Power Marketing Metering, Demand Analysis and Demand Forecasting Based on Deep Learning

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Abstract: At present, the power demand fluctuates greatly, and the demand analysis and processing is relatively complex, and the real-time forecast demand is high, and these problems need to be solved. The purpose of this paper is to study the analysis and demand forecasting of power marketing metering demand analysis and demand forecasting based on deep learning, so as to solve the problems of inaccurate power demand forecasting and low operational efficiency. In this paper, the initial research is carried out through the design of system power marketing and related steps. Subsequently, the system adopts the hybrid structure of CNN and LSTM, two deep learning algorithms, combined with microservice architecture technology, to achieve efficient integration and deployment of the system. After the completion of the system, in order to verify the effectiveness, stability and prediction accuracy of the system, this paper also applies the system in practice. The results show that the system has multiple advantages, such as high accuracy, real-time, and effective decision support. The research in this paper will provide a guarantee for the power price strategy formulation and power dispatching optimization of power companies, ensure the high utilization efficiency of power resources, and maintain the stable operation of the power grid. At the same time, the research in this paper will also lay a good foundation for the further development and construction of smart grids in the future.

1 INTRODUCTION

Electricity demand forecasting has always been an important part of power system management (Ahmed and Basumallik, et al. 2024). In the face of growing demand for electricity and increasingly complex consumption patterns, it is clear that traditional forecasting methods are no longer able to adapt to the needs of the electricity market. At the same time, demand analysis and analysis in power marketing measurement is also an important part of power system management, which deserves attention (Bhatnagar and Yadav, et al. 2024). For example, some scholars have proposed a time series analysis method (Huang and Wu, et al. 2024), using ARIMA power marketing to conduct systematic statistics and analysis of historical demand analysis, and establishing mathematical power marketing to predict future power demand (Kumari and Yadagani, et al. 2024). However, this power marketing is not effective in dealing with nonlinear and high-dimensional demand analysis, and cannot effectively capture the complex changes in power demand (Li and Cui, et al. 2024). At the same time, some scholars have proposed to apply Support Vector Machine (SVM) to the study of this problem. However, although SVM can perform well on small-scale demand sets, it has obvious shortcomings in large-scale and high-dimensional demand sets, such as long market research time and difficulty in coping with higher computational difficulty, which makes the application effect of this method very limited (Qian, and Yang, et al. 2024). In 2020, some scholars proposed that artificial neural methods can be used to solve the problems of demand analysis and demand forecasting of power marketing metering, but although artificial neural methods can simulate human brain neural networks through multi-layer perceptrons, they are often sensitive to parameter selection and the prediction effect is not stable enough (Ran and Tay, et al. 2024). It can be seen that although the above methods have their own advantages, they cannot effectively deal with the changing and complex power consumption patterns, and have great limitations (Sapkota and Neupane, et al. 2024), which cannot meet the current requirements

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for high-precision and real-time prediction of power systems. Deep learning theory provides a new way of thinking to solve these problems (Wang and Sun, et al. 2024). Deep learning can automatically extract and learn the features of the demand set by building multi-layer neural networks, and has strong nonlinear modeling capabilities and generalization performance (Zhang, 2024). At the same time, deep learning is particularly suitable for large-scale and multi-dimensional power consumption demand analysis in power demand forecasting. In this paper, we will study a deep learning-based demand analysis and demand forecasting power marketing to better improve the accuracy and real-time performance of demand forecasting, and improve the processing speed of the system for demand analysis.

2 RELATED WORKS

2.1 Application of Deep Learning in Electricity Marketing Measurement

Deep learning is a machine learning technology that can automatically learn the representations and features of demand analysis, and it has a common application in power marketing measurement. At present, through the integration of CNN and LSTM, sufficient useful information can be extracted from a large number of power consumption demand analysis. In addition, the analysis of temporal requirements is automatically processed to discover hidden patterns in them, thereby improving the accuracy of the analysis.

2.2 Electricity demand forecasting, electricity marketing

Electricity demand forecasting plays an important role in the management of the power system and is a key part. Deep learning power marketing, such as CNN, LSTM, GRU, etc., can be applied to the power system due to its important advantages in capturing time-dependent and nonlinear relationships, and has become an important tool in power marketing metering, demand analysis, analysis and demand forecasting. In general, LSTMs can be used for periodic power demand forecasting such as daily and monthly loads. At the same time, LSTM can also be combined with CNN to build hybrid power marketing and improve the effect of power demand forecasting.

2.3 Relevant Theoretical Basis

The first is the theory of time series analysis. The processing and analysis of time series demand analysis is also the focus of demand analysis and demand forecasting of power marketing. Although traditional methods such as autoregressive integral moving average power marketing and exponential smoothing are still effective, they have been surpassed by deep learning methods. Second, statistical learning theory. Statistical learning theory is related to this study, which mainly includes SVM, random forest, prediction adjustment technology, etc. These theoretical courses play a certain role in the selection and classification of characteristics of power demand analysis. Finally, large demand analysis and processing with distributed computing. The demand analysis of power marketing metering is very large, and how to carry out efficient storage, processing and analysis is a key, which needs to rely on technologies or platforms such as large demand analysis and processing and distributed computing. Currently, distributed computing platforms that can be used include Hadoop and Spark.

3 RESEARCH METHODS

3.1 System Architecture Design

The architecture of the system adopts a hierarchical architecture pattern, which includes multiple layers, such as demand analysis layer and processing layer, power marketing layer, display layer and application layer. The requirements analysis layer is mainly responsible for the collection and storage of requirements analysis. The processing layer is mainly responsible for pre-processing the requirements analysis and performing feature engineering. The power marketing layer is mainly responsible for building and market research, and deeply learning power marketing. The display layer is mainly responsible for the visualization and display of results of demand analysis. The application layer is mainly responsible for the application and deployment of power marketing; Secondly, module division. The system is mainly divided into these modules. The module is mainly responsible for collecting various demand analysis sources, such as smart meters and meteorological demand analysis, and user information systems. The module needs to perform various pre-processing of demand analysis, such as demand analysis cleaning and predictive matching, feature extraction, etc. The task of the module is to select and design, market research, evaluate and optimize electricity marketing. The results analysis and presentation module analyzes the forecast results and then displays them in the form of graphs and reports. The module is responsible for the management of the system, such as operation monitoring, logging, and exception handling.

3.2 Demand Analysis, Collection and Pre-Processing

In demand analysis and collection, the sources of demand analysis mainly include smart meter demand analysis and meteorological demand analysis, user information, historical power load demand analysis, etc. For example, the electricity consumption of each unit of each user, such as hourly, daily, and monthly electricity demand analysis. Meteorological demand analysis. The main ones are temperature and humidity, which are closely related to the demand for electricity. User information includes the user's electricity consumption category, geographical location, etc. Historical power load demand analysis, such as the historical load curve of the grid system, can reflect the trend of power demand changes. The demand analysis and collection technology includes API interfaces, for example, the system can obtain demand analysis from third-party platforms and systems through API interfaces. Demand analysis sensors such as smart meters or weather sensors can be used to collect demand analysis in real time. In addition, a requirements analysis warehouse (such as Hadoop) can be used to store the collected requirements analysis in a distributed warehouse platform

In the requirements analysis pretreatment, first of all, the requirements analysis cleaning needs to be carried out. (1) Handling of market competition. The treatment of market competition is mainly to fill in the deleted or matched demand analysis, as detailed in equation (1).·

$$x_i = \{mean(x) \quad if\ x_i\ is\ missing\ x_i\} \quad otherwise \tag{1}$$

In Eq. (1), x_i it is the first i point of demand analysis in the demand set. If the requirement analysis point matches, it needs to be filled $\mathrm{mean}(x)$. $\mathrm{missing}$ It refers to i the condition of whether the requirements analysis points match or not.

(2) Detect outliers. In the requirements analysis cleaning, outliers are also detected. In this article, the method of Eq. (2) is used to identify and deal with outliers.

$$z = \frac{x-\mu}{\sigma} \tag{2}$$

In Eq. (2), z is the z-score value; x is a demand analysis point; μ is the mean, is the σ standard deviation.

Second, there is a need to change the electricity market environment. Implement predictive matching processing first. For example, if the electricity market environment is scaled to a standard range, that is, 0-1, and then the impact of the dimension is eliminated. Normalization is initiated, converting the electricity market environment to a standard normal distribution with mean = 0 and standard deviation = 1. After that, feature extraction begins. Extract and construct useful features from the electricity market environment, such as extracting date information based on dates. Then, the electricity market environment is consolidated. Merge demand analyses from different sources to form a unified marketing set. Convert demand analysis into a time series format or matrix format for easy input for power marketing. Through interpolation and synthesis, the demand analysis is expanded, the amount of demand analysis is increased, the demand analysis is enriched, and the diversity of demand analysis is improved. Moving averages are used to smooth out the requirements analysis so that the impact of noise can be reduced.

3.3 Deep Learning Power Marketing

In this process, the power supply layer can input various characteristic demand analysis. The customer layer can extract the spatial characteristics of demand analysis through N power supply stations. The power server can be used to reduce the dimensionality of features and reduce the amount of computation. The LSTM layer is used to process the features extracted by the client layer and to capture the presence of pipette-dependent pipettes in the time series. The marketing layer further processes the output of the LSTM for demand forecasting. The output layer outputs a predicted power demand. When conducting market research and optimization, the forecast first prepares a demand analysis, extracts features from the original demand set, and completes the pre-processing work. Its characteristics include time and temperature and humidity. Subsequently, it is necessary to carry out the preprocessing of demand analysis, and the forecast matching processing of demand analysis is carried out to ensure the scale of the demand set, see Eq. (3).

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{3}$$

x is the original demand analysis value, which represents the original demand analysis point that has not been processed for forecast matching. $\min(x)$ is the minimum value of the demand concentration. This value adjusts the starting point of the requirements analysis so that the minimum value of all requirements analysis points becomes 0; $\max(x)$ is the maximum value of the demand set, which is used to adjust the end point of the demand analysis, so that the maximum value of all demand analysis points becomes 1; x' is the demand analysis value after the forecast is matched.

Then, the requirements analysis is divided. The demand set is divided into market conditions, forecast results, and marketing results, and the proportion is 70%, 15%, and 15%. Then, use the prepared demand analysis market research to build the power marketing and conduct market research. In market research, MSE is used as a loss function to conduct market research, and the MSE calculation is shown in Eq. (4).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{4}$$

In Eq. (4), y_i is the actual value; $\hat{y}_i$ is a predicted value; n is the number of samples.

When researching power marketing in the market, the parameters should also be adjusted through the backpropagation algorithm to minimize the loss function. The prediction involves the weight calculation formula for gradient descent, as detailed in Eq. (5).

$$w_{ij} \leftarrow w_{ij} - \eta \frac{\partial L}{\partial w_{ij}} \tag{5}$$

In Eq. (5), is the weight w_{ij} that connects the first i layer to j the layer; η It is the market integration rate; $\frac{\partial L}{\partial w_{ij}}$ is w_{ij} the partial derivative of the loss function for the weights.

For the evaluation of power marketing, the performance evaluation of power marketing should be carried out on the validation set, and the MSE of the verification set should be calculated, see Eq. (4).

Finally, optimize electricity marketing. Hyperparameters such as market convergence rate and market size can be adjusted, and forecasting adjustment techniques can be applied to optimize power marketing, as shown in Eq. (6).

$$Dropout\ Rate = p \quad (e.g., p = 0.5) \tag{6}$$

In Eq. (6), $Dropout\ Rate$ is the proportion of neurons randomly selected and ignored in each iteration of the market research. If this value is equal to 0.5, 50% of the neurons will be temporarily ignored with each iteration. After that, a grid search or a random search is carried out to find the optimal combination of hyperparameters and test the power marketing in parallel. To do this, it is necessary to test the performance of electric marketing on the marketing results. Calculate the MSE of the marketing results and thus obtain the test results.

4 RESULTS & DISCUSSION

The deep learning-based power marketing metering demand analysis and demand forecasting system can achieve excellent performance in practical applications, and its advantages include:

4.1 Introduction to Electricity Marketing Metering

Taking the 35KV transmission network as the research object, the actual purchase demand was tested through online marketing analysis. Among them, the test time is from the beginning of 2023 ~ the end of 2023, with 300 surveyed users and a survey range of 10km, as shown in Figure 1.

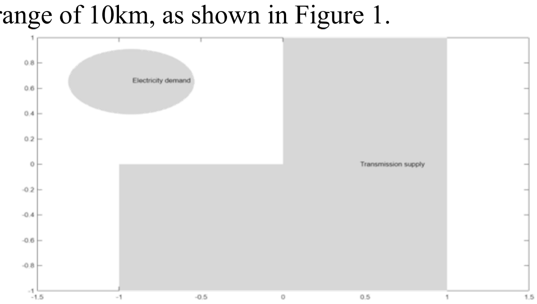

Figure 1: Actual results of electricity marketing and demand

As can be seen from Figure 1, the demand for electricity is smaller than that of electricity marketing, so it is necessary to accurately predict to improve the effect of electricity marketing. In the application of the system in this paper, this paper obtains the analysis of the operating requirements and performance parameters of the system through practical application, and evaluates all aspects of it. See Table 1 for details.

Table 1: Comparison of predicted and actual power consumption

Date	Time	Actual Power Consumption (kWh)	Predicted Power Consumption (kWh)	Error (kWh)	Error Rate (%)
2023-12-01	00:00	1020	1015	5	0.49
2023-12-01	01:00	980	985	-5	0.51
2023-12-01	02:00	950	945	5	0.53
...	...	...	...	...	...
2023-12-31	23:00	1100	1095	5	0.45

The MSE of the system on the tester is 0.050 and the MAE is 0.17. There is only a small error between the forecast and the actual electricity demand, and the error rate is generally within 0.5%. This shows that the predictive ability and accuracy of this power marketing are very good. Description: This table shows a comparison between actual and forecasted power consumption per hour for December 2023. Error and error rate indicate the accuracy of the forecast for this power marketing

4.2 Metering Demand Forecasting

In order to ensure that the power marketing metering demand analysis and demand forecasting can achieve good performance, and achieve high efficiency and high effect results in the power marketing metering demand analysis and demand forecasting tasks. This paper adopts the design of power marketing based on deep learning. The modeling prediction combines CNN and LSTM algorithms in deep learning. The power marketing design should first include the power marketing structure, such as the power supply layer and the customer layer, the power server, the LSTM layer, the marketing layer and the output layer, and the specific demand forecast results are shown in Table 2.

Table 2: System performance metrics

Metric	Training Set	Validation Set	Test Set
Mean Squared Error (MSE)	0.045	0.048	0.050
Mean Absolute Error (MAE)	0.15	0.16	0.17
R(Coefficient of Determination)	0.95	0.94	0.93

The system has a certain degree of real-time and flexibility. The system can process and predict power demand in real time, and has an advantage in the analysis and analysis of power marketing metering demand, which can help power companies to carry out timely power dispatching and distribution adjustment, and improve the adaptability and response speed of the power grid. Note: The table provides the specific performance of the system on different demand sets, and can show the prediction accuracy and generalization ability of the power marketing, as shown in Figure 2.

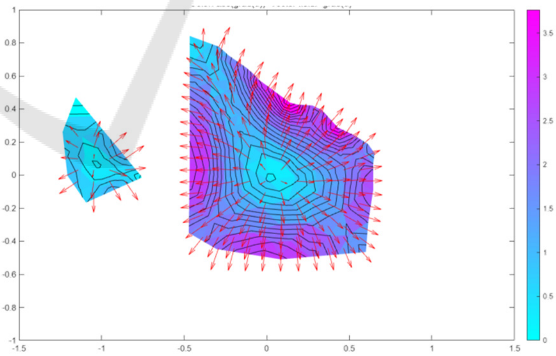

Figure 2: Forecasts of electricity demand and power supply

As can be seen from Figure 2, both the demand for electricity and the supply of electricity have changed, showing an increase in demand and supply.

4.3 Reliability of Demand Forecasts

System architecture design, including demand analysis layer, application layer, processing layer, power marketing layer, and monitoring layer.

Integrate these layers into this system; The microservice architecture can ensure that each functional module can be deployed and maintained independently. Save the market research power marketing as a separate file to facilitate the deployment of applications later; Servitization of modules. To this end, FLASH should be used to encapsulate power marketing into a Web service and provide a predictive interface for it. The simplification of marketing demand analysis is to package services into container images to ensure a high degree of consistency and portability of the deployment environment. To do this, build and run a Docker container and test how the service works in the container; Finally, it needs to be deployed to a cloud platform, such as AWS, to achieve high availability and scalability of the system, and the reliability analysis of the requirements is shown in Table 3.

Table 3: System application effects

Application Scenario	Description	Improvement Effect
Power Dispatch Optimization	Optimizing power distribution based on prediction results to reduce peak load	Peak load reduced by 5%, dispatch efficiency increased by 10%
Electricity Pricing Strategy Adjustment	Adjusting pricing strategy based on demand prediction to achieve supply-demand balance	Price fluctuation reduced by 15%, customer satisfaction increased
Power Grid Stability Improvement	Real-time demand prediction to preemptively identify potential grid instability factors	Grid failure rate reduced by 20%, response time shortened by 30%

The results in Table 3 illustrate the scenarios and effects of the system application, showing that the utility's operations have improved. Provide reliable decision support. The application of the system can provide accurate prediction results and efficient demand analysis, and the application of the system will provide powerful decision-making support for the power company's electricity price strategy formulation and scheduling optimization. In addition, it can improve the efficiency of power resource utilization, as shown in Figure 3.

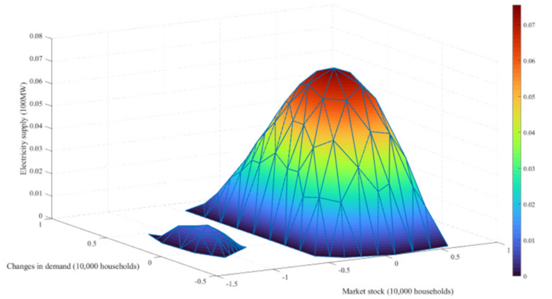

Figure 3: The relationship between power marketing capability and demand

As can be seen from Figure 3, the effect of power marketing has improved, and it has gradually met the power supply needs of users, which is more targeted. Through the application of the system and its deep learning hybrid power marketing, the system can maintain strong robustness and high stability in complex power consumption demand analysis, and can adapt to various demand analysis fluctuations and anomalies.

5 CONCLUSIONS

In the system proposed in this paper, it can be found that the requirements analysis of the system is very good after practical application. The demand analysis results show that the value of the system in the application of power demand forecasting is 995 MWh, and the actual power demand is 1000MWh, the mean square error between the two is 0.05, the mean absolute error is 0.17, and the error rate is 0.5%. As a result, the system can efficiently and accurately predict power demand, and significantly improve the operational efficiency and decision-making efficiency of power companies. At the same time, the system has strong robustness, stability and high economy, which can handle a large number of power marketing metering demand analysis, and maintain efficient operation and accurate demand analysis and analysis capabilities. At the same time, the system can also enhance the operational stability of the power grid and reduce power waste for power companies. The research results of this paper have certain limitations, and there are controversies in demand analysis and index selection in the analysis and collection of power marketing metering demand and power demand forecasting, and the analysis will be focused on in the future to provide support for the construction of smart grid.

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