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Exploration on the Application of Wireless Networks and Intelligent Perception in Power Load Forecasting and Dispatching

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ABSTRACT
Traditional power load forecasting (PLF) usually uses statistical models or time series analysis methods, but they often only consider historical load data and ignore the impact of meteorological, temperature, humidity and other factors on load, resulting in inaccurate load forecasting. Moreover, traditional methods have limited real-time performance in power load data transmission and cannot respond to changing load demands in a timely manner, which limits the real-time and accuracy of PLF. Wireless networks (WN) and intelligent sensing technology (IST) were used to obtain real-time charge data, and these data were intelligently analyzed to improve prediction performance. WN and IST were used to improve the transmission efficiency and prediction accuracy of PLF. This article studied the transmission delay and integration delay of power load data in WN, and conducted experimental tests on the root mean square error (RMSE) of CER Electricity Data, REFIT Power Data, and Umass Smart Data Set datasets using an intelligent sensing algorithm based on sensors to study their predictive effect on power load. As the number of users continues to increase, the transmission delay and integration delay of power load data were also increasing. During the process of increasing the number of users from 0 to 500, the transmission delay increased from 389ms to 735ms; the integration delay increased from 568ms to 1086ms. The power load prediction algorithm based on intelligent perception technology had average prediction RMSEs of 0.2885, 0.2716, and 0.2618 for CER Electricity Data, REFIT Power Data, and Umass Smart Data Set datasets, respectively. In WN, the transmission delay and integration delay of power load data are relatively small, and with the increase of the number of users, the impact of this delay is relatively small, which can have the effect of supporting the transmission and integration of power data for a large number of users. The power load prediction algorithm based on intelligent perception technology has good prediction results for different datasets and can accurately predict power loads.

Keywords: Power Load Forecasting, Wireless Network, Intelligent Awareness, Network Architecture, Root Mean Square Error

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1. Introduction

In order to solve the problem of energy shortage and promote the acceleration of industrialization and urbanization, PLF and scheduling have become an important and urgent task. However, traditional PLF methods usually only consider historical load data and ignore the impact of environmental factors such as weather, temperature, and humidity on the load, resulting in bias in the prediction results. Moreover, there are limitations in the real-time transmission of power load data. In this context, WN and IST have gradually become research hotspots in the field of power, and are widely used in PLF and scheduling. As a widely used technology in various fields, WN and intelligent sensing provide strong support for PLF and scheduling. Through WN, not only can information transmission and sharing between various links of the power system be achieved, but real-time monitoring and data collection can also be achieved, thereby providing accurate power load information. Intelligent perception technology can utilize big data analysis and machine learning algorithms to conduct in-depth mining and analysis of historical and real-time data, in order to predict future load conditions and make reasonable scheduling arrangements based on the predicted results. Therefore, this study optimized and improved PLF through WN and IST, thereby contributing to the development of the power industry and sustainable energy supply.

PLF refers to the analysis and prediction of load demand in the power system, in order to determine the future power consumption situation for a period of time. At present, multiple researchers have conducted relevant research. Zhao Yang pointed out that accurate short-term PLF is very important for the safe and stable operation of the power grid, energy optimization management, improving the utilization rate of power generation equipment, and reducing costs. However, traditional methods cannot effectively learn the nonlinear characteristics of power load data. He compared the applicability and effectiveness of classic machine learning methods such as support vector regression, Gaussian process regression, and feedforward neural networks in short-term PLF, and further proposed a short-term PLF method based on time convolutional deep learning networks [1]. Yang Boyu pointed out that the study of power system load forecasting is very important in the analysis of electricity consumption situation, electricity planning, resource deployment, and economic management. Tang Xianlun highlighted the vital importance of accurate PLF in ensuring the safe, stable and economic operation of the power system, especially the importance of short-term load forecasting for grid planning and decision-making [2]. With a focus on power system load forecasting, Veeramsetty Venkataramana noted the importance of application areas such as optimal power system operation, grid stability, demand side management and long-term strategic planning [3]. Specifically, they have studied the importance, application fields, and methods of PLF. However, in their research, there may be prediction errors when dealing with complex situations such as peak loads, seasonal changes, and unexpected events. In addition, there is also a significant delay in prediction due to slow data transmission. Through WN and IST, these issues can be optimized. Therefore, further research is needed.

In PLF and scheduling, WN are used to collect real-time data from various nodes in the power system, including load information, device status, and weather data. Intelligent perception refers to the collection, analysis, and understanding of various data in the power system through technological means such as sensors and intelligent algorithms, in order to achieve intelligent perception of power load and equipment status. Intelligent perception can obtain real-time power system status information, analyze and infer it, thereby providing accurate load forecasting and scheduling decision-making basis. Liu Jianming's research focused on electricity as an important component of the energy industry, which is of great significance for ensuring the safety and stability of the transmission and distribution system. He proposed a layered application system for monitoring, detection, security, and interactive services in power transmission and distribution systems based on wireless sensor network technology and combined with the monitoring and operational requirements of the system. In addition, his research also demonstrated the widespread application of the system on a large scale through a system validation project [4]. Yan Yingjie's research found that intelligent perception is the foundation of grid digitization. Due to the closest relationship between distribution networks and users, their information perception ability directly affects the reliability of power supply. However, due to the wide geographical distribution and equipment types of distribution networks, as well as limitations in technology and management, the application of intelligent perception is highly complex and dynamic. Therefore, his research first summarized the current application status of intelligent perception technology and equipment in distribution networks in the fields of distribution automation, measurement systems, and detection. Next, the constraints of existing intelligent perception applications were pointed out, and future research priorities were proposed. Finally, the development trend of intelligent perception technology in distribution networks was explored from the perspectives of basic technology, perception devices, and advanced applications [5]. In the above literatures, comprehensive research has been conducted on PLF through WN and IST, but they have only conducted ordinary prediction accuracy research and did not conduct more reliable experimental studies on RMSE and mean absolute error (MAE). These two indicators can provide more specific, comprehensive, and reliable evaluation results, which can improve the scientific and practical nature of research and provide more accurate and reliable basis for decision-making in practical applications.

With the continuous expansion of the power system scale and the increase of load demand, PLF and scheduling have become key tasks to improve the economic operation and reliability of the power system. By using WN for distributed load monitoring and data collection, real-time and accurate monitoring and prediction of power loads can be achieved. In this article, PLF was optimized through WN and IST. The innovation of this article lies in the real-time acquisition of environmental factor data through WN and the comprehensive analysis combined with intelligent perception technology, making the prediction results more accurate and reliable. In addition, the transmission delay and integration delay of power load data in WN were studied, which improved the transmission speed of power load data and provided important reference for designing and optimizing WN architecture, enabling the system to support the transmission and integration of power data for a large number of users.

2. Exploration of Power Load Collection Architecture and Load Forecasting

2.1. WN-based Power Load Collection Architecture

WN Based Power Load Acquisition Architecture is a system that utilizes wireless communication technology to realize power load data acquisition [6-7]. Real-time monitoring and data collection of power usage at each node can be achieved by this architecture, and can be transmitted to a data center or monitoring system for processing via wireless communication. Through WN-based power load collection architecture, users can monitor the load condition of the power system in real time, identify potential problems and optimize energy usage. Among other things, constructing the WN-based power load collection architecture can be performed according to the following process.

1) Determination of collection requirements. To take the first step, the power load information to be collected is identified, and the appropriate wireless communication technology is selected according to the need. In the meantime, security measures necessary to protect the privacy and integrity of the data are taken to ensure system security and compliance.

2) Design of sensor nodes. System nodes need to be designed to collect the load data from the sensor nodes. Each sensor node should include sensors, microcontroller, power management module etc. In addition, hardware and software compatibility, as well as optimization in terms of power consumption and reliability, need to be considered when designing sensor nodes.

3) Determination of wireless communication technology. Suitable wireless communication technologies need to be selected, such as Wi-Fi (Wireless Fidelity), ZigBee, LoRa (Long Range), etc. [8-9]. It is also important to consider that power load collection typically requires long-distance transmission and low power consumption. The detailed descriptions of these technologies are as follows:

Wi-Fi: Wi-Fi is a wireless communication technology widely used in local area networks and internet access. It has high bandwidth and short transmission distance characteristics, suitable for data-intensive applications.

ZigBee: It performs well in one-on-one or many-to-one communication, but may have limitations in long-distance transmission. If power load collection needs to cover a large area or span multiple buildings, ZigBee is also not the most suitable choice.

LoRa: It achieves low-power and long-distance transmission by optimizing modulation schemes and signal transmission ranges. It can transmit data several kilometers away in urban environments and operate in low-power mode. The comparison of wireless transmission technology parameters is shown in Table 1.

Table 1. Comparison of wireless transmission technology parameters

	Wi-Fi	ZigBee	LoRa
Transmission distance	<100m	<300m	>3000m
Work pattern	Full duplex	Half duplex	Half duplex
Data rate	1Gbps（Gigabits per second）	250kbps（kilobits per second）	50kbps
Maximum number of nodes	32	65536	Million
power dissipation	Relatively large	Relatively low	Relatively low

In this article, LoRa technology was chosen based on the requirements of long-distance transmission and low power consumption for power load collection. This technology can provide a wide coverage range while maintaining low power consumption, which can meet the requirements of long-distance transmission and low power consumption for power load collection, and establish a reliable and efficient collection architecture.

4) Construction of WN architecture. A WN architecture is constructed based on the distribution and communication requirements of sensor nodes. It can adopt star, mesh, or hybrid topology structures. Among them, the star topology structure is suitable for scenarios with a small or dense number of nodes, where all sensor nodes are directly connected to a central node or base station, providing reliable transmission. However, if the central node fails or communication issues occur, the entire network may be affected.

5) Deployment of sensor nodes. According to the design plan, the sensor nodes are deployed at the locations where power load data needs to be collected. This ensures that the sensor node has a stable power supply and considers the impact of environmental factors on the sensor, such as temperature, humidity, etc.

The above is the basic process of a WN-based power load collection architecture, which can be adjusted and optimized according to actual situations and needs. The power load collection architecture is shown in Figure 1.

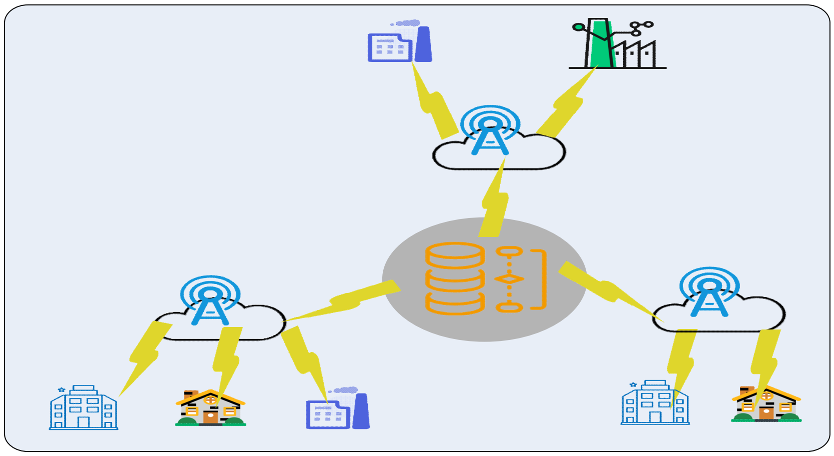

Fig. 1. Power load collection architecture

2.2. Power Load Data Collection and Processing Process

After completing the construction of the power load collection architecture, power load data can be collected and processed to monitor and manage the load situation of the power system, ensuring supply and demand balance and safe operation of the power grid [10-11]. Through the collection and processing process of power load data, real-time monitoring and analysis of the power system load situation can be achieved, which can provide support for power system operation and energy scheduling, and also provide refined electricity management and optimization suggestions for users. The detailed steps of this process are as follows:

1) Data collection and transmission. Sensor nodes measure power load data and send it to the data receiving end through wireless communication modules. The data receiving end can be a central server or cloud platform. The accuracy and real-time of data collection should be ensured.

2) Data processing and analysis. After receiving the power load data, the data is processed and analyzed. Technologies such as data mining and machine learning can be used to process data and extract useful information and features.

Before data processing, the original dataset may contain duplicate data, outliers, and missing values. It have a negative impact on statistical analysis and model building, leading to a decrease in sample size, inaccurate analysis results, and difficulty in model building.

Feature extraction: subsequently, feature extraction is performed. By utilizing techniques such as statistics, mathematical models, and signal processing, representative and discriminative features are extracted from raw data. The results obtained through this step in this article are as follows:

The basic statistical characteristics are as follows:

Average: 1200 kW

Standard deviation: 200 kW

Maximum value: 1500 kW

Minimum value: 800 kW

The frequency domain characteristics are as follows:

Peak frequency: 50 Hz

Amplitude spectral density: 1000 kW/Hz

The characteristics of the time series are as follows:

Autocorrelation coefficient: 0.8

Moving average: 1250 kW

These features are selected as representative features based on the following considerations:

The average and standard deviation of power reflect the concentration trend of power load and the degree of dispersion of data distribution. In this dataset, the average power is 1200 kW, with a standard deviation of 200 kW, indicating that the load changes are relatively stable and have small fluctuations.

The peak frequency is 50 Hz, indicating that in the power system, the main power is concentrated at 50 Hz, which may be caused by the specific operating mode of the load or special equipment.

The autocorrelation coefficient and moving average in the time series characteristics reflect the correlation and overall trend of load over time. The autocorrelation coefficient is 0.8, indicating a strong linear correlation between the current load and the previous load. The moving average value is 1250 kW, indicating a gradual increase or decrease in the overall load trend.

The selection of prominent features through the specific power load indicators mentioned above is based on statistical analysis of load data and comprehensive judgment of domain knowledge. These features are considered representative and distinguishable, and can be used for subsequent data analysis, predictive modeling, or other applications. Other power indicators may not have been highlighted because they are of low or insignificant importance in describing load characteristics in this analysis.

Data conversion: after feature extraction, it may be necessary to convert the data to meet the needs of further processing and analysis. Common data conversion operations include standardization, normalization, logarithmic transformation, differential processing, etc. The converted data is beneficial for reducing dimensions, eliminating bias, and improving comparability and stability of the data. In this study, power load data and meteorological data were normalized to eliminate the impact of different data types on estimation accuracy. Historical load data and meteorological data were transformed into the range of [0,1] through normalization formulas.

In summary, data processing and analysis are key steps in converting raw data into useful information in power load collection systems. Through data cleaning, feature extraction, and data transformation, power load data can be effectively processed and analyzed, and the results can be applied to decision-making and operation in the power industry.

2.3. PLF Process

After completing the collection and processing of power load data, power load prediction operations can be carried out. PLF based on intelligent perception technology is the use of perception technology to collect data and construct prediction models through data processing, analysis, and modeling. The detailed steps of this process are as follows:

1) Construction of predictive models. The prediction model can adopt various machine learning algorithms, such as neural networks, support vector machines, etc. The detailed steps are as follows:

Model selection and training: after feature selection and extraction are completed, a neural network algorithm is used to train the model based on the training samples, and a prediction model is established by learning the patterns and patterns in the samples.

Model evaluation: after completing model training, it is necessary to evaluate and validate the model. By using a portion of the data as a test set, predictions are made on the model and compared with the actual load. Next, evaluations are conducted based on RMSE and MAE.

Model tuning: finally, based on the evaluation results, the model is tuned and the model parameters are adjusted to improve the accuracy and robustness of the model. In this process, continuous iterative optimization is required to continuously improve the performance of the model.

In this operation, model tuning is carried out through the following two steps:

Adjustment of hyperparameters: te hyperparameters of the model should be adjusted according to its characteristics, and the performance of the model should be optimized by using regularization parameters, number of hidden units, etc.

Data preprocessing: proper preprocessing of input data can improve the performance of the model, and through operations such as feature selection, feature scaling, and feature standardization, the input data can be made more suitable for model use.

The comparison of results before and after tuning is as follows:

Before tuning

RMSE: 150

MAE: 120

After tuning

RMSE 120

MAE: 90

The RMSE has decreased from 150 to 120, indicating a smaller deviation between the predicted value and the actual load. In addition, the MAE has decreased from 120 to 90, indicating that the average prediction error of the model is also smaller than before.

Model application and prediction: by completing model evaluation and optimization, a reliable power load prediction model is obtained. After inputting new input data (including factors related to load forecasting) into the model, the model would provide corresponding load forecasting results. These prediction results can be used for decision-making such as power grid planning, resource scheduling, and load balancing, which can help power suppliers prepare in advance, optimize operations and resource allocation.

In the process of building a prediction model, it is necessary to pay attention to the following points: firstly, the sample selection should be representative and cover different load situations and factors. Secondly, feature selection and extraction should comprehensively consider the correlation and importance of factors. Finally, model evaluation and tuning are key steps in continuously optimizing model performance, and iterative improvements need to be made based on actual needs and feedback.

2) Correction of prediction results. After completing the construction of the prediction model, it is necessary to modify the prediction results of the power load to improve the prediction accuracy. The correction formula uses the difference between the actual load value and the predicted load value to adjust the predicted results. The purpose of correction is to make appropriate corrections to the prediction results based on the actual situation, in order to improve the accuracy of the prediction. The following steps can usually be used for correction:

Analysis of differences: for each predicted result, the difference between it and the corresponding actual load value is calculated. By calculating the difference, the deviation of the predicted results can be obtained, and its patterns and trends can be analyzed. Various statistical methods can be used. This study used RMSE and MAE to measure the overall difference between predicted results and actual values.

Determination of correction factors: based on the results of difference analysis, the factors or parameters that need to be corrected can be determined. These factors can be a certain time period, specific weather conditions, seasonal changes, etc. In this study, a temperature correction factor was introduced to correct the predicted results, considering that the increase in air conditioning usage during the high temperature season may lead to an increase in power load.

Correction formula design: based on the determined correction factor, the relationship between the correction factor and the prediction result is calculated, and it is applied to the prediction result for correction to ensure more accurate prediction results after correction.

Continuous optimization: Calibration results may vary in accuracy over time and with changes in the data. Therefore, continued evaluation and optimization of the calibration formulas is important. Feedback and improvements are made by monitoring the difference between the calibration's predicted results and actual load values. Depending on the new data and feedback, the parameters in the calibration formula are adjusted to fit the actual situation and improve the accuracy of the prediction results.

The PLF process is shown in Figure 2.

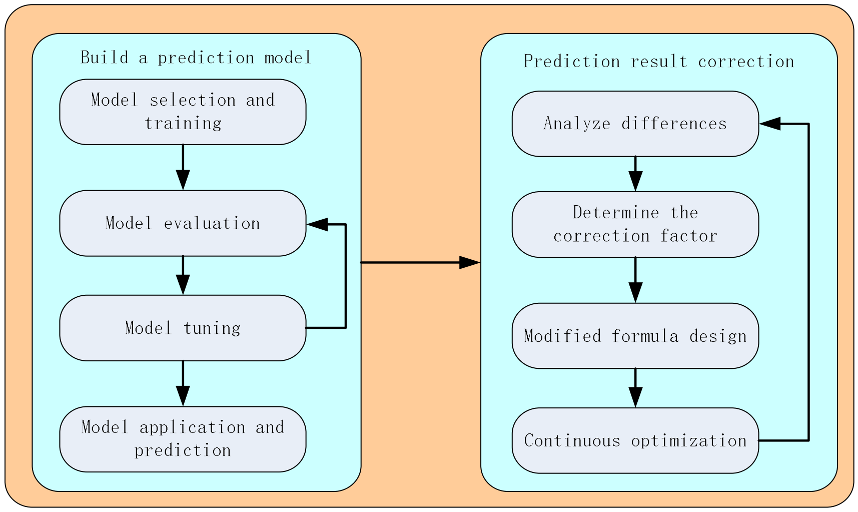

Fig. 2. PLF process

3. Exploration of WN and IST

3.1. WN Power Communication Algorithm

Building a wireless access communication model is crucial for WN architecture. Specifically, all mobile devices need to choose a computing mode, and different computing modes correspond to different decision variables. When the number of mobile devices meets certain conditions, local computing tasks can be offloaded through subchannels. Among them, the data transmission rate is as follows:

$$r_{i,n}^{m} = W\log_2\left(1+\frac{P_{i,n}g_{i,n}^{m}}{\sigma^2+K_{i,n}^{m}}\right) \tag{1}$$

Among them, W is the channel bandwidth. $P_{i,n}$ is the information transmission power of mobile device I. $K_{i,n}^{m}$ is the interference caused by other mobile devices on channel m. $g_{i,n}^{m}$ is the signal transmission gain between mobile device I and channel m. σ^2 is Gaussian noise.

When conducting local computing on mobile devices, it is necessary to first consider the local latency and energy consumption of the computing task. Local costs are defined by local delay and energy consumption as:

$$Z_i^l = \alpha t_i^l + \beta E_i^l \tag{2}$$

Among them, α and β are the weight parameters for mobile device execution delay and energy consumption, respectively. t_i^l and E_i^l are the local latency and energy consumption of the computing task, respectively.

When a mobile device loads a computing task on a remote server for execution, the cost of edge computing mainly includes execution delay and energy consumption [12-13]. In the process of edge computing, the total execution delay of the mobile device is as follows:

$$t_{i,n}^{m,e} = t_{i,n}^{m,s} + t_{i,n}^{x} \tag{3}$$

Among them, $t_{i,n}^{m,s}$ is the total delay of the data transmission process, and $t_{i,n}^{x}$ is the total delay of the system calculation process.

Next, the total energy consumption is calculated as:

$$E_{i,n}^{m,e} = E_{i,n}^{m,s} + E_{i,n}^{x} \tag{4}$$

Among them, $E_{i,n}^{m,s}$ is the energy consumption of the transmission process, and $E_{i,n}^{x}$ is the energy consumption of the calculation process.

Finally, the calculation method of mobile devices is changed to the form of decision variables to clearly describe the system model. The cost minimization model design is as follows:

$$\min_{c_i \in \{0,1\}} K_i\left(c_i, c_{i-1}\right) \tag{5}$$

Among them, $K_i\left(c_i, c_{i-1}\right)$ is the cost function.

Through the above algorithms, mobile devices can flexibly access WN and select computing tasks to achieve the goal of minimizing costs. This can better balance latency and energy consumption, and improve system performance and user experience. This algorithm can play an important role in PLF and scheduling.

3.2. Power Load Prediction Algorithm based on Intelligent Perception Technology

The first step is to preprocess the power load data. In practical application scenarios, there are still many uncertain factors that can lead to data anomalies, including noise, deviation, mutation, missing, etc. These adverse factors can reduce the effectiveness of power load data. Therefore, data preprocessing operations can improve the performance indicators of the entire prediction model. When preprocessing power load data, the data in the horizontal direction has continuity and the amplitude of load sudden changes is small, which can be processed through the horizontal processing method:

$$max[W\left(n,t\right)-W\left(n,t-1\right) | W\left(n,t\right)-W\left(n,t+1\right)] > \delta\left(t\right) \tag{6}$$

Among them, $W\left(n,t\right)$ is the power load value at time t on day n, and $\delta\left(t\right)$ is the load threshold.

After that, Formula (6) can be modified:

$$W\left(n,t\right)=\frac{W\left(n,t-1\right)+W\left(n,t+1\right)}{2} \tag{7}$$

The second step is to normalize the power load data.

The normalization of data does not scale it to a specific percentage within a set area, so the negative impact of data attributes on estimation accuracy can also be avoided.

During the normalization process, the historical load data is first normalized using the extremum method:

$$H_d^* = \frac{H_d - H_{\min}}{H_{\max} - H_{\min}} \tag{8}$$

The inverse normalization formula is:

$$H_d = \left(H_{\max} - H_{\min}\right) * H_d + H_{\min} \tag{9}$$

Among them, H_d is the historical load data, and H_d^* is the normalized historical load data, with a value range of [0,1]. $H_{\max}$ and $H_{\min}$ are the maximum and minimum values in the load data, respectively.

Next is the normalization processing of meteorological data [14-15]. Meteorological data mainly includes maximum temperature, minimum temperature, humidity, etc. To ensure the accuracy of model training and prediction, meteorological data also needs to be normalized. By analogy with the normalization method of historical load data, the temperature and humidity normalization formula is obtained:

$$T_m^* = \frac{T_m - T_{\min}}{T_{\max} - T_{\min}} \tag{10}$$

Among them, T_m is the original temperature and humidity data, and T_m^* is the normalized temperature data, with a value range of [0,1]. $T_{\max}$ and $T_{\min}$ are the maximum and minimum values of temperature and humidity, respectively.

The third step is to construct a PLF model, with the following training samples set:

$$S=\{(x_1,y_1),\dots,(x_n,y_n)\}\in R^n*R \tag{11}$$

Among them, n is the total training amount. The model for PLF is:

$$y=\varphi x+b \tag{12}$$

The final step is to modify the predicted results of the power load to further improve the accuracy of the load prediction. The formula is as follows:

$$\Delta_t=\frac{y_{t,true}-y_{t,forecast}}{y_{t,forecast}}\sim N\left(\mu,\sigma^2\right) \tag{13}$$

Among them, $y_{t,true}$ and $y_{t,forecast}$ represent the actual load value and predicted load value at time t.

By performing a correction operation on it, $y_{t,true}$ can be represented as:

$$y_{t,true}=\left(1+\Delta_t\right)*y_{t,forecast} \tag{14}$$

In practical situations, the final load forecasting model is obtained by learning from historical data. When variables that affect load changes are input into the trained model, future load forecasting values can be obtained. However, these variables that affect the load cannot be accurately obtained, such as future temperature, humidity, etc. Therefore, the distribution of Δ_t is determined through the training process of the model and dynamically updates with the increase of training data.

4. Relevant Experiments on Power load Prediction based on WN and Intelligent Perception

4.1. *Selection of PLF Dataset*

PLF is an important task. In order to achieve accurate load forecasting, reliable datasets are required. The following is the dataset for PLF used in this study:

1) CER (Commission for Energy Regulation) Electricity Data. CER is the energy regulatory agency in Ireland, responsible for overseeing and regulating the electricity market in Ireland. The data in CER Electricity Data includes information on electricity supply and demand, electricity generation, electricity prices, energy consumption, and other aspects.

2) REFIT Power Data. The power load measurement data set is a consortium composed of three universities in Loughborough, Strathclyde and East Anglia and ten industry stakeholders, which is funded by the Engineering and Physical Science Research Committee according to the funding plan of "transforming building energy demand through digital innovation".

This dataset includes raw power consumption data for 20 households at total power and electrical levels, in watts, with a timestamp and sampling interval of 8 seconds. In addition, this dataset is designed for research on energy conservation and advanced energy services, including non-invasive electrical load monitoring, demand response measures, customized energy and renovation recommendations, electrical usage analysis, consumption and time use statistics, as well as smart homes, building automation, and more.

3) Umass Smart Data Set. This dataset collects various data from three real households, including electrical (usage and power generation), environmental (such as temperature and humidity), and operational data. In addition, there are over 400 anonymous households with minute level electricity consumption data.

This dataset contains solar power generation data for 81 households in the United States. These files are in CSV (Comma Separated Values) format and have three columns: Timestamps, Local_Time and Solar. These files are called Home_N_X_Y.csv. N is the family number, and X and Y are rough latitude and longitude.

These datasets typically contain historical power load data, weather data (such as temperature, humidity, etc.), date time information, and other factors that may affect the load. Using these datasets for modeling and forecasting can improve the accuracy of PLF.

In this experiment, the information of some datasets is shown in Table 2.

Table 2. Information of partial datasets

Time	Current (A)	Voltage (V)	Power (W)
2021-01-01	2.3	230	529
2021-01-02	1.8	225	405
2021-01-03	2.5	240	600

In addition, this article collected real-time electricity data from three households A, B, and C using smart meters. Some of the data are shown in Table 3.

Table 3. Partial collected information

Time	Home	Current (A)	Voltage (V)	Power (W)
2023-08-01	A	1.5	220	330
2023-08-01	B	2.8	245	686
2023-08-01	C	2.2	230	506

4.2. Selection of Experimental Evaluation Indicators

The trend of power load changes is determined by multiple factors, and has the characteristics of randomness and volatility. Therefore, there would be more or less errors in PLF. In order to verify the effectiveness of the model and clarify whether its performance can be applied to real business scenarios, it is necessary to refer to multiple indicators to measure the performance of the prediction model in practical applications. This can avoid misjudgment of the overall performance of the prediction model caused by the error of a single indicator. Four error evaluation indicators were set here, namely RMSE, MAE, Mean Absolute Percentage Error (MAPE), and Pearson Correlation Coefficient (PCC).

1) RMSE. RMSE refers to the RMSE between the actual value of the load during the testing phase and the predicted value of the load, which can be expressed as:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}\left(y_{t,true} - y_{t,forecast}\right)^2}{T}} \tag{15}$$

Among them, T is the total time step; $y_{t,true}$ and $y_{t,forecast}$ represent the actual load value and predicted load value at time t.

2) MAE. MAE represents the MAE between the actual value of the load during the testing phase and the predicted value of the load, which can be expressed as:

$$MAE = \frac{\sum_{t=1}^{T} \left| y_{t,true} - y_{t,forecast} \right|}{T} \tag{16}$$

3) MAPE. It is the MAPE between the actual value of the load during the testing phase and the predicted value of the load. MAPE can be expressed as:

$$MAPE = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{y_{t,true} - y_{t,forecast}}{y_{t,true}} \right| \tag{17}$$

4) PCC. PCC represents the correlation between the actual value of the load during the testing phase and the predicted value of the load, which can be expressed as:

$$PCC = \frac{E\left[\left(L_{true} - \mu\left(L_{true}\right)\right)\left(L_{forecast} - \mu\left(L_{forecast}\right)\right)\right]}{\sigma_{L_{true}} \sigma_{L_{forecast}}} \tag{18}$$

Among them, L_{true} and $L_{forecast}$ represent column vectors composed of actual and predicted load values, respectively. $\sigma_{L_{true}}$ and $\sigma_{L_{forecast}}$ represent the standard deviations of L_{true} and $L_{forecast}$, respectively. $\mu\left(L_{true}\right)$ and $\mu\left(L_{forecast}\right)$ represent expectations for L_{true} and $L_{forecast}$, respectively.

Based on the values of the above prediction evaluation indicators, the accuracy of the prediction results can be evaluated. When the values of RMSE, MAE, and MAPE are smaller, it indicates higher prediction accuracy, and vice versa, lower prediction accuracy. In addition, the range of PCC values is [0,1]. The smaller the PCC, the lower the correlation between the actual load value and the predicted value, indicating a lower prediction accuracy. Conversely, the higher the correlation, the higher the prediction accuracy.

4.3. WN Testing Experiments

In the transmission of power load data in WN, performance testing is required to evaluate the impact of user numbers on charge data transmission delay and integration delay. Through these tests, it is possible to gain a deeper understanding of the potential latency during data transmission under different user numbers, and to optimize the efficiency of the transmission system accordingly. This is crucial for ensuring network stability and improving user experience. The detailed data is shown in Figure 3.

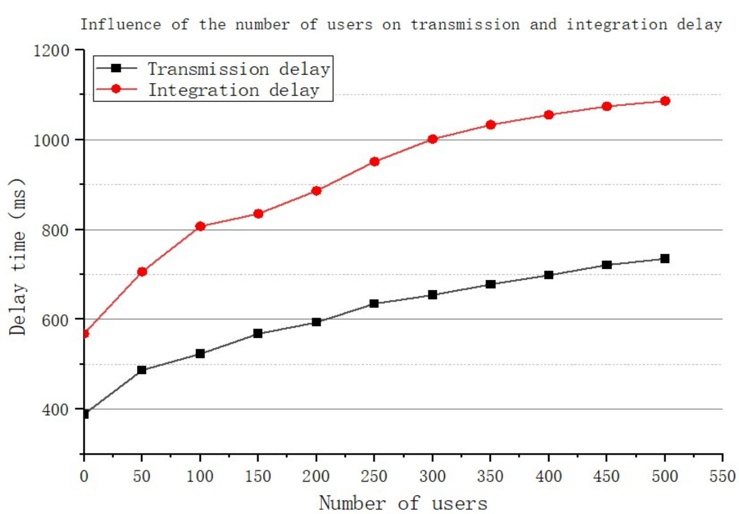

Fig. 3. The impact of user numbers on transmission and integration latency

In Figure 3, the horizontal axis represents the number of users and the vertical axis represents the delay time. Obviously, in WN, the transmission and integration latency of power load data was relatively small. In addition, it can be seen that as the number of users continued to increase, the transmission delay and integration delay of power load data were also increasing. During the process of increasing the number of users from 0 to 500, the transmission delay increased from 389ms to 735ms; the integration delay increased from 568ms to 1086ms. This indicated that as the number of users increased, the delay time of power load data transmission also increased accordingly. This was because as the number of users increased, the amount of data transmitted in the network also increased, leading to a decrease in transmission efficiency.

In order to comprehensively evaluate the power load data transmission of WN, this study also needs to use the same experimental method to test the impact of system operation time on charge data transmission delay and integration delay. Through this step, it is possible to understand the latency that data transmission may face under different system operating times, and further optimize the system to improve transmission efficiency. The detailed data is shown in Figure 4.

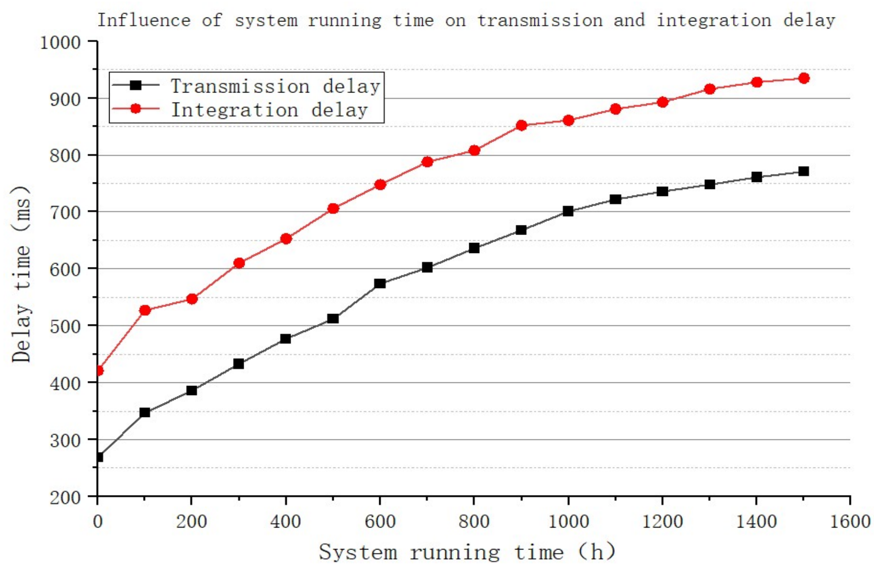

Fig. 4. The impact of system runtime on transmission and integration latency

In Figure 4, the horizontal axis represents the system running time and the vertical axis represents the delay time. Obviously, in WN, the transmission and integration latency of power load data was relatively small. It can be seen that as the system operation time continued to increase, the transmission delay and integration delay of power load data were also increasing. During the process of increasing the system running time from 0 hours to 1500 hours, both transmission delay and integration delay were increasing. This indicated that as the system operation time increased, the delay time of power load data transmission also increased accordingly. This was because as the system runtime increased, the gradual consumption of system resources and the increase in load led to a decrease in transmission efficiency.

4.4. *Testing Experiments for Power Load Prediction*

Firstly, the power load prediction algorithm based on intelligent perception technology was tested to assess its effectiveness in predicting power loads. The RMSE of the algorithm for each dataset was tested. The detailed data is shown in Table 4.

Table 4. RMSE of the algorithm for each dataset

Experimental serial number	CER Electricity Data	REFIT Power Data	Umass Smart Data Set
1	0.288	0.249	0.267
2	0.301	0.305	0.277
3	0.271	0.248	0.259
4	0.305	0.291	0.243
5	0.297	0.293	0.248
6	0.254	0.275	0.258
7	0.289	0.274	0.266
8	0.307	0.265	0.275
9	0.304	0.295	0.269
10	0.269	0.221	0.256

In Table 4, the average predicted RMSEs of the algorithm for the CER Electricity Data, REFIT Power Data, and Umass Smart Data Set datasets were 0.2885, 0.2716, and 0.2618, respectively. This indicated that the algorithm had certain accuracy in predicting power loads.

Next, the power load prediction algorithm based on intelligent perception technology was tested to assess its predictive performance on power loads. The MAE of the algorithm for each dataset was tested. The detailed data is shown in Table 5.

Table 5. MAE of the algorithm for each dataset

Experimental serial number	CER Electricity Data	REFIT Power Data	Umass Smart Data Set
1	0.244	0.195	0.186
2	0.238	0.165	0.172
3	0.209	0.201	0.196
4	0.218	0.168	0.149
5	0.259	0.216	0.198
6	0.251	0.241	0.137
7	0.236	0.171	0.234
8	0.204	0.176	0.162
9	0.223	0.201	0.175
10	0.221	0.217	0.134

In Table 5, the average prediction absolute errors of the algorithm for the CER Electricity Data, REFIT Power Data, and Umass Smart Data Set datasets were 0.2303, 0.1951, and 0.1743, respectively. This also indicated the excellent accuracy of the algorithm in PLF.

After that, the power load prediction algorithm based on intelligent perception technology was tested for the MAPE of each dataset. A total of 10 experiments were conducted. The detailed data is shown in Figure 5.

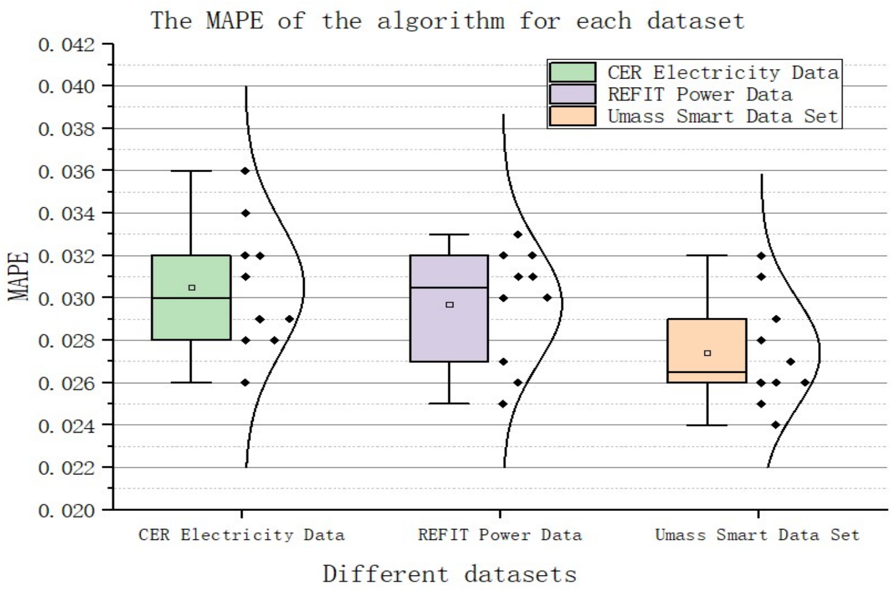

Fig. 5. Algorithm's MAPE for each dataset

In Figure 5, the horizontal axis represents different datasets, while the vertical axis represents MAPE. After calculation, it can be known that the average predicted MAPE of this algorithm for the CER Electricity Data, REFIT Power Data, and Umass Smart Data Set datasets were 0.0305, 0.0297, and 0.0274, respectively. The MAPE of this algorithm on these datasets was relatively low, indicating that its prediction accuracy was relatively high.

The power load prediction algorithm based on intelligent perception technology was tested, and the PCCs of each dataset were calculated. A total of 10 experiments were conducted. The detailed data is shown in Figure 6.

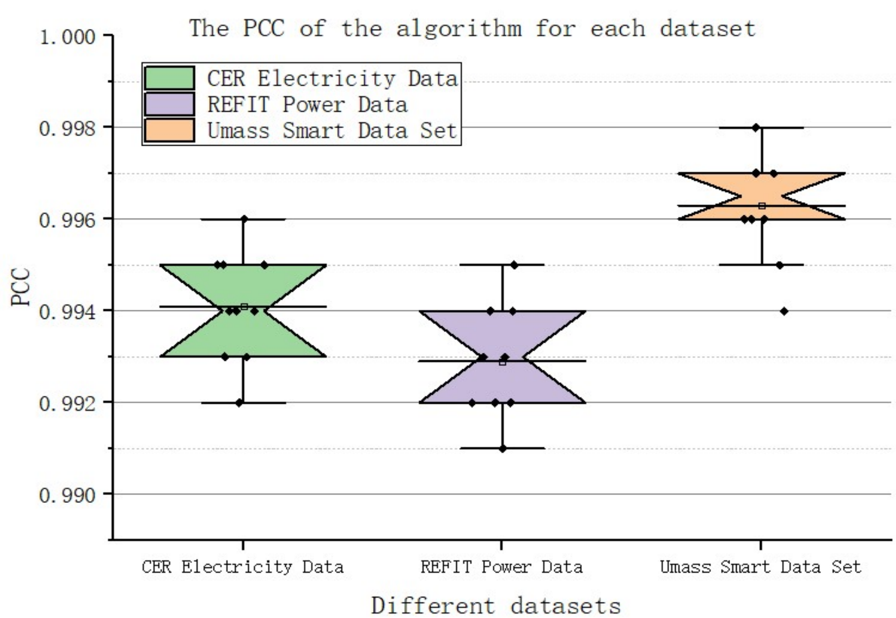

Fig. 6. Algorithm's PCC for each dataset

In Figure 6, the horizontal axis represents different datasets and the vertical axis represents PCC. After calculation, it can be known that the average predicted PCC of this algorithm for the CER Electricity Data, REFIT Power Data, and Umass Smart Data Set datasets were 0.9941, 0.9929, and

0.9963, respectively. This indicated that the power load prediction algorithm based on intelligent perception technology showed high accuracy and reliability on various datasets. This algorithm can effectively capture the trend of load changes and accurately predict future load demand. This would help improve the scheduling efficiency of the power system and reduce energy consumption and carbon emissions.

In the experiment, experimental tests were conducted on the generation loss rate and transmission loss rate of the power grid. The detailed data is shown in Figure 7.

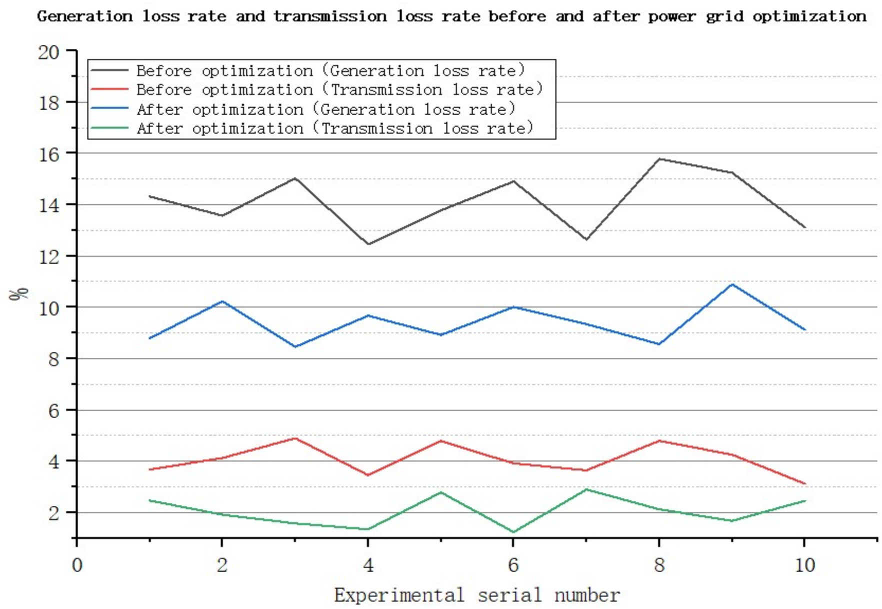

Fig. 7. Generation and transmission loss rates before and after grid optimization

In Figure 7, before the optimization of the power grid, the average generation loss rate and transmission loss rate were 14.086% and 4.062%, respectively. After optimization, the average generation loss rate and transmission loss rate were 9.398% and 2.042%. In this case, it reveals that after optimizing the power load forecasting algorithm using intelligent perception technology, the power grid has improved significantly in terms of both generation loss rate and transmission loss rate. Grid can more accurately predict the load demand and rationally arrange the generation plan and transmission strategy, thus realizing effective energy utilization and higher energy efficiency.

5. Conclusions

The use of the technology can improve the stability of the power system, energy utilization efficiency and user experience, and further promote the development of sustainable energy. In light of the experimental results of the WN test, the prediction algorithm based on intelligent perception technology shows a certain degree of accuracy. Algorithm proposed in this paper can accurately capture the trend of load change and effectively predict future load demand. With the optimization of the efficiency of the WN transmission system and the use of intelligent perception-based prediction algorithms, the stability, user experience and dispatch efficiency of the power system can be improved, thus achieving the goal of energy saving and emission reduction. However, as WN may face security risks such as data leakage and cyber-attacks during data transmission, it poses a potential threat to the stability of the power system and user privacy.

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