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Short-Term Power Demand Forecasting Using Blockchain-Based Neural Networks Models

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With the rapid development of blockchain technology, blockchain-based neural network short-term power demand forecasting has become a research hotspot in the power industry. This paper aims to combine neural network algorithms with blockchain technology to establish a trustworthy and efficient short-term demand forecasting model. By leveraging the distributed ledger and immutability features of blockchain, we ensure the security and reliability of power demand data. Meanwhile, short-term power demand forecasting research using neural networks has the potential to increase the stability of the power system and offer opportunities for improved operations. In this paper, the root mean-square-error model evaluation indicator was used to compare the back propagation (BP) neural network algorithm and the traditional forecasting algorithm. The evaluation was performed on the randomly selected five household power datasets. The results show that, by comparing the long short-term memory network (LSTM) model with the BP neural network model, it was determined that the average prediction impact increases by about 25.7% under stable power demand. The short-term power prediction model of the BP neural network has the average error values more than two times lower than the traditional prediction model. It was shown that the use of the BP neural network algorithm and blockchain could increase the accuracy of short-term power demand forecasting, allowing the neural network-based algorithm to be implemented and taken into account in the research on short-term power demand forecasting.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning algorithms

Applied computing → Operations research → Forecasting

Keywords: short-term power demand, BP neural network algorithm, back propagation, long and short-term memory network, blockchain, root-mean-square error

1. Introduction

Rapid growth in the demand for electricity is caused by increased energy demand and consumption. Forecasting the power demand hence needs to be done accurately and efficiently [1]. Power demand refers to the related activities carried out to improve the utilization efficiency of power resources, improve the way of electricity consumption, and realize the use of electricity in science. Energy sources that are difficult to store include the electricity itself. As a result, it would be challenging for a power system to create electricity in accordance with the amount of electricity demand and it usually results in the generation of either too much or too little power. Backpropagation (BP) neural network technology is a multi-layer feed-forward neural network trained by the error in reverse propagation algorithm, which is the most widely used neural network. A region's electricity demand can be better understood by the electricity production department if short-term electricity demand forecast research is conducted. The department can then make forecasts based on the learned scenario to carry out electricity production planning [2–3]. The operation and management of a power management department are further standardized with the assistance of the production department, which helps to more accurately estimate the demand and supply of electricity. The previous power demand data can be summarized, and the uncertain data in the summary data can play its role in the future short-term power demand prediction. The BP neural network algorithm and blockchain are employed to estimate short-term power consumption. The research presented in this paper develops a reliable and efficient short-term load forecasting model. Here, the blockchain technology provides a secure and immutable platform for storing power demand data, ensuring its integrity and reliability. The neural network algorithm enhances the accuracy and precision of the forecasting model.

The need for short-term electricity is continually growing. On the creation of a short-term electricity demand projection, numerous academics have done a number of related studies. According to Matsumoto and Yamada [4], power firms' ability to operate profitably depends on their ability to predict both the demand for power and the forecasting of solar power [4]. To estimate the demand for potential future bioelectric power systems in the community, Rushma *et al.* [5] employed the inverse matrix approach in conjunction with the loads compiled from the survey and the equipment end use method. Su *et al.* [6] thought that demand response signals were additional loads connected to meteorological conditions based on the predictability of demand response planning signals and the independence of seasonal base loads. Yang *et al.* [7] believed that the level of economic power demand and the relationship model between economic power systems—which was produced by utilizing the XGBoost algorithm and also included a prediction of future load—were closely related. Few researchers have thought of employing the neural network algorithm to explore the forecasting of short-term power consumption among the studies conducted by these scholars. Most research scholars use the tensor product spline function, using the inverse matrix method, based on demand response, and the XGBoost algorithm for power demand prediction. As a result, this publication conducted additional research on the neural network algorithm-based forecasting of short-term power demand.

Research interest in neural network algorithms has consistently been significant, and new publications of pertinent studies are consistently being published. In his event-driven deployment algorithm for collaborative neural networks, Zhuang *et al.* [8] suggested a neural network approach as a foundation. Utilizing BP neural networks, Chen and Zhang [9] improved the system performance while analyzing the cognitive transmission performance under diverse environmental disturbances using LFM signals. Through the use of a Convolutional Neural Networks (CNN) model, Zhang *et al.* [10] trained a resulting model that was effective for complicated scenarios with multipath effects or many access points. After training the model to improve the localization performance by considering a series of Received Signal Strength Indicator (RSSI) vectors and extracting local features, the GPR algorithm further improved the localization accuracy. Jin and Zheng [11] helped the new line to be adjacent to and close to the existing line, and overcame the existing line, as well as avoided the need to readjust the coverage of the original line network, thus increasing the construction difficulty and improving the investment cost. Zhang and Liang [12] reviewed the application of building demand prediction models, using machine learning performance and accuracy to build a new prediction model, including data engineering, preprocessing from sensor level to data level, feature extraction and selection, thus summarizing a well-researched and relatively untapped field. Nelson *et al.* [13] think that machine learning has powerful data processing ability, and without the exact physical model and expert prior knowledge, only according to the depth of the machine learning model structure, divided into shallow machine learning methods and methods based on deep learning. Machine learning leads to detailed analysis and expounds the residual life prediction of equipment . Different neural network methods were employed for analysis in the research these researchers conducted on forecasting power demand. Numerous neural network algorithms had a wide range of applications and research topics, demonstrating the importance of this subject for future study.

At the same time, due to the massive amount of data required for electricity data prediction and considering the privacy and security concerns surrounding electricity data, data owners operate almost independently, making it difficult for data to be shared among them. The prediction of electricity data is limited by the feature dimensions and quantity of sample data, and the decentralized and tamper-proof characteristics of blockchain make it an ideal choice for protecting sensitive data privacy and ensuring data security [14]. Ma [15] demonstrated that by storing neural network models and training data on the blockchain, the secure transmission and storage of data can be guaranteed, while preventing unauthorized access and tampering. Furthermore, blockchain can record all transactions and operations related to neural network models and data, providing complete transparency and verifiability. This enables the traceability of model origins and the credibility of data, thereby increasing the trustworthiness and reliability of the algorithm.

Generally speaking, departmental scheduling frequently uses short-term electricity demand forecasting, and it is beneficial for daily, weekly, and monthly scheduling. In order to establish a short-term forecasting model of power demand based on the neural network algorithm, this article mostly relied on the BP artificial neural network algorithm. The BP neural network algorithm and real-time embedded systems perform better with more data when compared to other algorithms. The network's computational power is likewise constantly increasing along with the ongoing growth of data. As a result, the objective of intelligent and integrated power resources can be better attained, and a significant research foundation will be established for the future allocation of power demand [16].

2. Short-Term Power Demand Forecasting Algorithm

2.1. Blockchain Network Architecture

Blockchain network is a decentralized distributed computing system, which is composed of multiple nodes. These nodes reach consensus through mutual communication and consensus mechanisms, validate and record transactions and data, and link them together in the form of blocks to form a growing block chain. Because there is no centralized control mechanism, the blockchain network has a high degree of security and transparency, because any node can verify and monitor the transactions that take place on the network [17–18]. Figure 1 illustrates the key components of a blockchain architecture. These components collectively form the fundamental architecture of blockchain, enabling decentralized, transparent, secure, and trustworthy data exchange and storage.

The decentralized and immutable nature of blockchain makes it ideal for protecting the privacy of sensitive data and ensuring data security. Storing neural network models and training data on blocks ensures secure transmission and storage of data and prevents unauthorized access and tampering. At the same time, while the blockchain is operating, the distributed ledger in the blockchain records all transactions and operations of the neural network model and data, providing a fully transparent and verifiable record. In this way, the source of the model and the credibility of the data can be traced, which increases the credibility and reliability of the algorithm. Finally, each data holder can provide prediction models and data on the blockchain through a distributed network to facilitate the innovation and development of prediction algorithms [19].

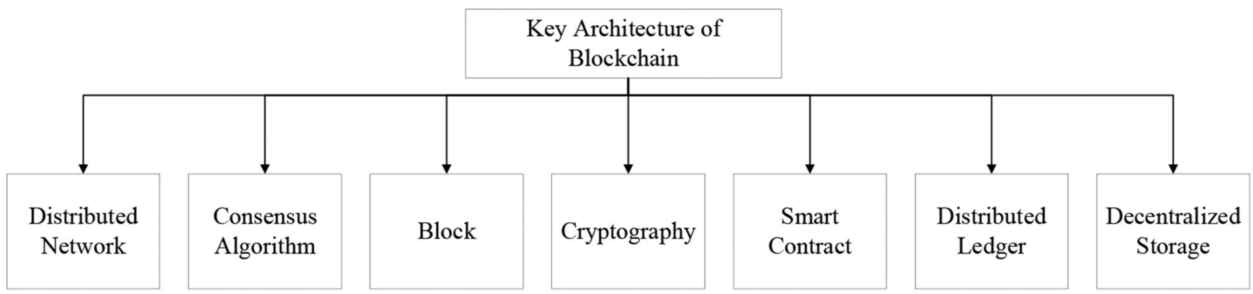

Figure 1. Illustration of the key components of a blockchain architecture.

Greater asset security, stronger KYC/AML procedures, and advanced analysis and monitoring will all result in more transparency and visibility. By putting these protections in place, businesses will become more confident in blockchain technology and it will be widely adopted. Because of the blockchain's capabilities for real-time information sharing, security, unmodification, and transparency, many stakeholders have high expectations for it. Blockchain technology, which uses proof-of-work and a distributed database structure, can increase supply chain transparency while utilizing real-time distributed data sharing to allow stakeholders to discover information about product quality, location, transactions, and procedures. In order to increase trust between trading partners, blockchain makes the supply chain more efficient and explicit by strengthening the connections between suppliers, customers, outsourcing, third-party logistics providers, and subcontractors. This is done by developing efficient strategic planning tools.

2.2. Classification of Electricity Forecast Duration

Forecasts of the demand for electricity typically contain a certain forecast period. The goal of the power system's demand forecasting is also different for different forecast durations. Other elements that affect power demand, such as some natural phenomena and policy changes, should also be taken into account while doing research on power demand forecasting in addition to the features of the research object's own power demand [20–21]. Based on the foregoing analysis, it is possible to categorize and study the forecasted power demand to facilitate various research projects on various demands and to help the research be more in line with the actual needs. Figure 2 depicts the power demand prediction categorization.

A projection of electricity consumption for the upcoming month, week, day, or hour is referred to as a short-term forecast of electricity demand. It is crucial for the entire process of power dispatching. This is due to the fact that forecasting

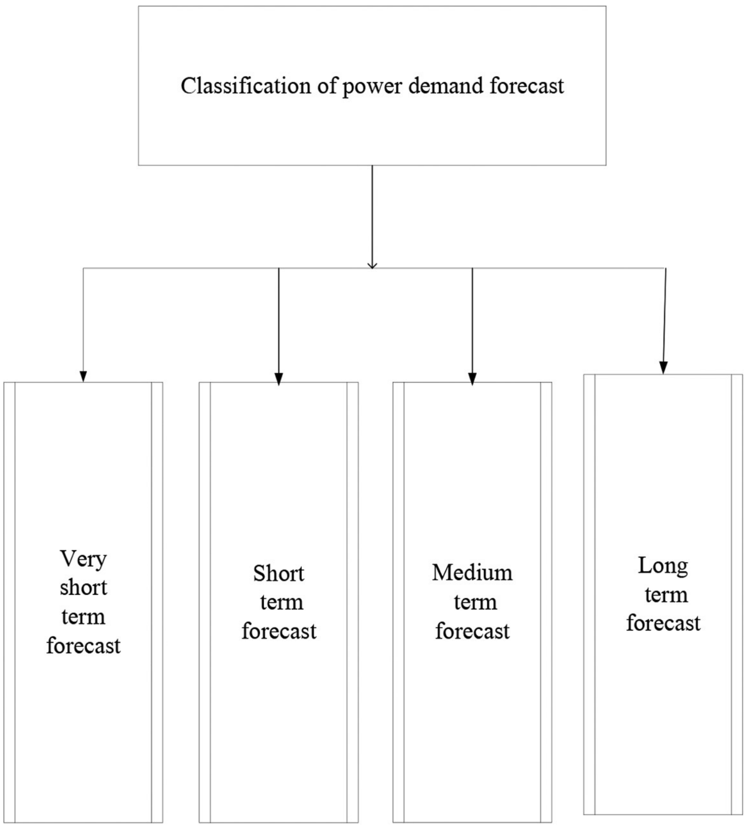

Figure 2. Classification of power demand forecast.

precision and electricity market economics are tightly intertwined. Forecasting has the potential to increase both the efficiency and security of the operating power system [22]. In order to guarantee the operating performance of a power system and assess the accuracy of electricity transactions, it is crucial to develop the best dispatching strategy, production plan, and short-term resource allocation plan for the producing units [23].

2.3. BP Artificial Neural Network Algorithm

One of the neural network models that is frequently used in many disciplines is the BP artificial neural network, which is a multi-layer feed-forward network trained by error back-propagation algorithm [24–25]. It is capable of memorizing and learning a sizable number of input-output pattern correspondences. The bidirectional mapping relationship of data can be seen without an algorithmic model [26–27], and the algorithm's formula is as follows:

$$X_q = \frac{1}{2}\sum_{j=1}^{n}\left(v_j^q - y_j^q\right)^2 \tag{1}$$

q learning samples are input, which is represented by x^1, x^2, ..., x^q. The value of the output layer can be obtained after inputting the sample into the neural network.

In the formula, v is the expected output.

The performance of the global maximum load and power consumption error in the q-th sample is:

$$X = \frac{1}{2}\sum_{G=1}^{Q}\sum_{j=1}^{n}\left(v_j^G - y_j^G\right) = \sum_{G=1}^{Q} X_G \tag{2}$$

The maximum demand global error X is reduced. In the formula, μ is the learning rate:

$$\Delta S_{jk} = -\mu\frac{\alpha X}{\alpha S_{jk}} = -\mu\frac{\alpha}{\alpha S_{jk}}\left(\sum_{G=1}^{q} X_G\right) \tag{3}$$

The error signal of electricity consumption is defined as:

$$\delta_{yi} = -\frac{\alpha X_G}{\alpha W_j} = -\frac{\alpha X_G}{\alpha y_j}\cdot\frac{\alpha y_j}{\alpha W_j}. \tag{4}$$

Formula for the maximum demand forecast value item 1:

$$\frac{\alpha X_G}{\alpha W_j} = \frac{\alpha X_G}{\alpha y_j}\left[\frac{1}{2}\sum_{j=1}^{m}\left(v_j^G - y_j^G\right) = -\sum_{j=1}^{n}\left(v_j^G - y_j^G\right)\right]. \tag{5}$$

Formula for the electricity consumption forecast value item 2:

$$\frac{\alpha y_j}{\alpha W_j} = f_2\left(W_j\right). \tag{6}$$

Finally, the partial differential of the transfer prediction function of the prediction effect is obtained, as shown in the formula:

$$\delta_{yi} = \sum_{j=1}^{n}\left(v_j^G - y_j^G\right) f_2\left(W_j\right). \tag{7}$$

From the chain theorem, the formula can be obtained as:

$$\frac{\alpha X_G}{\alpha S_{jk}} = \frac{\alpha X_G}{\alpha E_{jk}}\cdot\frac{\alpha E_j}{\alpha S_{jk}} = -\delta y_j \cdot Z_k. \tag{8}$$

The weight formula of each node of the prediction effect function is converted into:

$$\Delta S_{jk} = \sum_{G=1}^{q}\sum_{j=1}^{n}\mu\left(v_j^G - y_j^G\right) f_2\left(W_j\right)\cdot Z_k. \tag{9}$$

The algorithm is used to adjust the activation function, and the global error is reduced:

$$\Delta S_{jk} = -\mu\frac{\alpha X}{\alpha S_{jk}} = -\mu\frac{\alpha}{\alpha S_{jk}}\left(\sum_{G=1}^{q} X_G\right). \tag{10}$$

The revised formulas for the final output layer weights:

$$\delta y_j = -\frac{\alpha X_G}{\alpha E_i} = -\frac{\alpha X_G}{\alpha y_i}\cdot\frac{\alpha y_i}{\alpha X_i} \tag{11}$$

$$\frac{\alpha y_i}{\alpha X_i} = f_2^1\left(E_j\right). \tag{12}$$

2.4. Model Evaluation Indicators

In order to characterize the prediction accuracy of the model, this study chooses the following model assessment indicators of the prediction effect: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percent Error (MAPE).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{M}\left(\hat{y}_1 - y_i\right)^2}{M}} \tag{13}$$

$$MAE = \sqrt{\frac{\sum_{i=1}^{M}\left|\hat{y}_1 - y_i\right|}{M}} \tag{14}$$

$$MAPE = \frac{\sum_{i=1}^{M}\left|\frac{\hat{y}_1 - y_i}{y_i}\right| \cdot 100}{M} \tag{15}$$

3. Short-Term Power Demand Forecast Assessment Based on Blockchain

The data on China's entire electricity consumption from 2017 to 2021 published by the China Electricity Council is utilized to analyze China's recent electricity demand, as illustrated in Figure 3.

In Figure 3, the annual electricity consumption for 2017 is shown as 645 million kWh, followed by annual electricity consumption for 2018 of 699 million kWh, annual electricity consumption for 2019 of 733 million kWh, annual electricity consumption for 2020 of 762 million kWh, and annual electricity consumption for 2021 of 798 million kWh. The graph clearly shows that the amount of electricity consumed rises each year, making anticipated control of electricity demand crucial [28]. In order to better propose demand supply measures and advance short-term power demand forecast research, it is required to conduct specific short-term power demand forecast analysis and research. This will help to better understand how short-term power demand will evolve in the future [29–30].

3.1. Investigation on Short-Term Power Demand Forecasting Based on BP Neural Network Model

The BP neural network algorithm creates a self-induction mechanism that can successfully prevent issues when connecting weights. Artificial neural networks, which often employ the steepest descent approach as the default calculation method, have significantly advanced as a result of the discovery of this law. The idea behind this approach is that the error from the output layer to the derivation layer of the upper layer may be calculated by comparing the error of the output layer, and this cyclic method estimates the error of the upper layer. The error values of the remaining layers can be computed by back-propagating iteratively [31]. Although it is important to note that this transfer is made step-by-step, this mode is the transfer direction of the error of the output layer opposite to the input signal.

3.1.1. Factors Affecting Electricity Demand

The economy is the primary influencing element of effective communication, as follows. Typically, the growth of the economy has a direct impact on the demand for electricity. The demand for electricity and effective communication will rise while the economy is doing well, and vice versa. As a result, there is a proportionate relationship between the two. In addition, a family's or a region's intensity of electricity use can serve as a proxy for a region's economic health and its relationship to the overall volume of the consumption. In general, there is a strong correlation between the distribution of economic industries in a location and the amount of electricity demand in that location. The distribution of the primary, secondary, and tertiary industries in this area can be understood from this. There is a direct correlation between the demand for electricity and the amount of secondary industry that is based mostly on industry in the economy [32].

The next set of influencing elements is social. The demand for electricity consumption is influenced by the quality of life and residents' economic levels. The higher the level and effective communication, the greater the demand for electricity consumption. This is mostly due to the fact that when citizens' disposable income

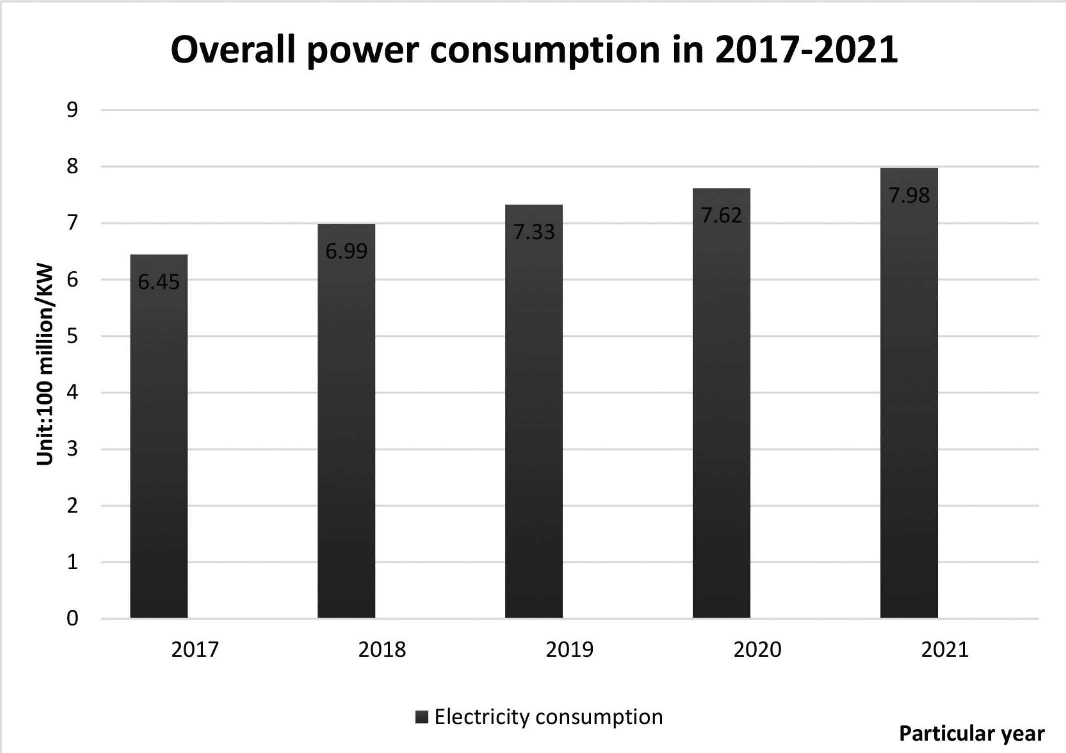

Figure 3. China's overall electricity consumption from 2017 to 2021.

per capita rises, so does society's general level of consumption. The demand for electricity would rise in line with an expanding population. The amount of electricity throughout the period would be greatly reduced under marketization conditions when the price of electricity is so high that it surpasses the capacity of the firm to bear it [33]. This would also have an impact on the distribution of high energy-consuming industries. Due to the significant energy use during production and the associated expense, it is frequently transferred from regions with high electricity costs to regions with cheaper electricity prices, increasing regional electricity demand. Furthermore, changing pricing at different times are advantageous to increase the effectiveness of power utilization [34–35].

Politics and effective communication is another set of influencing factors: Power policies vary as well, depending on the various developmental requirements of the nation at various times. To fulfill the needs of a country and effective communication development, the power policy and other policies can be merged. This will allow the industrial structure to be further adjusted, as well as enable the upgrading of the industrial structure and better layout of the high-polluting, high-energy consumption businesses [36].

Finally, the meteorological factor is an influencing factor. Varying weather conditions also result in different electricity demand. On summer days, when it is sunny, more electricity is needed. Air conditioners would be used if the weather was warm. Additionally, the demand for electricity would rise in the winter due to the rainy weather. Data is based on the potential summer weather in a certain province. Generally speaking, it is uncommon for most places to encounter really cold weather throughout the summer, such as snow, hail, and frost. The extreme weather that is practically never experienced is categorized into one category, which is called other, using the summer weather in a particular place as an example. The primary research objects are separated by weather conditions, including cloudy, light rain, sunny, thunderstorm-prone, and others. Figure 4 displays the power load outcome based on weather conditions.

Figure 4 illustrates some of the influencing elements, and it is anticipated that additional components exist in addition to those depicted there. It is evident that the maximum electrical load varies depending on the type of weather: the load of cloudy weather is 3500/kW; the load of light rain weather is 3200/kW; the load of sunny weather is 4000/kW; the load in showery weather is 2900/kW; the load in rainy weather is 2700/kW; the load in moderate rainy weather is 2500/kW; the load in heavy rain weather is 2300/kW. It can be clearly analyzed that the clearer the weather in summer, the greater the load value of electricity.

3.1.2. Model Structure

The constructed grid framework must first demonstrate its ability to maintain a stable and long-lasting functioning state before the development of the prediction model can proceed. Next, a significant amount of application data for short-term power demand is transmitted via the neural network, and finally, a physical connection to the prediction system is established. The BP neural network typically comprises three layers. The previously communicated power application data would be instantly transformed into the needed connection state once the neural network's layer count achieves the prediction standard. The goal of normalizing the demand data is achieved when all power demand variables in the big data environment stay stable, as this would also show a stable condition in the multivariable cycle.

3.1.3. Experimental Data

Family data forms a database that includes all aspects of power demand data. The information is divided into five family datasets, each of which includes information on the number of family members, the year the house was built, its size, and the living patterns of the population. The electricity consumption data sets for these five households are collected using smart meters. Each household is based on the original power demand data at the frequency of power collection every ten seconds. Therefore, the data units must first be converted. If the power units are not converted, the calculation results will be incorrect. The demand data will be converted to electricity consumption within 10 seconds, and then the data will be merged. The combined data selects 85% of the data as the training set, of which 10% is used as the verification set; 5% is used as the test set, and the specific data values are shown in Table 1.

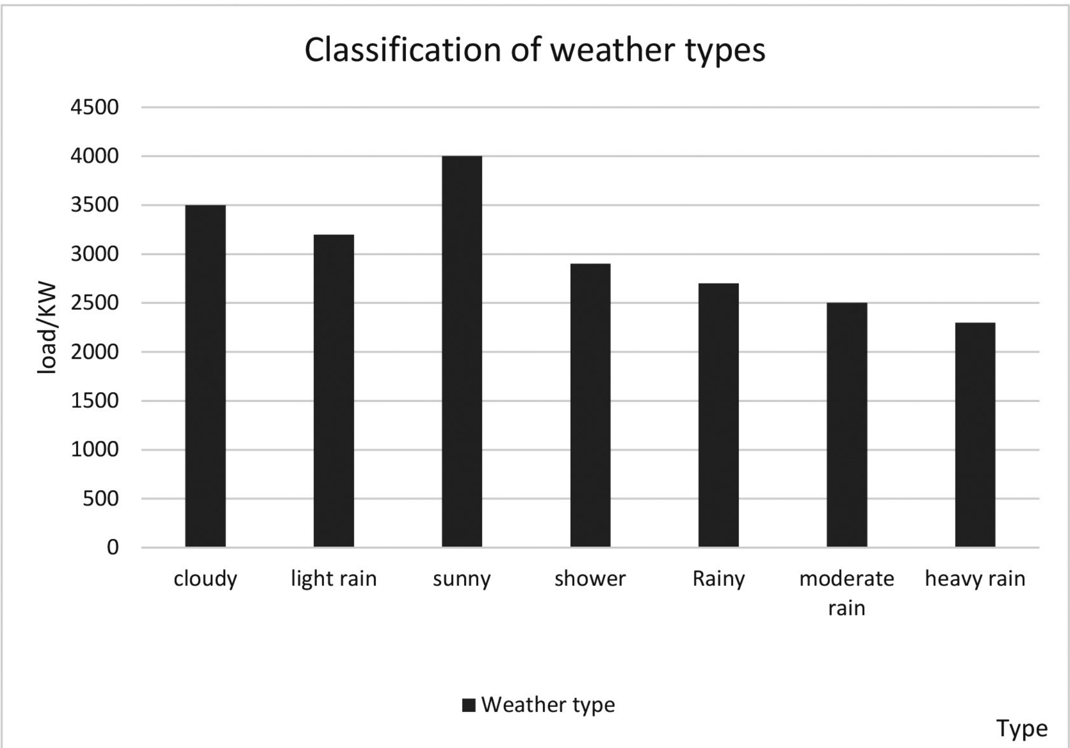

Figure 4. Classification of weather types with respect to influence on the power load.

As shown in Table 1, there are 15,352 training sets from family No. 1 and1,716 test sets, 3,399 training sets from family No. 2 and 385 test sets, 751 training sets from family No. 3 and 82 test sets, 3,190 training sets from family No. 4 and 370 test sets, 2,630 training sets from family No. 5 and 295 test sets.

3.2. BP Neural Network Model and Long Short-Term Memory (LSTM) Model for Electricity Demand Prediction

The five household electricity data sets from Table 1 are used for model performance tests in this paper to confirm the BP neural network model's prediction to forecast outcomes. As the assessment criteria, the mean absolute error and the root mean square error are utilized, and the results are contrasted with those of the current LSTM techniques. When the demand for residential electricity is stable, Mean Absolute Error (MAE) concentrates on the prediction error. LSTM is a temporal recurrent neural network, mainly designed to solve the problem of vanishing gradient and exploding gradient during training on a long sequence. The effect of prediction is improved by a smaller MAE value [37–38], and Table 2 displays the predicted values on the test sets.

Table 1. Number of experimental training sets and test sets.

Data set	**Raw data (10S)**	**1 minute**	**1 hour**	**Training set**	**Test set**
Family 1	10580000	10580000	17160	15352	1716
Family 2	2350000	2350000	3856	3399	385
Family 3	511900	511900	821	751	82
Family 4	2285600	2285600	3700	3190	370
Family 5	1762500	1762500	2950	2630	295

Table 2. MAE comparison of BP and LSTM models on five family datasets.

Data set (KWh)	**LSTM**	**BP**
Family 1 dataset	0.0150	0.0135
Family 2 dataset	0.0040	0.0010
Family 3 dataset	0.0090	0.0058
Family 4 dataset	0.0060	0.0045
Family 5 dataset	0.0032	0.0025
Average	0.0074	0.0055

Table 2 displays the MAE performance for the BP and LSTM models on the five family datasets. The experimental results show unequivocally that, in the stationary state, the BP neural network power demand prediction method suggested in this research has a substantially greater prediction accuracy than the LSTM method: According to the BP model, the value of MAE for family 1 is predicted to be 0.0135, while the values for families 2, 3, 4, and 5 are predicted to be 0.0010, 0.0058, 0.0045, and 0.0025, respectively. Using LSTM, the value of MAE for family 1 is predicted to be 0.0150; that of family 2 is predicted to be 0.0040; that of family 3 is predicted to be 0.0090; that of family 4 is predicted to be 0.0060; and that of family 5 is predicted to be 0.0032. The BP neural network performs significantly better than the LSTM method in terms of the prediction effect of each home stationary state. The BP neural network outperforms the LSTM method in terms of the mean predicted MAE values for the two methods, and this results in an improvement of roughly 25.7% in the prediction effect's average accuracy in the stationary state.

In addition to examining the forecast effect in a steady state, it is essential to further examine the forecast error at the peak period of short-term power demand for the forecast research of short-term power demand. The Root Mean Square Error (RMSE) is used as the assessment standard for the BP neural network method developed in this paper, which focuses on the prediction error of the peak period of power demand. Since the term "RMSE" stands for "root mean square error," the peak's accuracy of prediction would be highlighted. In light of this, the constructed model's predictive power improves with decreasing RMSE values [39–40], and Figure 5 displays the predicted value.

The results of the BP and LSTM models based on RMSE on five family datasets are shown in Figure 5. Figure 4 demonstrates that the model of forecasting power demand using a BP neural network is significantly superior to the LSTM method when the power demand hits its peak. Using LSTM, the model's RMSE for family 1 is predicted to be worth 0.0299; the model's RMSE for family 2 is predicted to be worth

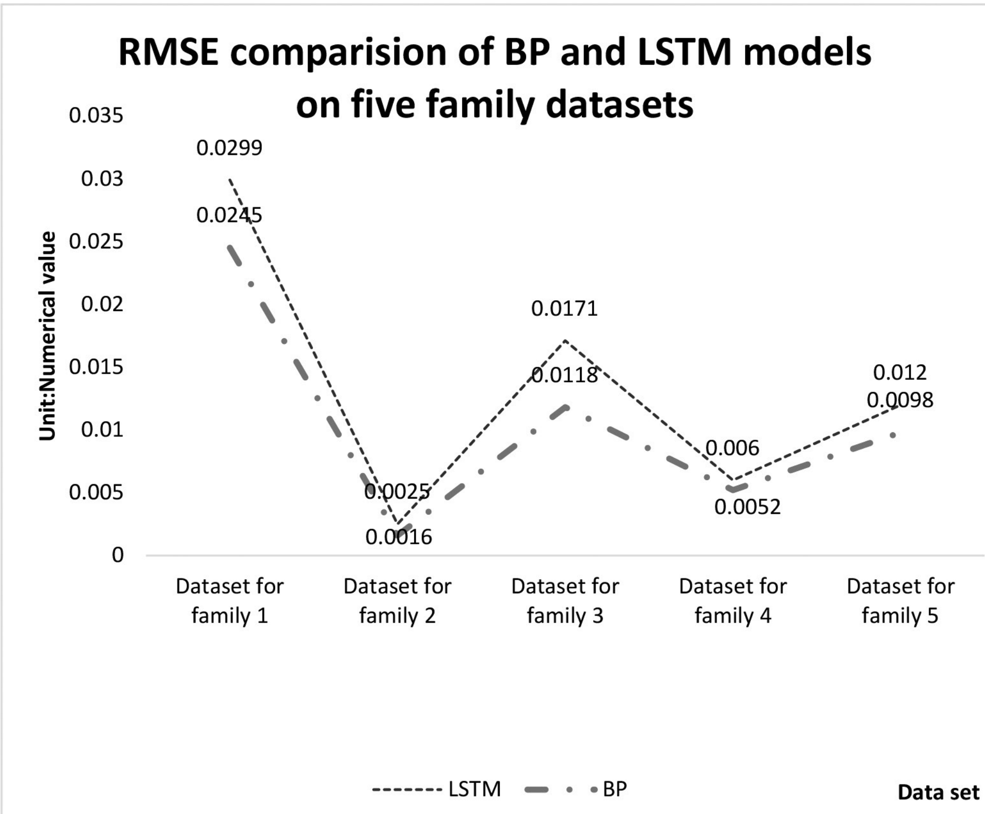

Figure 5. RMSE comparison of BP and LSTM models on five family datasets.

0.0025; the model's RMSE for family 3 is predicted to be worth 0.0171; the model's RMSE for family 4 is predicted to be worth 0.006; and the model's RMSE for family 5 is predicted to be worth 0.012. The predicted value of the model's RMSE for family 1 created by BP is 0.0245; the predicted value of the model's RMSE for family 2 is 0.0016; the predicted value of the model's RMSE for family 3 is 0.0118; the predicted value of the model's RMSE for family 4 is 0.0052; and the predicted value of the model's RMSE for family 5 is 0.0098. The BP neural network outperforms the LSTM method in terms of prediction accuracy as evaluated by RMSE at each period of high power demand [41–42].

3.3. Traditional Forecasting Model Scheme and Establishment of Short-Term Power Forecasting Model Based on BP Neural Network

MAPE, which represents the total forecasting impact of home electricity demand, is the average of the sum of absolute percentages. Concerning the validation of the prediction model established by the BP neural network algorithm, this study will compare the actual maximum demand data, electricity consumption, and predicted values for eight days in January 2022 from the data set using the first family of the five selected families as the research object. For comparison with the true value, the comparison objects include the short-term power forecasting model for the BP neural network and the conventional forecasting model. MAPE is the measurement metric employed to assess the precision of maximum load and electricity consumption forecasting. Table 3 displays the results of the true value of the maximum demand and electricity consumption in the eight-day sample extraction, as well as the predicted value obtained by applying the BP neural network shortterm power forecasting model and the conventional forecasting model. Further information are, as follows.

Table 3. Real and predicted values for eight days in the test set.

Date	Maximum load WM	BP neural network model		Traditional model		Electricity consumption (ten thousand/kW/h)	BP neural network model		Traditional model	
		Estim-ate	MA-PE%	Estimate	MAPE%		Estimate	MA-PE%	Estimate	MAPE%
2022/1/1	2213.2	2300	3.90	2080.2	6.00	44500	45200	1.57	41500	6.74
2022/1/2	2243	2355	4.99	2506	11.74	46000	48000	4.34	49200	6.96
2022/1/3	1900.5	2010.6	5.79	2120.5	11.58	45500	46800	2.86	47100	3.52
2022/1/4	2100	2200	4.76	1800	9.52	46203	48454	4.87	49353	6.82
2022/1/5	1924	1914	0.54	2140	11.20	42000	42800	1.90	43000	2.38
2022/1/6	1890	1950	3.17	1700	10.05	39200	41200	5.10	42500	8.42
2022/1/7	2150.5	2250.5	4.65	2300.5	6.98	37980	38131	0.58	36010	4.98
2022/1/8	2400	2509	4.54	2215	7.71	40700	41120	1.18	38800	4.86
MAPEaverage value			4.04		9.35			2.80		5.59

The average value of the data collected by the conventional prediction model is 9.35% in MAPE, as can be seen in Table 3 for the predicted value of the maximum demand. The predicted MAPE value for family 1 on January 1, 2022 is 6.00%; the predicted MAPE value on the 2nd day is 11.74%; the predicted MAPE value on the 3rd day is 11.58%; the predicted MAPE value on the 4th day is 9.52%; the predicted MAPE value on the 5th day is 11.20%; the predicted MAPE value on the 6th day is 10.05%; the predicted MAPE value on the 7th day is 6.98%; the forecasted MAPE value on the 8th day is 7.71%. Even as much as 11.74% separates the maximum demand that actually occurred from the maximum load that was predicted. The BP neural network short-term power prediction model's average value of the data extracted as evaluated by MAPE is 4.04%. Among them, the forecast MAPE value on January 1, 2022 is 3.90%; the forecast MAPE value on the 2nd day is 4.99%; the forecast MAPE value on the 3rd day is 5.79%; the forecast MAPE value on the 4th day is 4.76%; the forecast MAPE value on the 5th day is 0.54%; the forecast MAPE value on the 6th day is 3.17%; the forecast MAPE value on the 7th day is 4.65%; the forecast MAPE value on the 8th day is 4.54%. Only 5.79% separates the maximum demand that actually occurred from the maximum demand that was predicted. The short-term power prediction model of the BP neural network has an average error value that is more than twice as low as the conventional prediction model. Further evidence is provided to support the claim that the BP neural network short-term power prediction model has a higher prediction accuracy than the conventional prediction model.

The average value of the data collected by the conventional prediction model using MAPE is 5.59%, as can be shown in Table 3 for the predicted value of electricity consumption. The forecast MAPE value on January 1, 2022 is 6.74%; the forecast MAPE value on the 2nd day is 6.96%; the forecast MAPE value on the 3rd day is 3.52%; the forecast MAPE value on the 4th day is 6.82%; the forecast MAPE value on the 5th day is 2.38%; the forecast MAPE value on the 6th day is 8.42%; the forecast MAPE value on the 7th day is 4.98%; the forecast MAPE value on the 8th day is 4.86%. Even as much as 6.96% of real power consumption deviates from the predicted power consumption. The short-term power prediction model for the BP neural network's average value of the data extracted and evaluated by MAPE is 2.80%. Only 5.10% separates the actual power consumption from the predicted power consumption. The short-term power prediction model of the BP neural network has an average error value that is more than twice as low as the conventional prediction model. Further evidence is provided to support the claim that the BP neural network's short-term power prediction model has a higher prediction accuracy than the conventional prediction model.

The association between the predicted value curve of the BP neural network short-term power prediction model and the true value curve is better than that between the traditional prediction model and the actual curve, as shown in Figure 6, regarding the daily comparison between the predicted value of the maximum load and the true value curve of the maximum load of the BP prediction model and the traditional prediction model. The distance between the two curves is also smaller when comparing the two models. For the purpose of predicting the power demand, the prediction model based on the BP neural network is more accurate, which can contribute to the prediction of relevant information for the establishment of the prediction of the power demand.

As seen in Figure 7, when the predicted value and true value curves of the short-term electric power prediction model of the BP neural network and the traditional prediction model are compared, the predicted value curve ratio and the true value curve of the short-term electric power prediction model of the BP neural network are better than those of the traditional prediction model, and the distance between the two curves is better. The accuracy of short-term forecasts of power demand is significantly increased by the short-term power demand forecasting method based on BP neural network. Figures 6 and 7 make it abundantly evident that the prediction method of the BP neural network can be used to analyze short-term power demand and demand forecasting. It has been discovered that the short-term power demand prediction effect based on the BP neural network model is more efficient than the conventional prediction model and has the advantage of greater accuracy. By accurately forecasting electricity demand and load curves, this would not only lay the groundwork for the power plant to dispatch power producing capacity and arrange the start and stop of generators in a fair manner. It would also make it easier to implement targeted demand-side management.

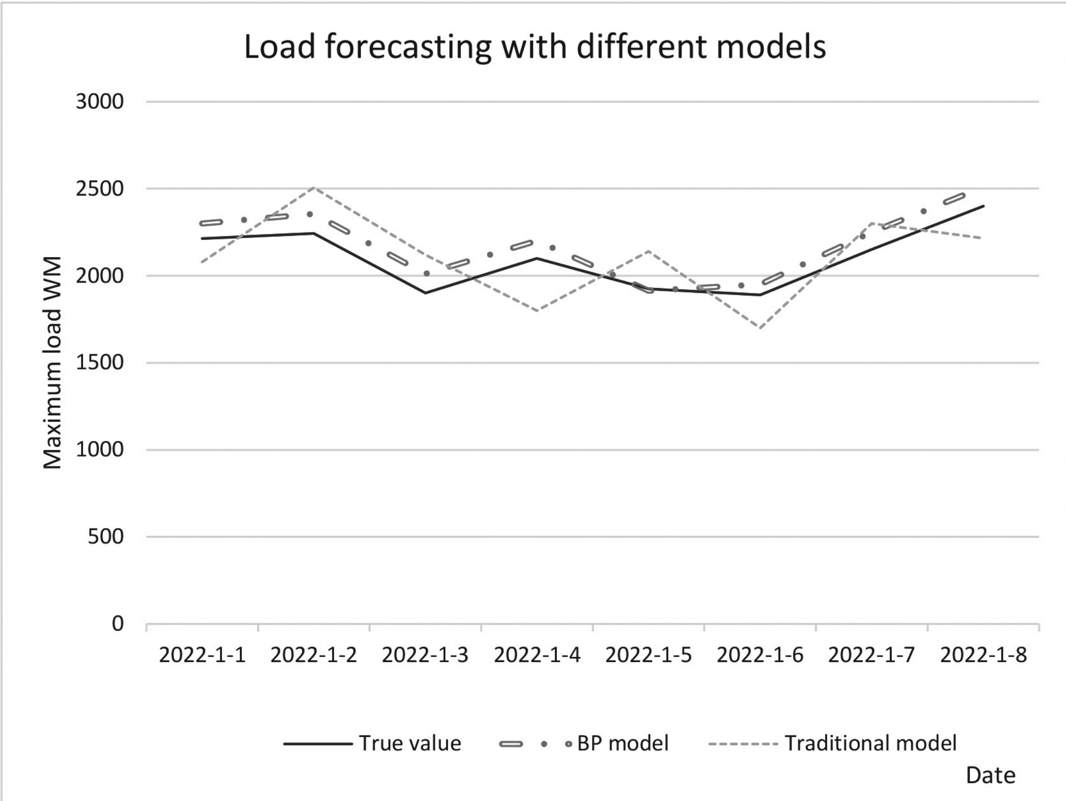

Figure 6. BP forecasting model, traditional forecasting model and load forecasting compared to the true value.

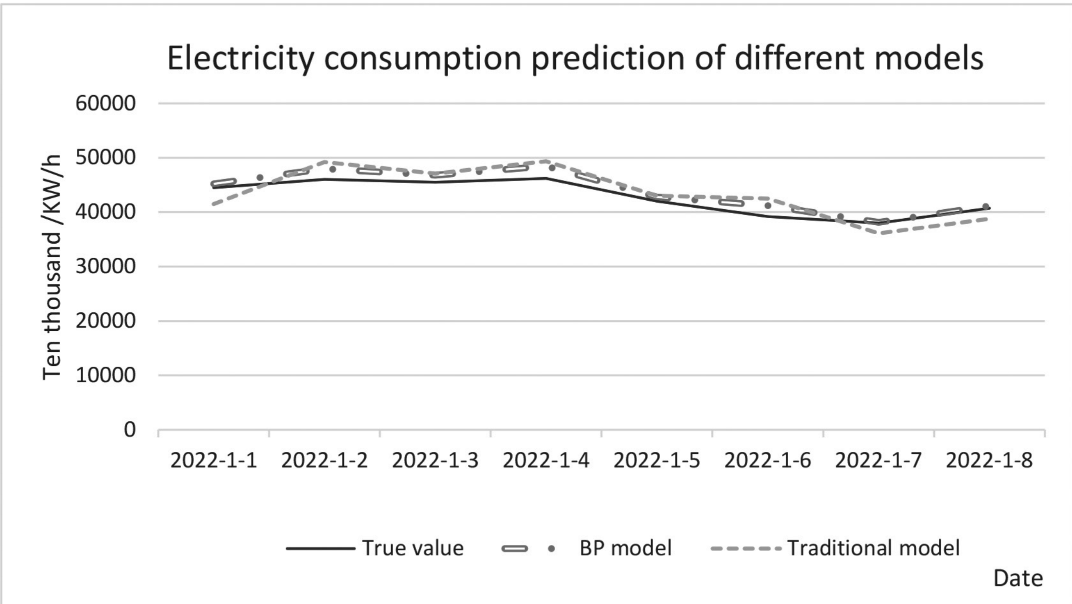

Figure 7. BP neural network short-term power prediction model and traditional prediction model and power consumption prediction compared to the true value.

The previous article compares the use of BP neural network prediction model and traditional prediction model and the true value. In order to better reflect the neural network, the research method in this paper has the advantages of BP neural network compared to other algorithms. Comparing it with the LSTM neural network algorithm can further reflect the advantages of BP neural network, and compare with the support vector machine (SVR) algorithm, it can better reflect the comparison with other algorithms. Does BP neural network have advantages in the establishment of power prediction models? BP algorithm, LSTM algorithm, traditional model and SVR are compared with respect to their power prediction model, and the extracted samples are taken for eight days. Predictive analysis of electricity is carried out, and the power values predicted by the models established by these four methods are compared with the true power values. The specific comparison results are shown in Figure 8.

As shown in Figure 8, regarding the daily comparison of the predicted value of the BP neural network short-term power prediction model and the predicted value of the electricity consumption of the other three models with the true value curve, the BP model and the true value curve are more closely related. The comparison between the BP model and the traditional model in Figure 7 has been studied. In Figure 8, the LSTM model and the SVR model are compared with the true value curve, but they are also very different. There is no other model that is more closer to the true value than the BP model. Therefore, compared with other models, the BP model's prediction is more accurate, and compared with other models, it is better to predict data close to the true value. In Figure 8, the comparison between the LSTM model and the SVR model and the true value curve also shows significant differences. The results may help power plants to better make large-scale power forecasts, predict future electricity consumption, and better adjust electricity consumption.

4. Discussion

Many crucial details can be found in power load history data that can be utilized as guidance for short-term power load forecasting. Traditional and LSTM short-term power demand forecasting techniques must use manually created forecasting functions, such as peak power, standby power load, *etc.* The significant information loss caused by these human filtering processes will seriously impair the usefulness of historical data. In addition, researchers must take into account more constraints and relationships

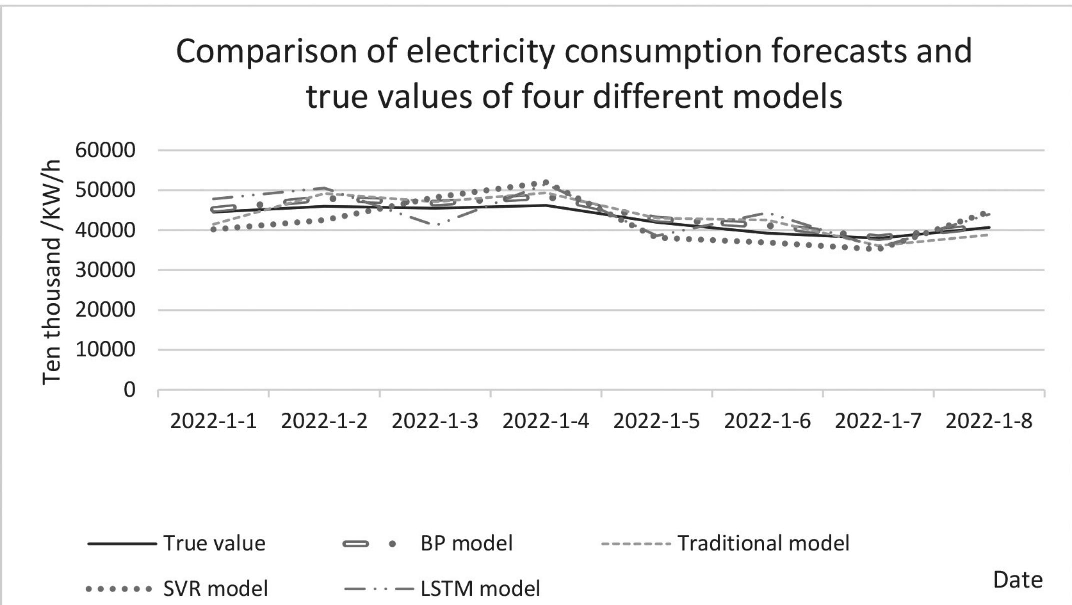

Figure 8. Comparison of electricity consumption forecasts and true values of four different models.

when identifying features, which takes a great deal of time and effort. As clean energy sources like wind and water are integrated into the grid and the scale of grid data transmission increases dramatically. LSTM and traditional methods are unable to handle this data scaling.

The power demand is influenced by a wide range of variables. Only the influence of date type, temperature, and rainfall is taken into account in this work due to the sparse original data; additional elements like humidity and wind speed are not taken into account. The quantification of many influencing factors is dependent entirely on experience and lack of theoretical guidance, and there is no set procedure for doing so. Different quantitative approaches are used by various researchers. It is yet unknown which quantitative model is more accurate in capturing the diversity of components.

5. Conclusion

The research on short-term electricity demand forecasting has a variety of development outcomes and due to the application of different intelligent technologies and algorithms. The usage of the BP neural network algorithm for short-term power demand forecasting study was always superior during the steady time or at the peak, according to this paper's comparison of the BP neural network algorithm and the LSTM method. When compared to the conventional prediction model, it was shown that the predicted values of the maximum demand power consumption were less dissimilar from the true values, the forecasting effect was better, and the forecasting accuracy was higher. A short-term power demand forecasting study was conducted using the BP neural network algorithm. The construction of a better intelligent power grid, which was crucial for achieving energy conservation and environmental protection as well as balancing power demand, could be aided by the prediction accuracy and power utilization and effective communication, which could also assist to prevent resource waste. Of course, there are still many shortcomings in the research and investigation of this aspect, therefore, in the future research, it is necessary to further develop and improve, so that the neural network algorithm can be better applied to the short-term power demand prediction research. Although the short-term power load prediction using blockchain technology and BP neural networks has now shown pleasing results, there are still many issues that need to be addressed. Research should continue, primarily focused on the following aspects: (1) the sample data has a significant impact on the neural network's ability to train, and choosing a sample of days that are similar to one another is helpful for increasing the model's ability to predict outcomes accurately; (2) the data and information limitations. There are numerous variables that determine demand size, such as typical large events, particular special events, *etc.* These variables are not recorded, therefore they are not stored in the original data, which may lead to a reduction in prediction accuracy.

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