowchart of the system is shown in Figure 6.

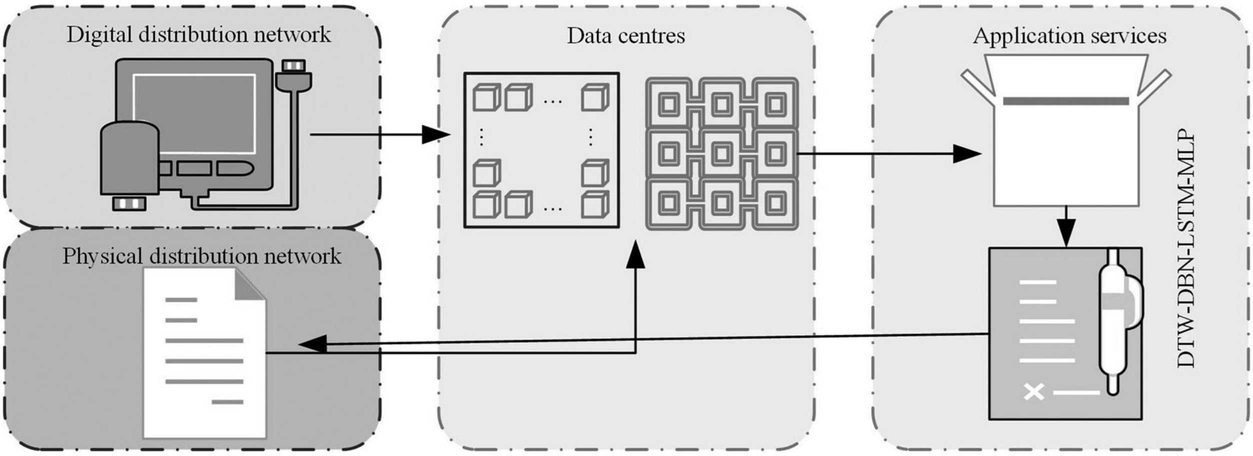


Figure 6. Flow chart of the system.

As shown in Figure 6, the power load prediction system, which combines DWT and digital twin, mainly consists of four parts: digital distribution network, physical distribution network, data center, and application services [24–25]. Firstly, the data center integrates the data input from the digital distribution network and the physical distribution network to quickly extract the time-frequency domain features of these fused data. Secondly, load identification is carried out using the DTW-DBN-LSTM-MLP algorithm. Finally, the recognition result is output. Due to the significant differences between values in the power load data, to assess the effectiveness of power load prediction, the study selects Mean Absolute Percentage Error (MAPE) as the main evaluation indicator for power load prediction. The MAPE is shown in equation (11).

$$MAPE = \frac{\sum_{i}^{N} \left| Y_i^* - Y_i \right|}{Y_i} \times \frac{100\%}{N} \tag{11}$$

In equation (11), Y_i* and Y_i represent the predicted and true values, respectively. N represents the number of experiments.

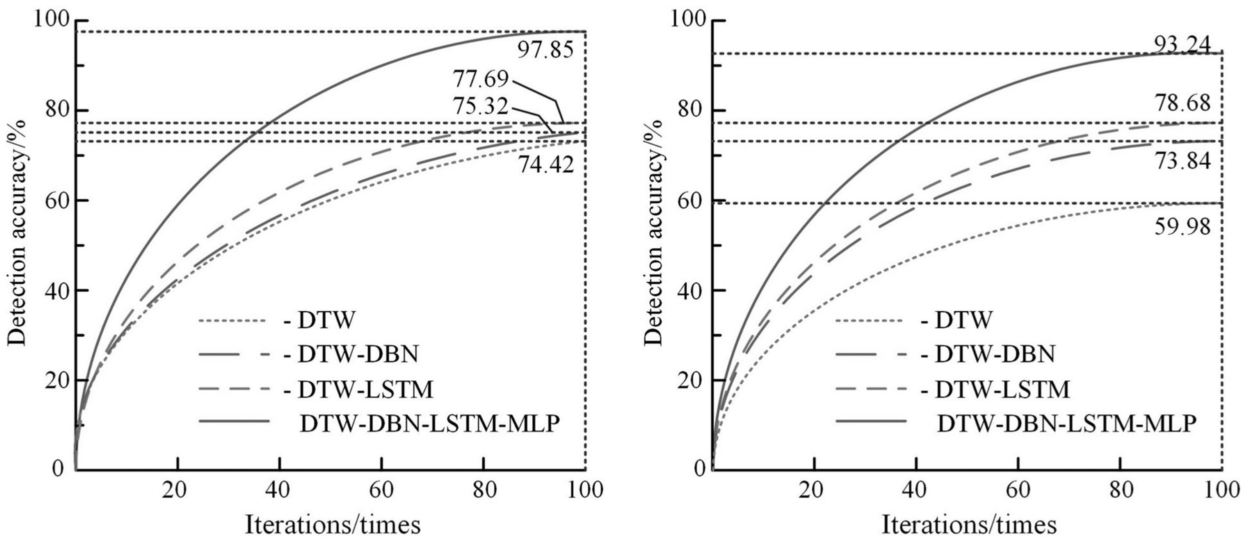
3. Results

To verify the performance of the DTW-DBN-LSTM-MLP algorithm and the power load prediction system combining DWT and digital twin, a suitable experimental environment is first established. The test data are preprocessed, with a portion of the data used for training. Secondly, performance and simulation experiments are conducted on the DTW-DBN-LSTM-MLP algorithm and the power load prediction system combining DWT and digital twin to verify the actual effectiveness.

3.1. Performance Testing of DTW-DBN-LSTM-MLP Power Load Prediction Algorithm

The study uses the Windows 10 operating system, equipped with Intel Core i7 CPU, NVIDIA GeForce GPU, and 64GB of memory. The PLAID dataset and Simulink dataset are used as test data sources, dividing into training and testing sets in a 6:4 ratio. The number of neurons in the first hidden layer of the MLP is set to 15, and the number of neurons in the second hidden layer is set to 4. For the DBN, the first hidden layer has 42 neurons, and the second hidden layer has 8 neurons. To verify the overall impact of each module in the DTW-DBN-LSTM-MLP power load prediction algorithm, the study first conducts ablation testing with detection accuracy as the indicator. Figure 7 displays the test results.

Figures 7 (a) and 7 (b) show the ablation test results on the PLAID and Simulink datasets at 20, 40, 60, 80, and 100 iterations, respectively. In the Simulink dataset, the detection accuracy of the four algorithms DTW, DTW-DBN, DTW-LSTM, and DTW-DBN-LSTM-MLP were 74.42%, 75.32%, 77.69%, and 97.85%, respectively. However, due to the relatively



(a) Simulink. *(b)* PLAID.

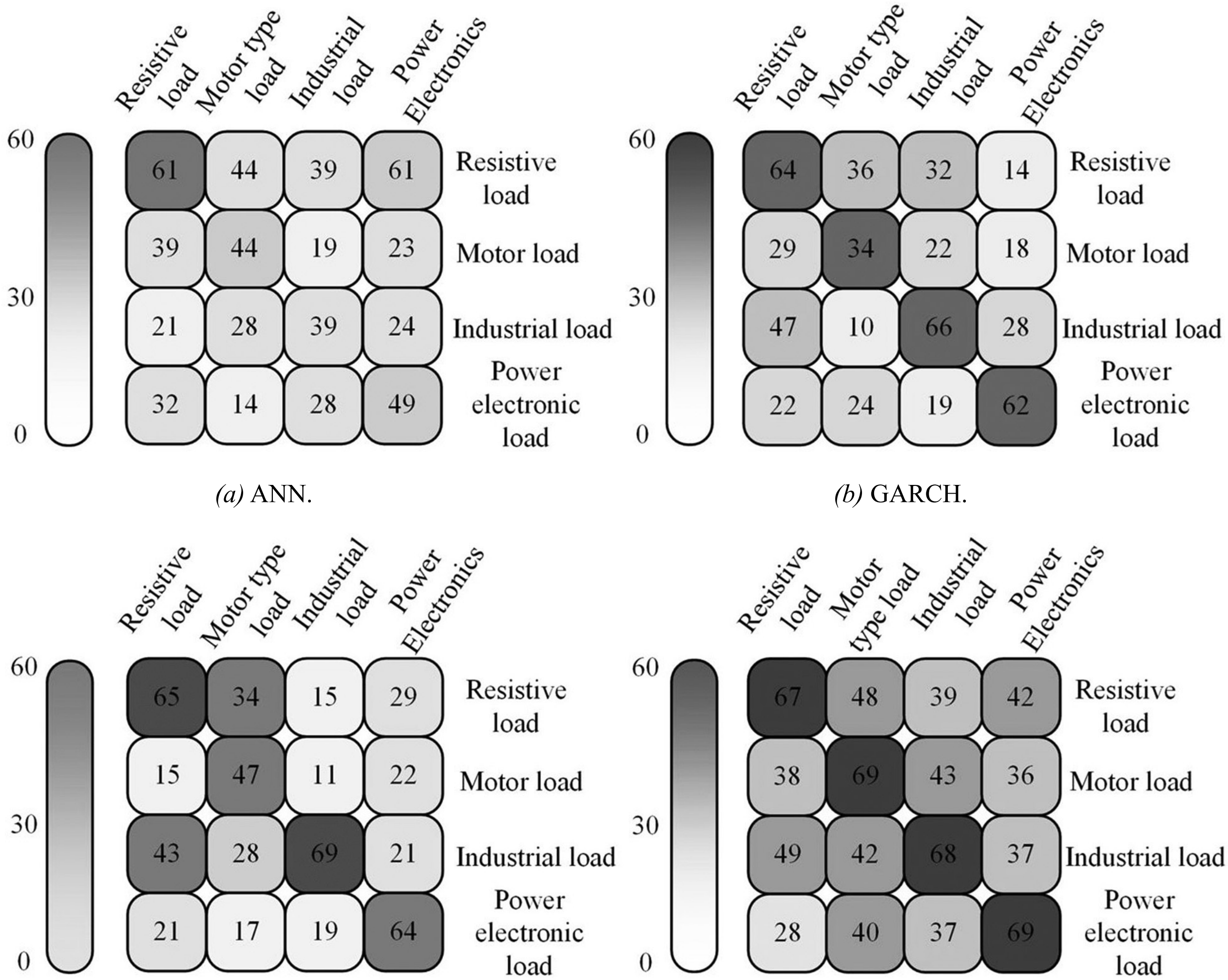
Figure 7. Overall impact of each module in the DTW-DBN-LSTM-MLP algorithm.

single collection environment and fixed electrical parameters on the PLAID dataset, there is a significant difference between the extracted sample instances and the original dataset. As a result, the detection accuracy is relatively reduced [26]. The detection accuracy of the four algorithms DTW, DTW-DBN, DTW-LSTM, and DTW-DBN-LSTM-MLP were 59.98%, 73.84%, 78.68%, and 93.24%, respectively. The DBN, LSTM, and MLP modules all play a positive role in promoting the final DTW-DBN-LSTM-MLP algorithm. Secondly, the study introduces the Generalized Auto-regressive Conditional Heteroscedasticity (GARCH), Auto-regressive Integrated Moving Average model (ARIMA), and Artificial Neural Network (ANN) as comparison algorithms for power load prediction. Subsequently, the study conducts multi-indicator tests on the four algorithms, including Precision (P), Recall (R), F1 value, and average detection time, as displayed in Table 1.

Table 1. Comparison test results of multiple indicators.

Data set	Algorithm	P/%	R/%	F1/%	Average detection time/s	T-test
PLAID	ANN	64.24	57.67	62.08	8.28	0.053
	GARCH	73.89	70.62	73.87	7.02	0.042
	ARIMA	76.97	68.88	73.43	6.38	0.031
	DTW-DBN-LSTM-MLP	93.67	89.37	91.65	3.74	0.012
Simulink	ANN	89.31	88.18	88.35	5.69	0.048
	GARCH	88.54	88.80	88.72	4.78	0.036
	ARIMA	91.46	90.76	91.15	3.06	0.029
	DTW-DBN-LSTM-MLP	95.58	93.88	95.42	2.61	0.008

Table 1 presents a comprehensive performance comparison of four algorithms on both the PLAID and Simulink datasets, including ANN, GARCH, ARIMA, and DTW-DBN-LSTM-MLP. The DTW-DBN-LSTM-MLP algorithm demonstrates exceptional performance in power load prediction, achieving high precision and efficiency on both PLAID and Simulink datasets. On the Simulink dataset, the average detection time of the DTW-DBN-LSTM-MLP algorithm was 2.61s, with P, R, and F1 scores reaching as high as 95.58%, 93.88%, and 95.42% respectively, and a T-test significance level of 0.008, indicating a statistically significant advantage. On the PLAID dataset, the algorithm's average detection time was 3.74s, with P, R, and F1 scores of 93.67%, 89.37%, and 91.65%, respectively, and a T-test significance level of 0.012, proving its superior predictive performance. The DTW-DBN-LSTM-MLP algorithm has achieved the best performance on both datasets, confirming its efficiency and accuracy in power load prediction tasks, and the significance level of the T-test also verifies the statistical significance of these results. These outcomes suggest that the DTW-DBN-LSTM-MLP algorithm is suitable for precise power load prediction, which can provide reliable decision support for the operation and management of smart grids. Subsequently, the detection classification confusion matrices of the four algorithms on the Simulink dataset are shown in Figure 8.



(a) ANN. *(b)* GARCH. *(c)* ARIMA. *(d)* DTW-DBN-LSTM-MLP.

Figure 8. Confusion matrix results for electricity load prediction algorithms.

Figures 8 (a), 8 (b), 8 (c), and 8 (d) show the confusion matrix results of ANN, GARCH, ARIMA, and DTW-DBN-LSTM-MLP algorithms for four types of power loads: resistive load, motor load, industrial load, and power electronic load. As shown in Figure 8, faced with four different types of power loads, the ANN algorithm detected two types of power loads well, while GARCH and ARIMA detected three types of power loads. Relatively speaking, the DTW-DBN-LSTM-MLP algorithm detected all types of power loads, with excellent detection applicability and classification efficiency, and its scores were all above 60 points.

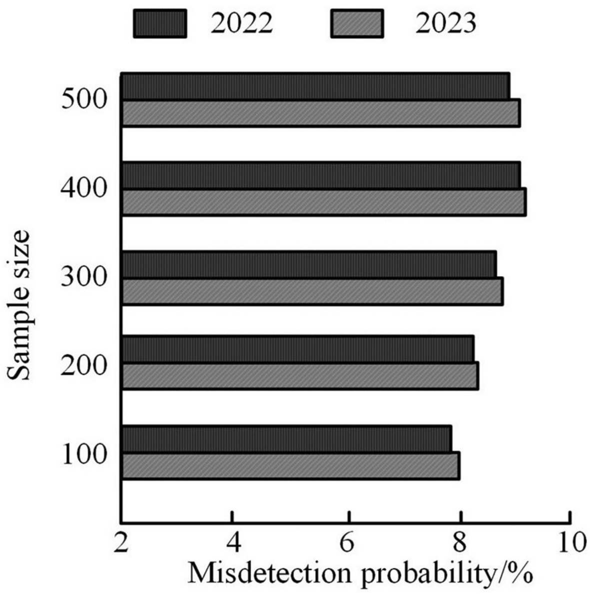
3.2. Simulation Testing of Power Load Prediction System Combining Wavelet Transform and Digital Twin

After verifying the performance of the power load prediction algorithm DTW-DBN-LSTM-MLP, further experimental tests are conducted on the power load prediction system combining DWT and digital twin. The power system load information data of the Fuxin region from 2022 to 2023 is selected as the simulation environment. Based on the DTW-DBN-LSTM-MLP power load prediction algorithm framework, it is integrated with the improved power digital twin application framework to construct a power load prediction system. To evaluate the robustness of the proposed system to noise, the power load prediction system is tested. Taking the signal-to-noise ratios of 10 dB, 15 dB, 20 dB, and 30 dB as examples, the power load prediction system combining DWT and digital twin is tested. Table 2 displays the test results.

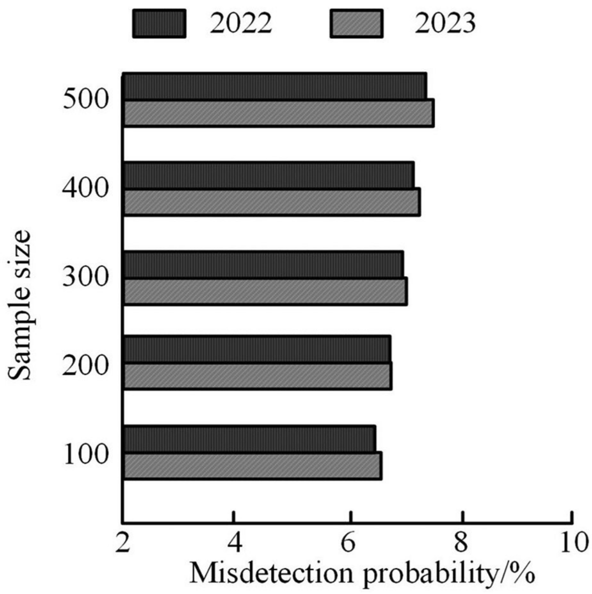
According to Table 2, the new power load prediction system only showed a significant performance decrease when the signal-to-noise ratio dropped to 10dB. Before improving the power digital twin application framework, the highest accuracy of the proposed power load prediction method was 95.34%, and the lowest MAPE and RMSE were 4.58% and 61.08%, respectively. After improvement, the highest accuracy of power load prediction application system was 97.26%, and the lowest MAPE and RMSE were 3.96% and 3.96%. The above experimental data effectively proves that the power load prediction system combining WT and digital twin technology has excellent noise resistance. The method of integrating various deep learning algorithms enhances the robustness of the system to noise and improves its ability to grasp load change patterns. In addition, the study also introduces power load prediction algorithms commonly used in power digital twin application systems, namely FFT-BDT, VI image-CNN, HT-LSTM, and the DTW-DBN-LSTM-MLP algorithm for comparative testing. The test results are shown in Figure 9.

Table 2. Test results for different signal-to-noise ratios.

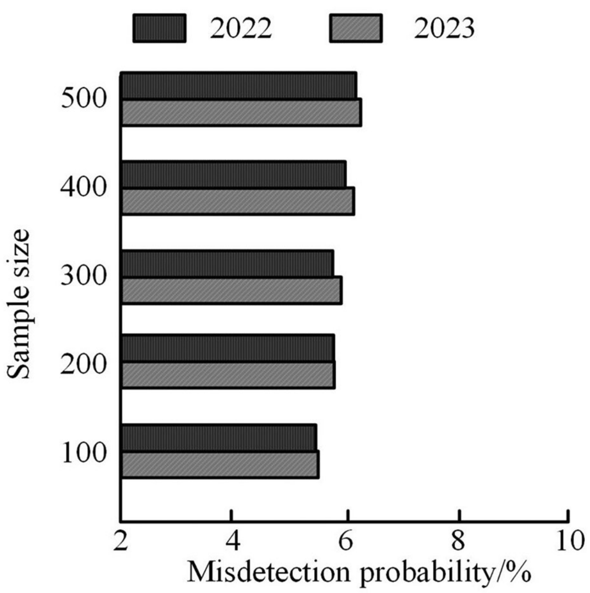
Framework	Signal-to-noise ratio/dB	Accuracy/%	MAPE/%	RMSE/%
Before improvement	10	80.27	7.63	68.34
	15	89.68	6.34	66.32
	20	91.25	5.68	64.25
	30	95.34	4.58	61.08
After improvement	10	82.65	7.01	65.25
	15	90.09	6.12	62.18
	20	93.56	5.07	60.29
	30	97.26	3.96	59.87



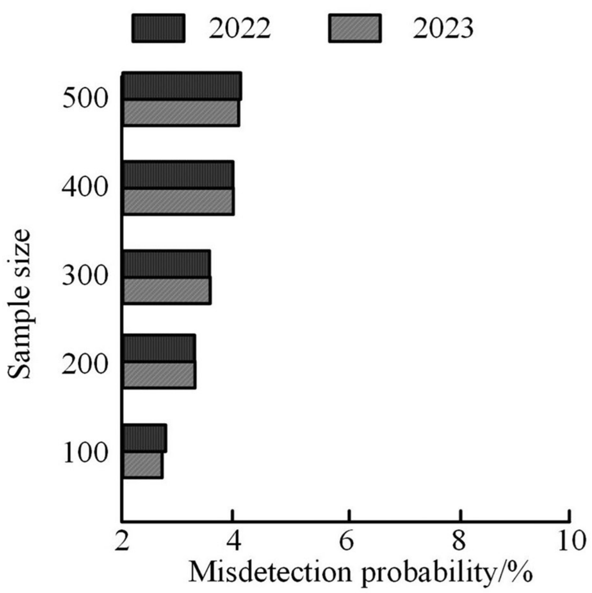
(a) FFT-BDT.



(b) VI image-CNN.



(c) HT-LSTM.



(d) DTW-DBN-LSTM-MLP.

Figure 9. False detection rate test result.

Figure 9 (a), Figure 9 (b), Figure 9 (c), and Figure 9 (d) respectively show the false detection rate test results of the load information data obtained by the power digital twin application system combining FFT-BDT, VI image-CNN, HT-LSTM, and DTW-DBN-LSTM-MLP in the Fuxin area power system in 2022 and 2023. As shown in Figure 9, when the number of data samples was 100, the power digital twin application system combining FFT-BDT, VI image-CNN, HT-LSTM, DTW-DBN-LSTM-MLP power load prediction algorithms had a false detection rate of 7.89%, 6.58%, 5.74%, and 2.86% in the load information data obtained by the power system in Fuxin area in 2022. When the number of data samples was 500, the false detection rates of each system were 9.64%, 7.48%, 6.28%, and 4.22%, respectively. The false detection rate of the proposed system was the lowest. When the number of data samples was 100, 200, 300, 400, and 500, the false detection rates of the load information data obtained by the power system in Fuxin area in 2023 were 2.71%, 3.32%, 3.76%, 4.07%, and 4.22%, respectively. In conclusion, the proposed system has good accuracy in power load prediction. Finally, due to the high variability of data resources in small sample sizes, the study conducts 10 repeated experiments on the system, taking stability as an indicator. The test results are shown in Figure 10.

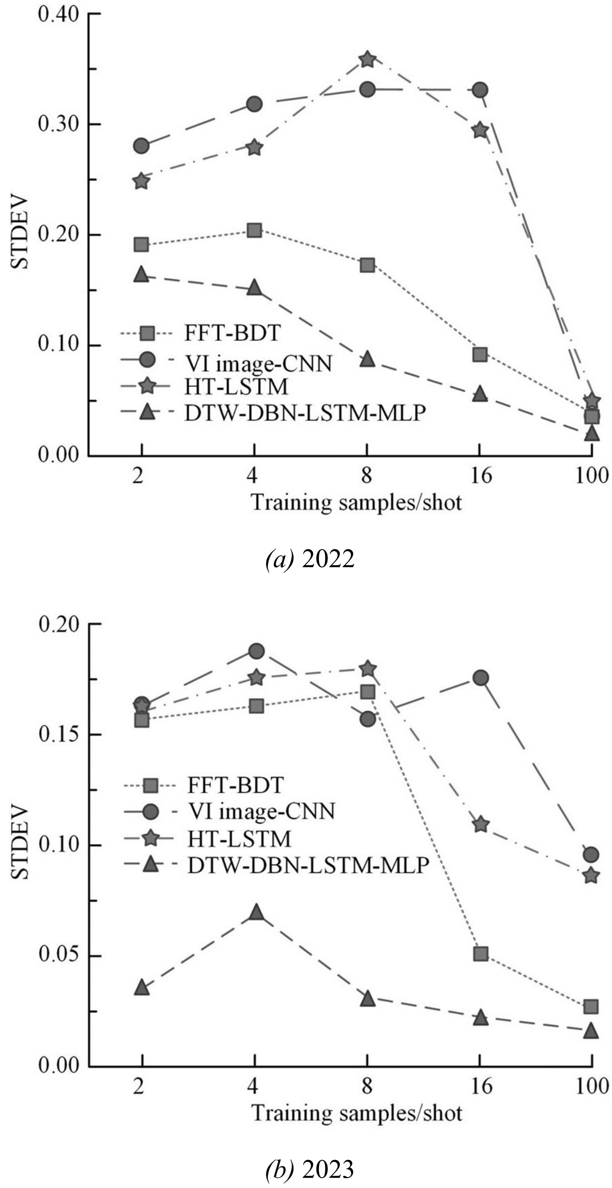


Figure 10. System stability test results.

Figures 10 (a) and 10 (b) show the Standard Deviation of F1-score (STDEV) test results obtained by four different power digital twin application systems in the Fuxin area power system in 2022 and 2023, respectively. If the value of STDEV is small, it indicates that the performance of the system fluctuates less in different experiments, and the stability of the system is better. In low-shot scenarios, the STDEV of each system was relatively high. As the number of shots increased, the STDEV values of each system gradually decreased in high-shot scenarios. The reason is that the system can obtain more training data in high-shot environments, which can make it better generalize to new data. In Figure 10 (a), at 100-shot, the STDEV values of the power digital twin application system combined with FFT-BDT, VI image-CNN, HT-LSTM, DTW-DBN-LSTM-MLP prediction algorithms were 0.041, 0.045, 0.050, and 0.025, respectively. In Figure 10 (b), the STDEV values of the power digital twin application system combined with FFT-BDT, VI image-CNN, HT-LSTM, and DTW-DBN-LSTM-MLP prediction algorithms at 100-shot were 0.028, 0.096, 0.085, and 0.013, respectively. From this, the power digital twin application system combined with the DTW-DBN-LSTM-MLP power load prediction algorithm has a lower STDEV value, proving that the power digital twin application system has superior stability.

4. Discussion

With the rapid development of smart grids, power load prediction has attracted widespread attention as a key technology for optimizing the operation and management of power grids. Accurate load prediction not only contributes to the economic dispatch of the power grid, but also improves its reliability and stability, effectively addressing the challenges brought by supply and demand fluctuations. Therefore, this study uses DWT to perform frequency decomposition on load sequences, in order to address the characteristic multi period variations of current power system loads. Furthermore, leveraging the distinct features of various deep learning methods, a robust learner based on deep learning is established through a simple averaging ensemble method, providing a foundation for the subsequent development of intelligent power load prediction systems. Jalalifar R *et al.* discovered that the combining DWT and deep learning is effective in time series and load prediction for distribution networks. In the two-week short-term power load prediction, the method combining DWT with deep learning outperforms algorithms such as Support Vector Machines (SVM), LSTM, and Convolutional Gated Recurrent Units [27]. Gimonkar R M *et al.* processed multiple neural networks with DWT, decomposing historical power load data into multiple wavelet coefficients, which were then used to train neural networks and served as inputs for power load prediction. Case studies showed that the proposed method offered high predictive accuracy [28]. Kelly *et al.* applied Deep Neural Networks (DNNs) and digital twin technology to power load prediction systems with good results. This indicates that the integration of deep learning algorithms with digital twin technology is beneficial for load prediction in power systems [29].

In summary, the research findings support the hypothesis of combining DTW, DBN-LSTM-MLP and digital twin technology. In balancing accuracy and load calculation scenarios, attempting to combine more deep learning algorithms with digital twin technology can further explore the potential of deep learning applications in load prediction and provide intelligent technology and decision support for distribution networks.

5. Conclusion

With the increasing complexity of the power system and the rapid growth of power data, traditional analysis and optimization methods were unable to meet the requirements of load prediction in new power systems. A comprehensive and innovative power load prediction algorithm based on DWT digital twin was proposed in response to this current situation. The ablation test results indicated that the DBN module, LSTM module, and MLP module all had a certain positive promoting effect on the DTW-DBN-LSTM-MLP power load prediction algorithm. In multi-indicator testing, the DTW-DBN-LSTM-MLP power load prediction algorithm had the best detection accuracy and comprehensive quality on both PLAID and Simulink datasets. The average detection time on the Simulink dataset was 2.61s, and the P, R, and F1 values were 95.58%, 93.88%, and 95.42%, respectively. Compared with other power digital twin application systems that combined different power load prediction algorithms, the power digital twin application system combined with DTW-DBN-LSTM-MLP power load prediction algorithm achieved the highest power load prediction accuracy, at 97.26%, and the lowest MAPE and RMSE were only 3.96% and 3.96%, respectively. The system had the lowest false detection rate. When the number of data samples was 100, 200, 300, 400, and 500, the false detection rates of the load information data obtained by the power system in Fuxin area in 2023 were only 2.71%, 3.32%, 3.76%, 4.07%, and 4.22%, respectively. In summary, the proposed method outperforms most existing methods in various indicator and simulation tests, achieving a high detection accuracy, low false alarm rate, stability, and excellent operational efficiency. However, the proposed method is only applicable to power load prediction. In the future, other methods will be combined to construct a more accurate and robust power comprehensive system detection method.

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