CIT. Journal of Computing and Information Technology, Vol. 33, No. 1, March 2025, 25–42
doi: 10.20532/cit.2025.1005946


# Grid Data Analysis and Load Forecasting Model Based on Federated Learning Technology and LSTM Algorithm

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With the continuous improvement of the national economy, the development of power enterprises is gradually accelerating, and the popularity of smart grids is also increasing. The power grid data center contains a large amount of user data, and analyzing this data can help power companies predict the load of power plants, thereby improving the resource utilization efficiency of power enterprises. However, current load forecasting models still suffer from information leakage and inaccurate predictions during data transmission, storage, and analysis processes. To solve the above problems, this study uses federated learning technology to optimize the long short-term memory network algorithm and analyzes power grid data and load forecasting based on the optimized algorithm. This study first conducted comparative experiments on the optimized algorithm and found that the prediction accuracy of the optimized algorithm reached 94.5%, with a prediction time of only 1.2ms. The analysis of the data using a load forecasting model based on this algorithm showed that the data security of the model has been improved by 23.4%. After using this model, the power company's electricity resource utilization rate increased by 31.8% and operating costs decreased by 27.5%. The proposed power grid data analysis and load forecasting model can ensure the privacy of power grid data and improve prediction accuracy, thereby improving the power grid operation efficiency of power enterprises and optimizing enterprise resource allocation.

*ACM CCS (2012) Classification:* Computing methodologies → Machine learning → Machine learning approaches → Neural networks

*Keywords*: federated learning, long short-term memory network, data analysis, load forecasting

## 1. Introduction

The progress of power enterprises has led to the continuous improvement of the intelligence level of the power grid, gradually forming a smart grid [1]. The smart grid can achieve the goals of reliability, safety, efficiency, and environmental friendliness through advanced sensing and measurement technologies as well as advanced control methods [2]. The smart grid contains a large amount of user, electricity, energy, energy efficiency, and environmental data [3]. By analyzing these data, it is possible to predict the load of the power grid, aiming to arrange power generation plans reasonably, optimize power resource allocation, improve power grid operating efficiency, and reduce power grid operating costs [4]. However, many Load Forecasting Models (LFM) currently suffer from issues such as low data analysis accuracy, poor prediction performance, and power grid data privacy leakage [5]. Therefore, designing a Power Grid Data Analysis (PGDA) and LFM that can enhance the precision of load forecasting effectiveness, and prevent data privacy leakage is an urgent problem to be solved.

Long Short-Term Memory (LSTM) algorithm is a type of recurrent neural network (RNN) that can process and predict sequence data [6]. However, this algorithm has poor performance in data privacy protection and cannot guarantee data security [7]. Federated Learning (FL) is a machine learning (ML) framework. This framework can effectively assist multiple participants in data usage and ML modeling while ensuring data privacy protection and security [8]. Therefore, this study organically integrates FL and LSTM, using LSTM to analyze and predict power grid data, and then using FL to ensure the safety of power grid data during data analysis and load forecasting by LSTM, preventing privacy leakage.

The innovation of this study lies in the distribution of the FL-LSTM algorithm to each grid equipment of the power enterprise. The LSTM algorithm directly trains and analyzes data locally and finally transmits the trained data and analysis results to the global model of FL to protect the privacy of user data. The contribution of the research lies in the fact that this predictive model can optimize resource allocation, reduce operating costs, promote the construction of smart grids, and address the challenges brought by the integration of new energy into the grid.

## 2. Literature Review

To predict the load of the power grid, many scholars have researched LFM. For example, Dewangan *et al.* proposed a load forecasting method built on smart meter information statistics to predict the load of smart grids. This method was used in practical situations, and its prediction accuracy was only 73.5% [9]. Wang *et al.* designed a personalized joint method for individual consumption load forecasting to address the current inability of LFM to predict individual loads for each consumer. Compared with traditional load forecasting methods, this method could predict the load of each user [10]. In addition, to ensure the safety of the power system operation and achieve its sustainable development, Ibrahim *et al.* proposed a power LFM based on AI and IoT. This prediction model could improve the security of the system by 12.7% when used in practical situations [11]. Guo *et al.* designed a combined LFM based on bidirectional LSTM and multi-task learning to address low economic dispatch and operational efficiency in multi-energy systems. Compared with traditional prediction models, this model could improve the operational efficiency of multi-energy systems by 23.7% [12].

The LSTM algorithm is widely used in various fields due to its excellent data processing and prediction capabilities. For example, Xiang *et al.* put forward a deep learning framework grounded on LSTM network optimization to address the problem of low computational efficiency of deep learning algorithms in the seismic design of high-speed railways. Compared with the unoptimized framework, this deep learning framework could improve computational efficiency by 21.1% [13]. In addition, Limouni *et al.* put forth a photovoltaic power prediction model built on LSTM. In practical situations, this model could improve the prediction accuracy of photovoltaic power by 32.1% [14]. In addition, FL technology was often used in various fields due to its excellent privacy protection features. Wen *et al.* designed a privacy and security protection mechanism based on FL to address data silos and data privacy in joint modeling. This mechanism could improve data privacy by 23.6% [15]. Banabilah *et al.* analyzed the application and market status of previous FL technologies in the future development trends of AI, IoT, blockchain, natural language processing, and resource allocation. FL technology used in the above-mentioned fields could effectively improve the rationality of resource allocation in enterprises [16]. Further structured subdivision of the above research content was conducted, classified by method type, and the results are shown in Table 1.

In summary, the current LFM still has problems with poor load forecasting performance and low data security. Therefore, this study organically combines LSTM with FL, proposes a FL-LSTM algorithm, and uses this algorithm to construct LFM to improve the efficiency of load forecasting.

## 3. Research Methodology

### 3.1. LSTM Algorithm Optimized Based on FL Technology

Grid data refers to various datasets related to grid operation, including power plant generation, user electricity consumption data, energy utilization efficiency, and other datasets [17]. By analyzing power grid data and load fore-

*Table 1*. Literature classification.

| Type | Author | Application Analysis |
|---|---|---|
| Statistical analysis | Dewangan *et al.* [9] | Smart meter information prediction |
| | Wang *et al.* [10] | Personalized prediction of personal consumption load forecasting |
| Artificial Intelligence (LSTM, Deep Learning) | Ibrahim *et al.* [11] | Artificial Intelligence Load Forecasting Model |
| | Guo *et al.* [12] | A combined load forecasting model based on LSTM and multi task learning |
| | Xiang *et al.* [13] | LSTM deep learning network |
| | Limouni *et al.* [14] | Photovoltaic power prediction model based on LSTM algorithm |
| FL Technology | Wen *et al.* [15] | FL's Privacy and Security Protection Mechanism |
| | Banabilah *et al.* [16] | FL application field |

casting, the operating costs of the power grid are able to be reduced, and the operational efficiency of the system can be enhanced [18,19]. However, current LFM still faces issues of information leakage and inaccurate predictions during data transmission, storage, and analysis [20]. LSTM is a special type of RNN that can analyze data in time series [21]. This study applies the LSTM algorithm to PGDA and LFM to improve the accuracy of data analysis. Figure 1 displays the basic framework of the LSTM algorithm.

In Figure 1, the Input Gate (InG) of LSTM controls the flow of new information, including an Activation Function (AF) and a dot multiplication operation. In the InG, the AF is utilized to determine which information requires to be retained and discarded. The dot multiplication operation can multiply new input information with the AF, resulting in a new vector that represents the information that needs to be retained. The Forget Gate (FoG) controls the flow of old information, and it also includes an AF and a dot multiplication operation. The AF in the FoG has the same function as dot multiplication, which is to preserve the old information that needs to be left behind. The Output Gate (OuG) controls the output of new states through AFs and dot multiplication operations. The memory unit in LSTM is the core component of the algorithm, used to store and transmit information states. It updates the state at each time step to enable the LSTM algorithm to remember long-term information. When analyzing data, sequence data first uses a FoG to decide which information in the data needs to be forgotten and then uses an InG to determine which new information requires to be added to the memory unit. Finally, the OuG controls the output time of information in the memory unit. The calculation method for information retention in the InG of the LSTM algorithm is shown in equation (1).

$$I_1 = sigmoid(W_1 * x_t + U_1 * h_{(t-1)} + b_1) \quad (1)$$

In equation (1), $I_1$ and $b_1$ are the Output and Bias Vector (O&BV) of the InG, $W_1$ and $U_1$ are the weight matrices of the InGs, $x_t$ and $h_{(t-1)}$ are the input and hidden state for the current and previous time-step. The calculation of deleting information from the memory unit in the FoG is shown in equation (2).

$$I_2 = sigmoid(W_2 * x_t + U_2 * h_{(t-1)} + b_2) \quad (2)$$

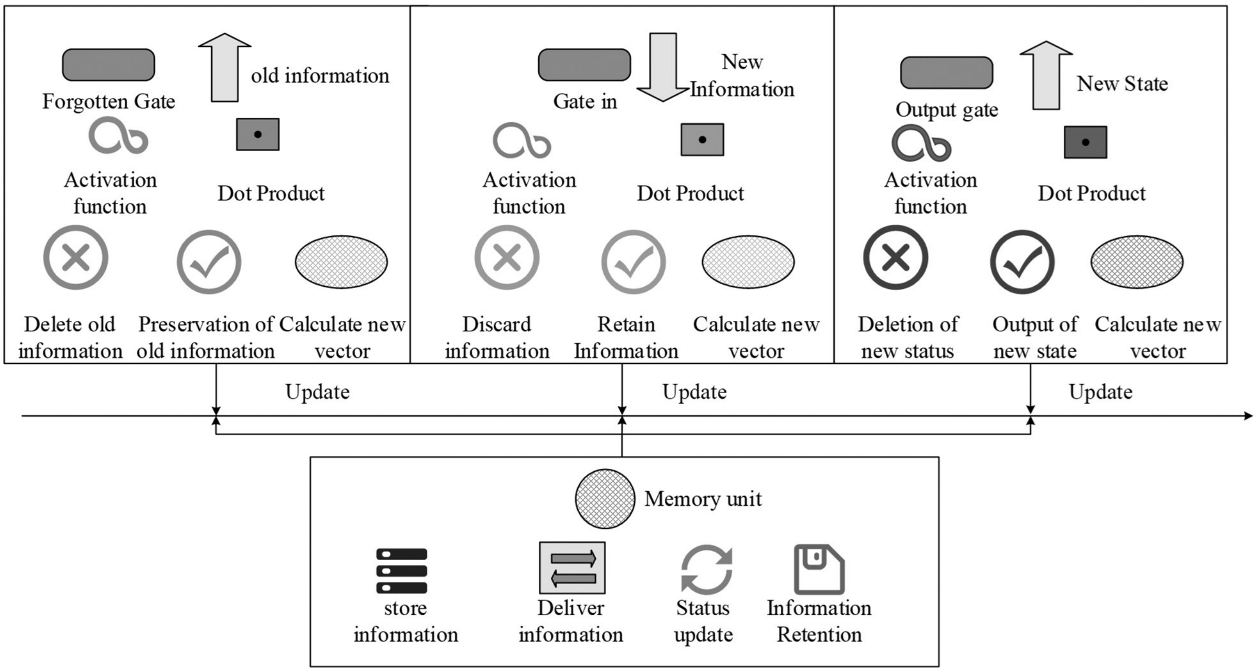



*Figure 1.* Framework diagram of the LSTM.

In equation (2), $I_2$ and $b_2$ denote the O&BV of the FoG, $W_2$ and $U_2$ represent the weight matrix of the FoG. After data deletion, the update method of the memory unit is shown in equation (3).

$$G_t = \tanh(W_c * x_t + U_c * h_{(t-1)} + b_c) \quad (3)$$

In equation (3), $G_t$ and $b_c$ stand for the O&BV of the memory unit, $W_c$ and $U_c$ are the weight matrices of memory units. The calculation of the OuG is shown in equation (4).

$$I_3 = sigmoid(W_3 * x_t + U_3 * h_{(t-1)} + b_3) \quad (4)$$

In equation (4), $I_3$ and $b_3$ are the O&BV of the OuG, $W_3$ and $U_3$ are the weight matrices of the OuGs. The time-dependent sequence data are processed through the above calculation, and the processed data are classified. However, in practical applications, when LSTM algorithm is used for data analysis, data privacy is easily leaked and the security of the data cannot be guaranteed, which can lead to inaccurate subsequent data analysis [22]. FL is a ML framework that can protect data privacy [23–24]. This study utilizes FL technology to optimize the LSTM algorithm to improve the protection of data privacy. The data training process of FL and the basic process of the optimized FL-LSTM algorithm are shown in Figure 2.

From Figure 2 (a), it can be seen that FL collects data from the stations during data processing, directly preprocesses the data, conducts data training, and then transmits the trained parameters to the central server. The central server then trains the parameters and sends them to each station.

In Figure 2 (b), the rule of the FL-LSTM algorithm is to distribute the LSTM algorithm to different devices or sites through the FL method. Each site is independent of each other and uses its own local data for LSTM algorithm training and data analysis, ultimately aggregating all data analysis results together. For example, when analyzing large-scale datasets, the FL-LSTM algorithm collects datasets through different devices, normalizes the collected datasets, and directly trains them in the LSTM model without uploading the collected data to the central server, avoiding data loss or data privacy exposure issues. Instead, it uploads the parameters of the trained LSTM model to the central server, which updates the model parameters in each site using the federated averaging algorithm and analyzes the data using the updated LSTM model. During this process, the

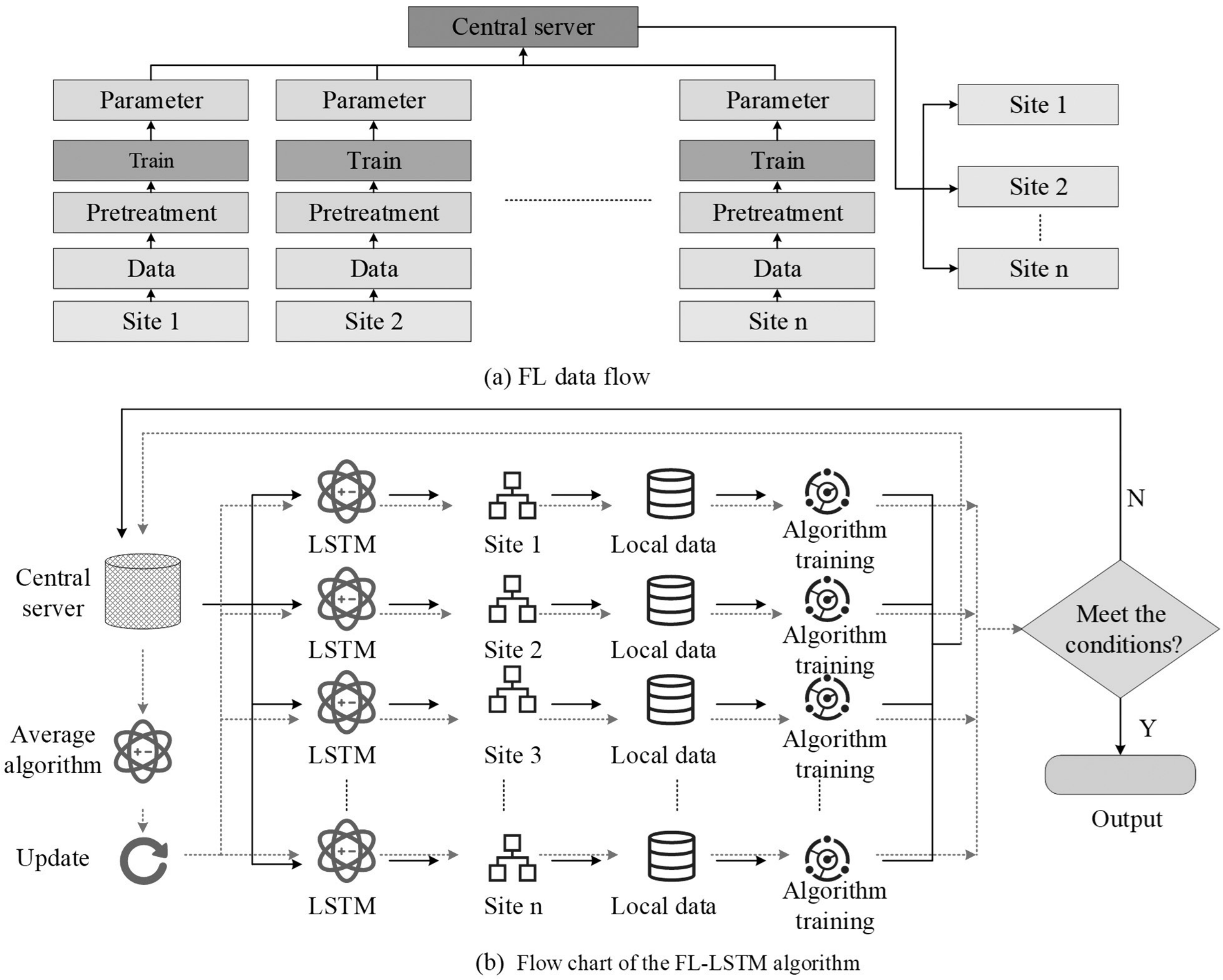



*Figure 2.* The training process of FL and the basic process of FL-LSTM algorithm are shown in the figure.

collected dataset was stored at various sites without being uploaded.

Through local training and parameter sharing, the transmission frequency of data is reduced, thereby reducing the possibility of data privacy leakage and ensuring data security. In this process, the expression of the global objective function of FL technology is shown in equation (5).

$$\begin{aligned}\min_{x\in\chi} f(x) &:= \sum_{i=1}^{N} \lambda_i f_i(x) \\ &:= \sum_{i=1}^{N} \lambda_i E_{\xi i\sim Di}[fi(x,\xi i)]\end{aligned} \quad (5)$$

In equation (5), $x \in \chi$ is the parameter of the ML model. $f(x)$ is weighted, and $\lambda_i$ is the local experience loss function. $f_i(x)$ is the expected form, while $\xi_i$ is local random batch data. $D_i$ means the dataset of the $i$-th client. The expression of the FL averaging algorithm is shown in equation (6).

$$W^{t+1} = \sum_{k=1}^{K} \frac{nk}{N} W^{t}{}_{k} \quad (6)$$

In equation (6), $W^{t+1}$ and $W^{t}{}_{k}$ are the global model parameters for round $t + 1$ and client $k$ in round $t$. $nk$ is the sample size of client $k$, and $N$ is the sum of the sample sizes of all clients. Using the above calculation, the global optimal model can be obtained, which can be used to analyze and predict the data for each device and site.

## 3.2. FL-LSTM Power Grid Data Analysis and LFM

The current PGDA and LFM still suffer from poor prediction performance due to data privacy breaches [25]. To solve this problem, this study utilizes the FL-LSTM algorithm mentioned in the previous section to optimize the current model, to ensure the security of data in the model through FL-LSTM. The basic framework of data analysis and prediction model based on FL-LSTM is shown in Figure 3.

In Figure 3, the FL-LSTM data analysis and prediction model first needs to clarify the purpose and requirements of data analysis to ensure that the analysis results can match the requirements. The next step is to collect and organize the data, including handling duplicate values, outliers, and normalization. Then, descriptive analysis is conducted on the data to understand the meanings and computational logic of different features, and to check whether the distribution of data features meets expectations and basic logic. Unreasonable data are excluded. Afterwards, the selected FL-LSTM algorithm is used to analyze the data. In data analysis, the collected data are segmented into the training and validation sets to train, validate, and evaluate the model. Through model validation and evaluation, the parameters of the model are optimized and adjusted. Finally, the adjusted model is used for data analysis and prediction in practical problems. The basic process of using FL-LSTM data analysis and prediction model for PGDA and load forecasting is shown in Figure 4.

In Figure 4, based on FL-LSTM PGDA and LFM, the load forecasting objectives are first determined, and a forecasting plan is formulated. The purpose of this study is to optimize the operation and reduce resource waste. Secondly, historical data related to load are collected according to the prediction purpose. Then, the collected data are sorted, including data outlier processing, data duplicate processing, and data normalization processing, to ensure the data accuracy.

After data preprocessing is completed, the data are subjected to descriptive processing by drawing dynamic line charts or scatter plots to observe the trajectory of data changes and prepare for model establishment. Based on historical data and descriptive analysis, as well as the FL-LSTM algorithm, PGDA and LFM are constructed. Using this model, power grid data are analyzed, and load is predicted based on the

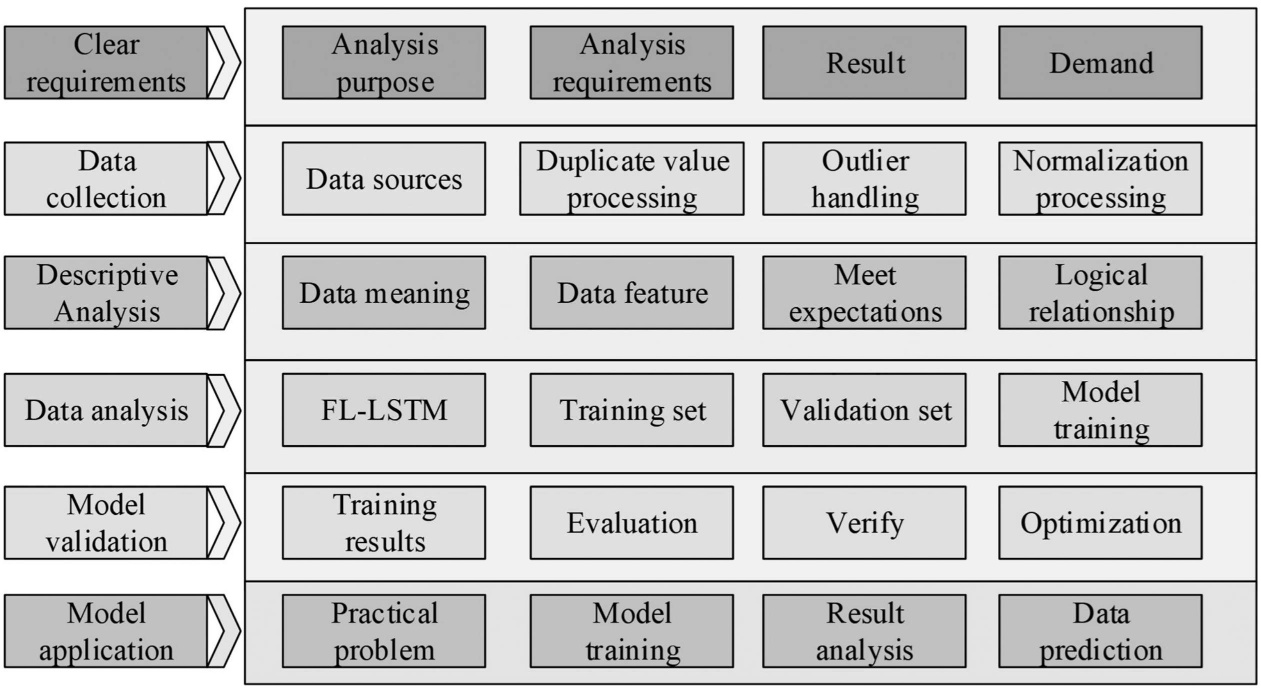



*Figure 3.* FL-LSTM data analysis and prediction model.

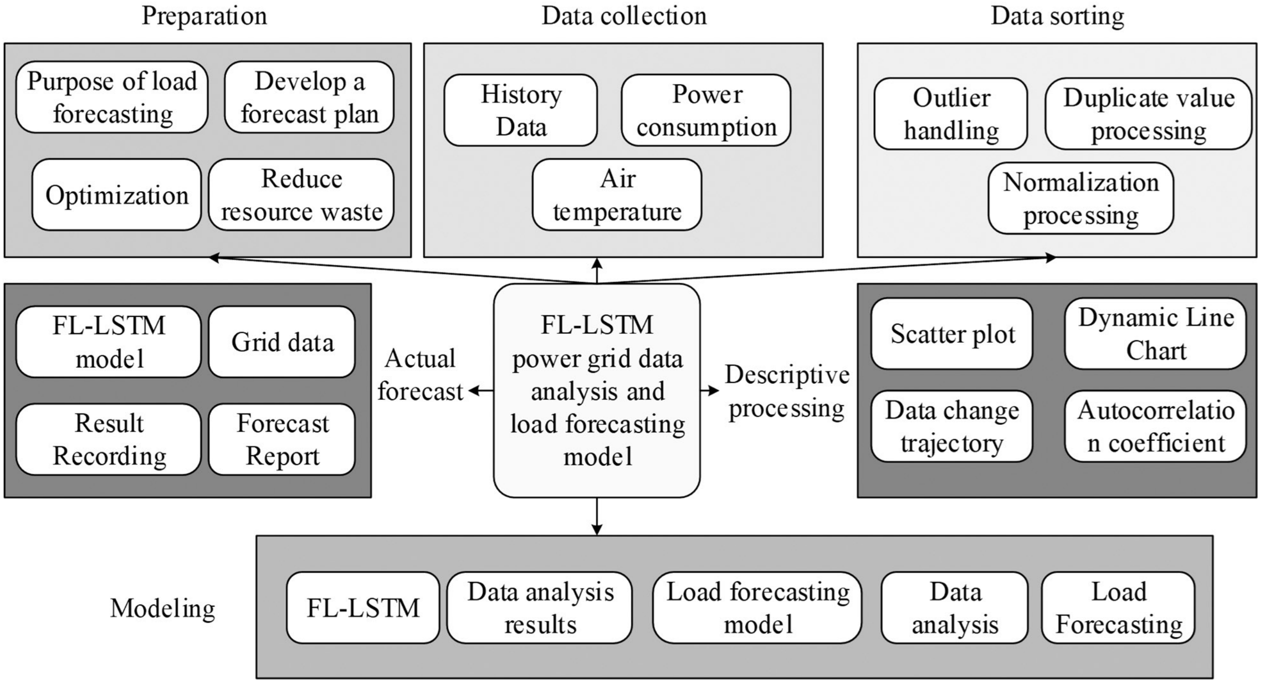



*Figure 4.* FL-LSTM power grid data analysis and LFM.

analysis results. Using historical data, the model is validated and evaluated, and based on the validation results, the parameters of the model are continuously adjusted and optimized to improve the accuracy of model predictions.

Finally, using the optimized model, the actual power grid data are analyzed, and load forecasting is carried out. The results are recorded, and a forecasting report is written and delivered to relevant departments. In this process, descriptive analysis of data generally uses central tendency and dispersion to analyze the data, with central tendency represented by mean, median, and mode. The degree of dispersion is represented by variance and range, and the variance is shown in equation (7).

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \tag{7}$$

In equation (7), $S^2$ is the variance and $x_i$ is the input data. $\overline{x}$ is the average value of the data, and $n$ is the quantity of data. When conducting load forecasting, it is required to calculate the load in the electrical equipment, including three types of loads: active power load, reactive power load, and existing power load. The active power load is shown in equation (8).

$$P_c = K_x \cdot P_e \tag{8}$$

In equation (8), $P_c$ is the active power, $K_x$ is the demand factor, and $P_e$ is the rated capacity of the electrical equipment group. The calculation method for reactive power load is shown in equation (9).

$$Q_c = K_x \cdot Q_e \tag{9}$$

In equation (9), $Q_c$ represents reactive power. $Q_e$ is the capacity of the capacitor at actual operating voltage. The current power load is shown in equation (10).

$$S_c = \sqrt{P_c^2 + Q_c^2} \tag{10}$$

In equation (10), $S_c$ is the existing power load. The loads in distribution lines and substations also have an impact on the total load of the power system, so it is necessary to calculate the load data for this part. Through the above calculations, various load data in the power system can be obtained and analyzed to predict the load. The process of FL-LSTM PGDA and LFM analysis of power grid data is shown in Figure 5.

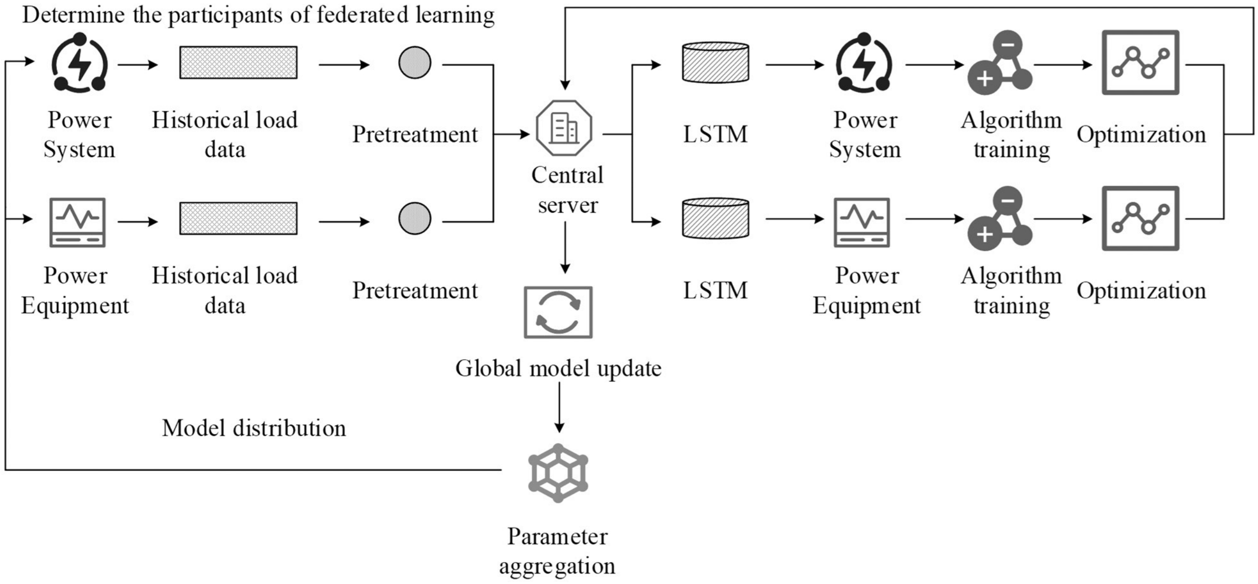



*Figure 5.* FL-LSTM power grid data analysis and load forecasting process.

In Figure 5, when the FL-LSTM model analyzes power grid data, the first step is to determine the participants of FL, namely the power system and power equipment involved in load forecasting, collect historical load data from these participants, and preprocess the data. Then, the FL and LSTM models are distributed to each participant.

Each participant uses historical data to train the LSTM model and uploads the trained LSTM parameters to the central server of FL. The parameters are aggregated and shared in the central server. By aggregating the parameters, the global model is updated again, and the updated model is distributed to each participant again. The power grid data are used for training again, and the above operations are repeated until the model can meet the final requirements. Through FL, the transmission frequency of load data is reduced to ensure data security.

## 4. Results and Discussion

### 4.1. Performance Analysis of FL-LSTM Algorithm

To verify the predictive performance of the FL-LSTM algorithm, this study collects various historical load data such as power generation, generation capacity, substations, user electricity consumption, and energy loss from a power company's power system within one year as the dataset for empirical analysis. The data from the first 6 months of this dataset are used as the experimental dataset, and the data from the last 6 months are utilized as the validation dataset. Using the experimental dataset, the data from the last 6 months are predicted and compared with actual data to validate the predictive performance. Table 2 shows the experimental configurations used for algorithm performance analysis.

Through experimental verification, the above computing resources can achieve optimal performance of the LSTM model and eliminate potential impacts caused by computing resources.

During the experiment, the learning rate of the LSTM algorithm was set to 0.01, the iteration number of the algorithm was set to 500, the batch size was set to 5, the local training iteration number of the federated learning technique was set to 3, the local training batch size was set to 32, and the learning rate was set to 0.001. Through the above configuration and dataset, the predictive performance of FL-LSTM algorithm has been experimentally analyzed. The experiment first compares the predictive performance of algorithms on transformer utilization rate, generator parameters, substation location, and communication circuit location in power grid data, as shown in Figure 6.

*Table 2*. Experimental environment configuration.

| **Environment** | **Index** | **Type** |
|---|---|---|
| Hardware environment | OS | Windows10 |
| | Processing element | Intel Core i5 |
| | EMS memory | 4GB |
| | GPU | RTX 4090 |
| | Network device | Switch |
| | Hard drive | M.2 SSD |
| Software environment | Python version | Python3.6 |
| | C++ version | VC++6.0 |

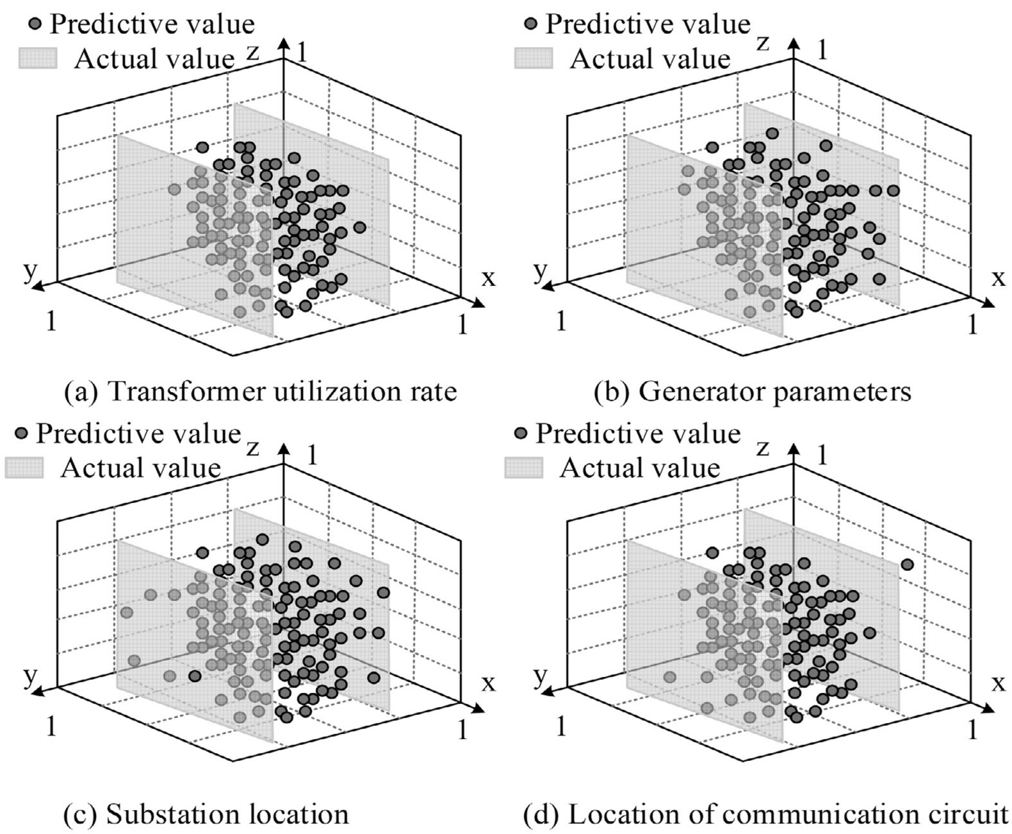



*Figure 6.* Comparison of power grid data prediction effect.

In Figure 6, the FL-LSTM algorithm performs well in predicting various components of the power grid data. Moreover, in Figures 6 (a) and 6 (b), the predicted values of transformer utilization rate and generator parameter related data are within the actual range, indicating excellent prediction performance. In Figures 6 (c) and (d), although the FL-LSTM algorithm still has errors in predicting data related to the location of substations and communication circuits, the errors are extremely small. The reason why the FL-LSTM algorithm has excellent predictive performance in data may be that the FL mechanism in the model can effectively reduce data transmission frequency and avoid data loss by analyzing the data locally, thus reducing the prediction error of the model. Figure 7 compares the prediction time and Explained Variance Score (EVS) of the FL-LSTM algorithm for predicting four types of power grid data.

EVS is an indicator that measures the accuracy of algorithm predictions, representing the ratio between explanatory data variances. When EVS is 1, it indicates that the algorithm can make perfect predictions. In Figure 7 (a), when FL-LSTM predicts four different types of power grid data, the algorithm's EVS values fluctuate within the range of 0.8~1.0, indicating a relatively high EVS value. In Figure 7 (b), FL-LSTM has a relatively short prediction time for all four types of power grid data, with an average prediction time of 1.2ms. The reason for the short prediction time and high EVS value of FL-LSTM algorithm may be that when analyzing data, FL-LSTM algorithm saves upload time and accelerates calculation speed by not uploading data to the central server.

In addition, the data in the FL-LSTM algorithm are independent of each other and do not affect each other, avoiding mutual influence between data and thus improving the EVS value of the algorithm. Figure 8 shows the space occupancy and prediction accuracy of the FL-LSTM algorithm when predicting four types of power grid data.

In Figure 8, the FL-LSTM algorithm has a similar spatial occupancy rate for predicting four types of power grid data, with a low occupancy rate of only 34.2%. Moreover, the prediction accuracy of FL-LSTM for different power grid data is roughly the same, fluctuating within the range of 90% to 100%, with an average of 94.5%.

The reason for the low space occupancy of the FL-LSTM algorithm may be that the central processor of the FL-LSTM algorithm only contains the parameters used for training the LSTM model, and does not receive datasets from different devices, which can significantly reduce the utilization of space resources. FL-LSTM can accurately predict different power grid data in a short period of time.

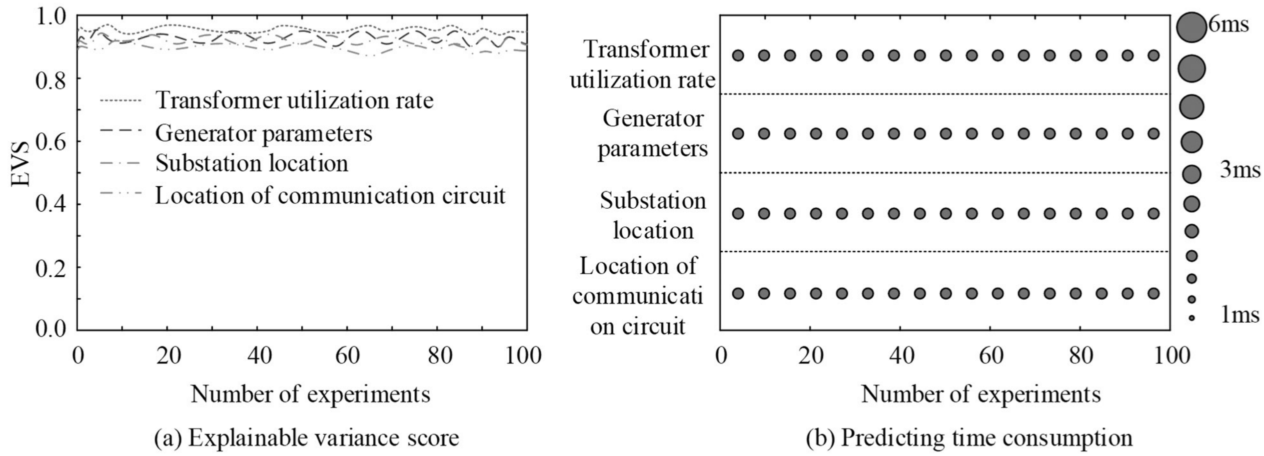



*Figure 7.* Prediction of the time-consuming and EVS values of the FL-LSTM algorithm.

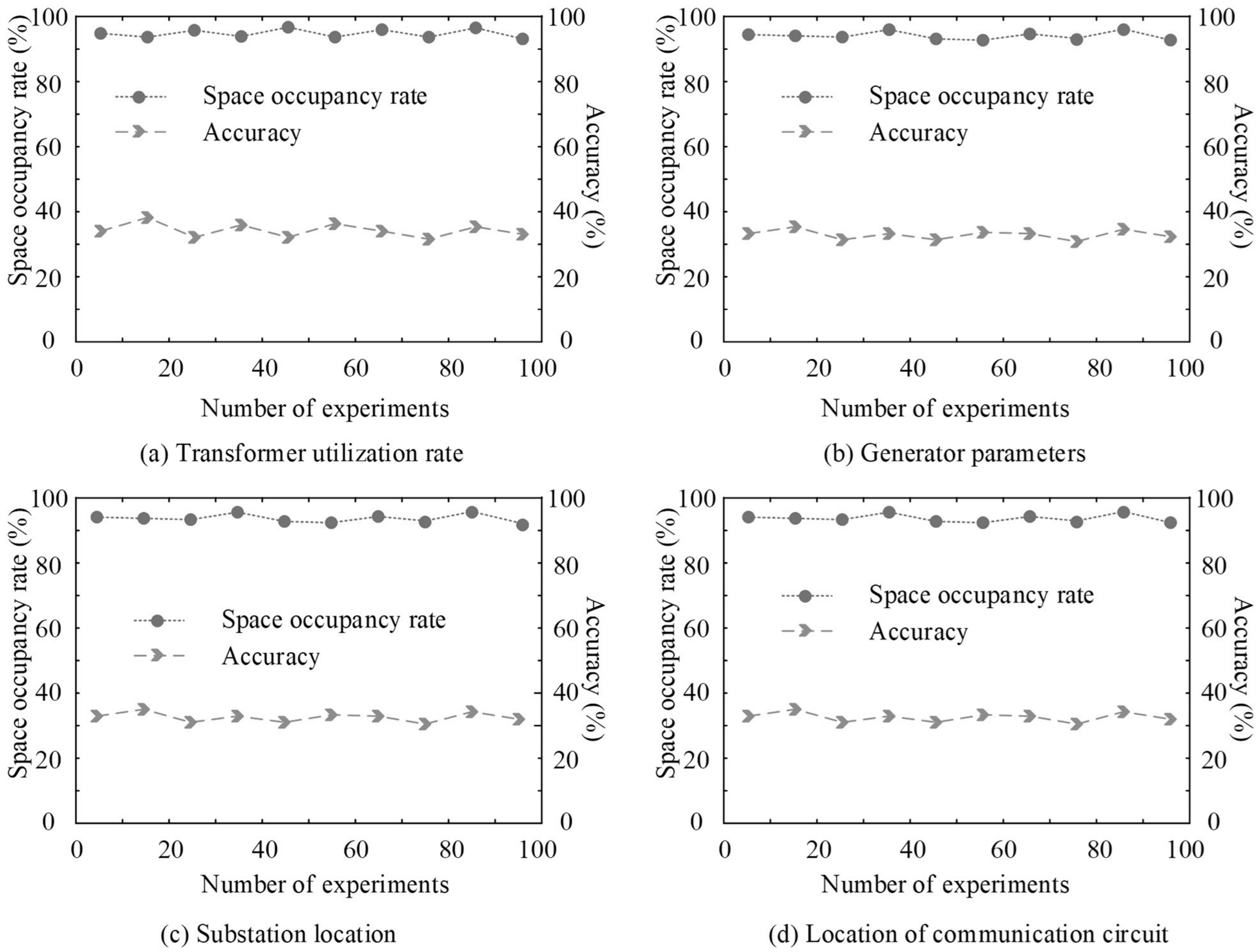



*Figure 8.* Comparison of algorithm space occupancy and prediction accuracy.

## 4.2. Analysis of the Actual Effect of FL-LSTM Model

After verifying the predictive performance of the FL-LSTM algorithm, the performance of the FL-LSTM is analyzed. This paper compares the performance of FL-LSTM with the widely used Variational Mode Decomposition-Temporal Convolutional Network (VWD-TCN), Dynamic Convolutional Neural Network-LSTM (DCNN-LSTM), and traditional Grey Prediction Model (GM) to verify the superiority of FL-LSTM data analysis and LFM. The experimental dataset is the same as the previous section. Figure 9 compares the prediction errors and data analysis errors of four models on power grid data.

In Figure 9 (a), among the four models used for load prediction, FL-LSTM has the smallest prediction error of only 0.5%. The prediction errors of VMD-TCN and DCNN-LSTM are 1.2% and 2.3%, while the error of GMLFM reaches 3.7%.

In Figure 9 (b), the analysis errors of FL-LSTM, VMD-TCN, DCNN-LSTM, and GM in analyzing power grid data are 0.4%, 1.2%, 1.9%, and 2.8%, respectively. The reason for the low prediction error and data analysis error of FL-LSTM may be that FL-LSTM can effectively capture the long-term dependency relationship of power grid data, thereby improving the prediction accuracy.

Furthermore, the FL mechanism can reduce the frequency of data transmission, avoid data loss, so it can reduce the prediction error of the model and improve the prediction accuracy. Figure 10 shows the comparison of power resource utilization and operating costs of power companies using four prediction models.

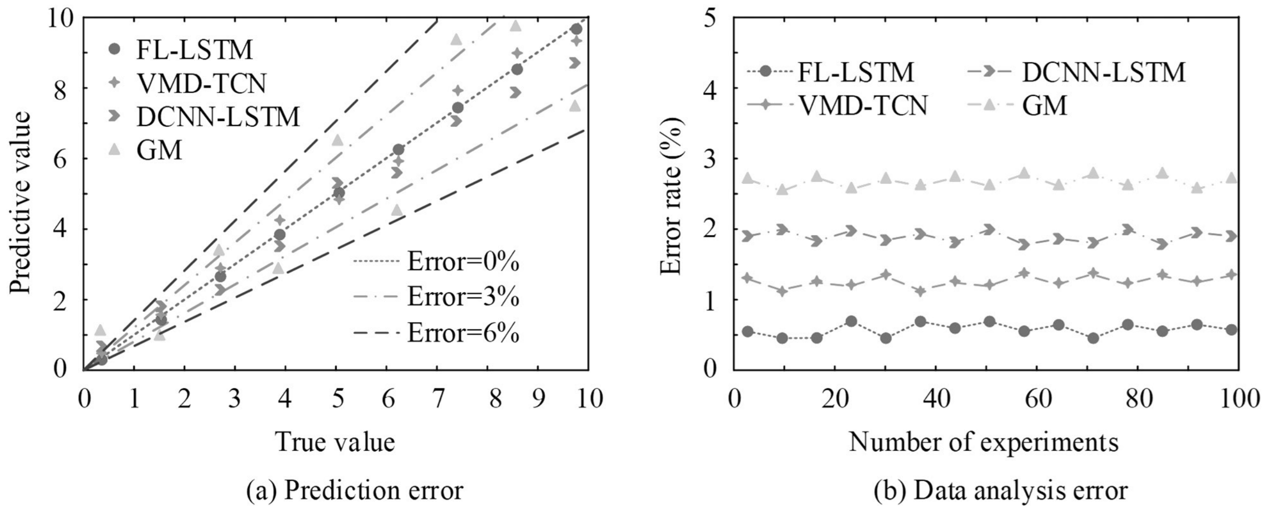



*Figure 9.* Model data analysis error and prediction error comparison.

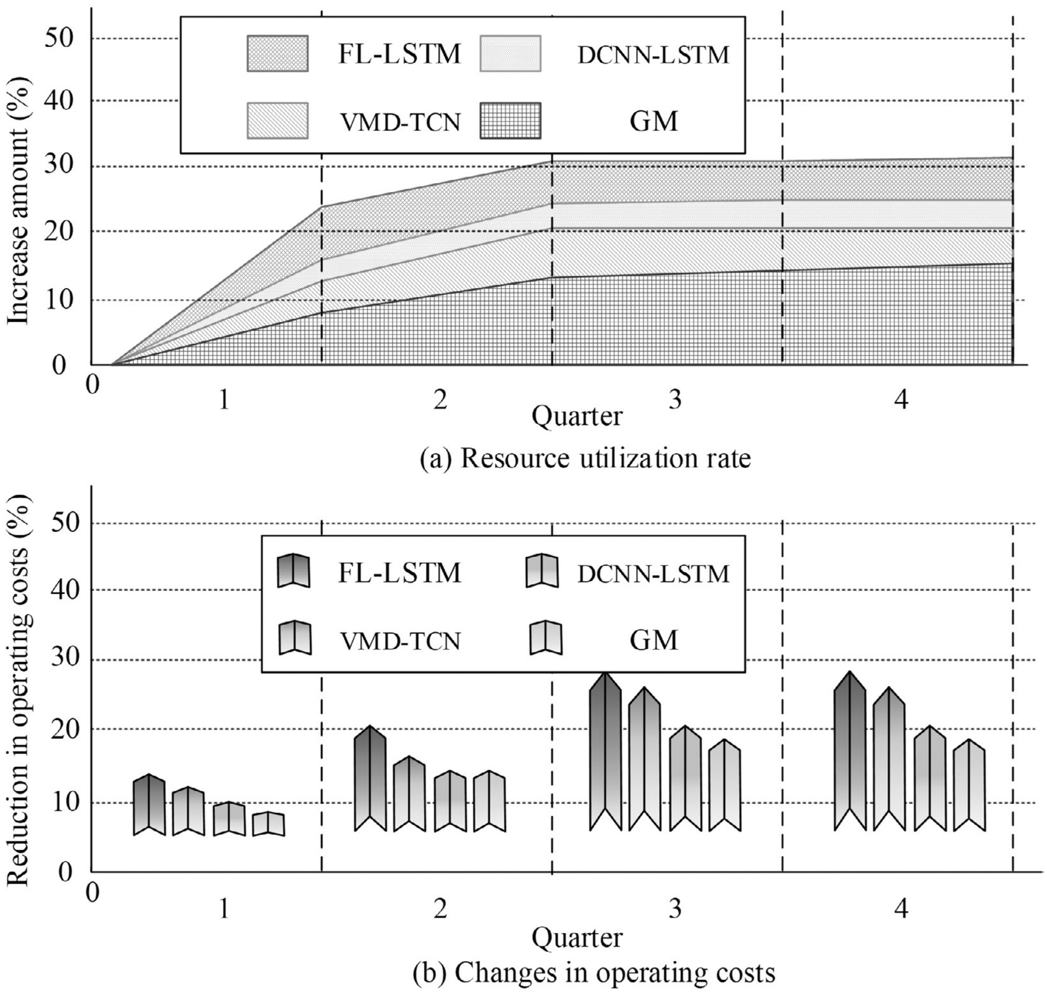



*Figure 10.* Comparison of the changes in power resource utilization rate and operating cost.

In Figure 10 (a), after using FL-LSTM, the resource utilization rate in power companies increased rapidly from the first quarter to the second quarter. By the third and fourth quarters, the increase in resource utilization remains unchanged, with a utilization rate of 31.8%, which is far higher than VMD-TCN's 23.4%, DCNN-LSTM's 17.3%, and GM's 12.9%.

In Figure 10 (b), FL-LSTM has the highest reduction in operating costs for power companies, reaching 27.5%. The reason may be that FL-LSTM has high accuracy in power grid data and load forecasting, which enables power companies to adjust resource distribution and operating costs based on forecast results, thereby improving resource utilization and reducing operating costs. However, the other three models have inaccurate analysis of power grid data due to their low prediction accuracy, resulting in errors in decision-making, low resource utilization, and increased operating costs. Table 3 compares the security improvements of various models on power grid data.

In Table 3, after using four types of LFM, the security of power grid data can be improved, but only FL-LSTM can achieve the expected standards for data security indicators. This model can increase data confidentiality by 34.3%, data integrity by 29.1%, and overall data security by 23.4%. VWD-TCN, DCNN-LSTM, and GM only achieved 22.7%, 22.1%, and 20.3% improvement in data security, which does not meet the expected requirements.

In order to analyze the performance of the models, t-test was used to conduct significant statistical analysis on the data. The results showed that all four models had statistical significance ($P<0.05$). The reason for the excellent security performance of the FL-LSTM model may be that the federated learning framework of the FL-LSTM prediction model can analyze data locally, reducing privacy breaches and data security issues caused by data transmission, and improving the security of power grid data. The complex power grid network containing multiple power plants, substations, and voltages was analyzed using this model again, and the results are shown in Figure 11.

As shown in Figure 11 (a), under complex power grid conditions, the load forecasting accuracy of the FL-LSTM model is also high, reaching 96.7%. Moreover, the FL-LSTM model can improve resource utilization by 30.8% and reduce the operating costs of the power grid by 24.5%.

As shown in Figure 11 (b), under complex power grid conditions, the use of FL-LSTM model has improved its safety performance. From the above results, it can be seen that the FL-LSTM model can still significantly improve the accuracy of load forecasting and grid safety in complex power grid conditions. Further analysis of the performance of the FL-LSTM model under different types of power grids, market conditions, and extreme conditions is shown in Table 4.

*Table 3*. Improvement of data security performance.

| Model | Data confidentiality | Data integrity | Backup | Data monitoring | Overall safety | *P* |
|---|---|---|---|---|---|---|
| FL-LSTM | 34.3% | 29.1% | 23.5% | 26.4% | 23.4% | 0.0001 |
| VWD-TCN | 32.4% | 28.3% | 20.1% | 19.7% | 22.7% | 0.0004 |
| DCNN-LSTM | 30.7% | 26.9% | 20.5% | 18.9% | 22.1% | 0.0012 |
| GM | 29.8% | 25.7% | 19.6% | 17.3% | 20.3% | 0.0002 |
| Expected boost | 32.3% | 27.1% | 20.2% | 23.2% | 23.0% | <0.05 |

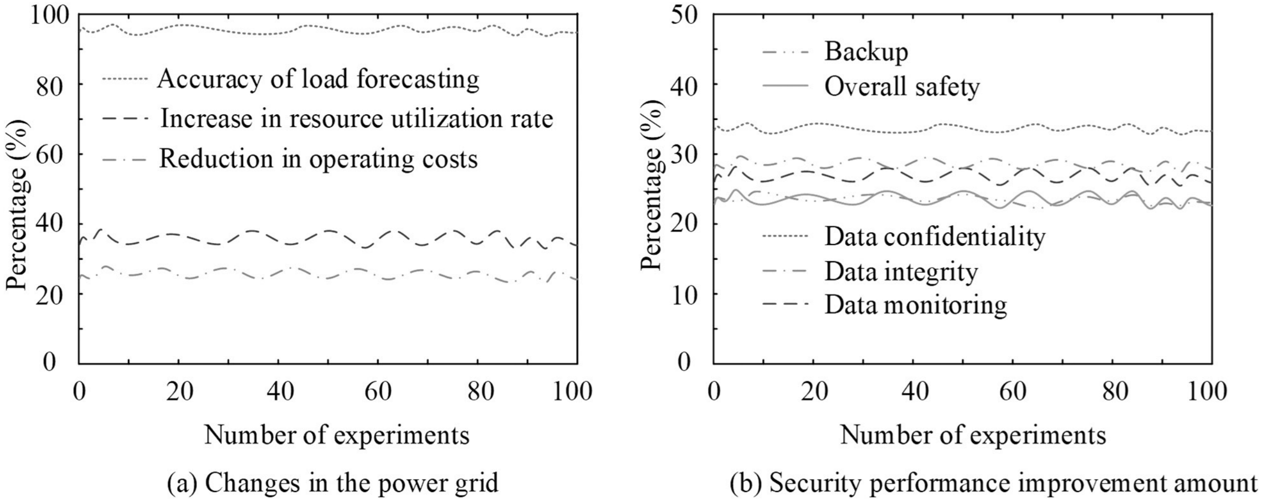



*Figure 11.* Performance changes of the model under complex power grid conditions.

*Table 4*. Performance analysis of FL-LSTM model under different conditions.

| **Classification** | **Type** | **Accuracy of load forecasting** | **Reduction in operating costs** |
|---|---|---|---|
| Grid type | Local power grid | 96.8% | 23.5% |
| | Regional power grid | 93.6% | 24.1% |
| Market conditions | Medium and long-term contract trading market | 94.1% | 22.1% |
| | Futures and options trading market | 92.3.% | 20.9% |
| | Daily trading market | 90.6% | 21.7% |
| | Auxiliary trading market | 93.5% | 24.7% |
| | Real time trading market | 91.9% | 23.1% |
| Extreme conditions | Mountain landslide | 85.6% | 13.6% |
| | Debris flow | 87.2% | 14.7% |
| | Equipment failure | 83.5% | 13.5% |
| | Transmission line rupture | 80.7% | 16.7% |
| | Substation damage | 79.4% | 12.4% |

According to Table 4, the FL-LSTM model has a prediction accuracy of over 90% for different types of power grid loads, and the reduction in power grid operating costs is greater than 20%. And under different market conditions, its prediction accuracy can also reach over 90%.

As shown in Table 4, under extreme conditions, the FL-LSTM model reduces the accuracy of load forecasting for the power grid, although the operating costs of the power grid also decrease, the amount of reduction will be smaller. The above results indicate that the FL-LSTM model is also applicable under different types of power grids and market conditions. However, under extreme conditions, the prediction accuracy of the FL-LSTM model and the reduction in grid operation costs will both decrease.

### 3.3. Potential Limitations and Failure Modes

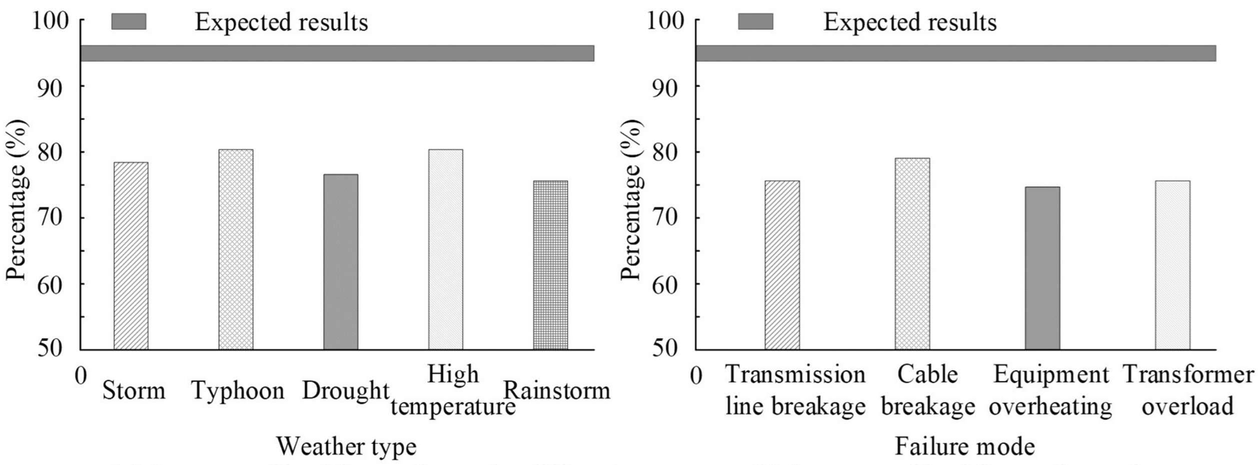
Finally, the potential limitations and failure modes of the FL-LSTM model were analyzed, and the results are shown in Figure 12.

It can be seen from Figure 12 (a) that under the weather conditions of storm, typhoon, drought, high temperature and rainstorm, the prediction accuracy of FL-LSTM model cannot reach the expected prediction accuracy. According to Figure 12 (a), it can be seen that in the fault modes of power transmission line breakage, cable breakage, equipment overheating, and excessive load on power grid transformers, the prediction accuracy of the FL-LSTM model cannot reach the expected accuracy. From the above results, it can be seen that the FL-LSTM model has certain limitations under extreme weather conditions and different fault mode conditions.

## 5. Conclusion

In response to the issues of poor prediction performance, long prediction time, and low data security in current LFM, this study integrated FL and LSTM, proposed an FL-LSTM algorithm, and constructed LFM based on this algorithm. To validate the performance, this paper first analyzed the actual prediction performance of FL-LSTM.

When predicting different power grid data, the EVS values of the algorithm fluctuated within the range of 0.8~1.0, and the prediction accuracy of the algorithm reached 94.5%. The FL-LSTM was compared with VWD-TCN, DCNN-LSTM, and GM. The prediction error of FL-LSTM was as low as 0.3%, and it could reduce the operating costs of power companies by 27.5%. Its reduction was much higher than VMD-TCN's 23.4%, DCNN-LSTM's 19.8%, and GM's 15.7%.




(a) Accuracy of load forecasting under different weather conditions

(b) Accuracy of load forecasting under different fault modes

*Figure 12.* Potential Limitations and FL-LSTM Prediction Accuracy under Different Failure Modes.

Overall, FL-LSTM can optimize the prediction accuracy and reduce the operating costs of power companies. Through load forecasting, relevant information on future electricity demand can be provided to power grid operators, which helps them to produce and schedule electricity resources reasonably, optimize the allocation of electricity resources, and adjust power generation plans. Consequently, through accurate load forecasting, power grid operators can better schedule power resources, ensure supply-demand balance, improve market competitiveness, and reduce operating costs and market risks.

However, in practical applications, the power load is often affected by weather, holidays, and economic fluctuations, which can increase the uncertainty of forecasting. In order to prevent the impact of weather on power grid load forecasting in the future, we can optimize power grid planning, enhance its disaster resistance capabilities, improve its emergency response capabilities, and reduce equipment damage and power supply risks. For the impact of holidays and economic fluctuations on prediction performance, historical databases can be established, event series data or regression analysis can be used to predict data, data mining techniques can be used to predict load trends and training data and model parameters can be adjusted to improve the adaptability of the model in different regions and times.

## Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Funding

This research work was not funded by any program.

## Data Availability

The data used in this study is proprietary.

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*Received:* December 2024
*Revised:* January 2025
*Accepted:* January 2025

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