# Cloud-Enabled Real-Time Monitoring and Alert System for Primary Network Resource Scheduling and Large-Scale Users

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***Abstract*—This paper innovatively combines cloud computing with Bayesian networks, aiming to provide an efficient and real-time prediction and scheduling platform for power main network scheduling and large-scale user monitoring. The core of the research lies in the development of a set of novel intelligent scheduling algorithms, which integrates multi-objective optimization theory and deep reinforcement learning technology to achieve dynamic and optimal allocation of power grid resources in the cloud environment. By constructing a comprehensive evaluation system, this study verifies the advancement of the proposed model in multiple dimensions: not only does it make breakthroughs in the in-depth parsing and accurate prediction of electric power data, but it also significantly improves the prediction accuracy of the main grid load changes, tariff dynamic adjustments, grid security posture, and power consumption patterns of large users. The empirical study shows that compared with the existing methods, the model proposed in this study effectively reduces energy consumption and operation costs while improving prediction accuracy and dispatching efficiency, demonstrating its significant innovative value and practical significance in the field of intelligent grid management. The innovation of this paper lies in the development of a composite prediction model that integrates the powerful classification and prediction capabilities of Bayesian networks and the efficient learning mechanism of deep reinforcement learning in complex decision-making scenarios.**

***Keywords*—*Cloud computing; main network scheduling; large users; real-time monitoring; monitoring and prediction; systems research***

## I. Introduction

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In order to ensure the stable operation of the power system, it is necessary to carry out real-time monitoring and forecasting of the scheduling of the main power network and the power consumption of large users, so as to realize the optimal allocation and scheduling control of power resources [1].

Therefore, the scheduling of the main power grid is particularly important in order to ensure the stability of power in each region [2]. The dispatching of the main power grid requires the process of planning, organizing, directing and controlling the operation of the main power grid according to the operating status of the power system, load demand, power market transactions and other factors [3].

This study confronts the reality of the continuous growth of power demand in the booming smart home market in China, revealing the significance of real-time monitoring and forecasting of main grid scheduling and large-scale users' power consumption for ensuring the stable operation of the power system. By proposing a real-time monitoring and forecasting system based on cloud computing, the article solves the limitations of the traditional system in data processing, analysis and forecasting, and resource sharing, and utilizes the elasticity and scalability characteristics of cloud computing to build a high-performance data processing platform, which realizes the efficient management of the whole chain from data collection to application. This system not only improves the intelligent level of main grid scheduling, but also significantly enhances the insight and management of large users' power consumption behavior, providing strong support for the development of the power market and the optimal allocation of power resources. The innovation of this study lies in the new prediction model combining Bayesian network and deep reinforcement learning, and the intelligent scheduling strategy of multi-objective optimization, which brings revolutionary progress to the power system scheduling and large-scale user management.

Large users refer to users with large power consumption capacity and power consumption impact in the power system, whose power consumption demand and power consumption behavior have an important impact on the operation of the power system and the formation of the power market [4]. Therefore, we need to carry out real-time monitoring of large users, specifically through the collection, transmission, processing and analysis of large users of electricity data, real-time access to the state of electricity consumption, characteristics of electricity consumption, quality of electricity consumption and other information, to provide data support for the scheduling of the main power grid and the management of electricity consumption of large users [5]. And also to further predict its power consumption, specifically refers to the use of mathematical models and methods to predict the future power demand, power load, power cost and other indicators of large users based on their historical power consumption data, power consumption behavior, power consumption environment and other factors, so as to provide a decision-making basis for the dispatch of the main power grid and the optimization of power consumption of large users [6].

As the scale of the power system continues to expand and the quantity and complexity of power data continue to increase, the traditional power scheduling system and large user monitoring and forecasting system face problems such as insufficient data collection and processing capabilities, weak data analysis and forecasting capabilities, and poor data sharing and collaboration capabilities. In order to solve these problems, this paper proposes a real-time monitoring and prediction system for main network dispatching and large users based on cloud computing, which utilizes the elasticity, scalability, and low-cost characteristics of cloud computing to construct a distributed, parallel, and high-performance power data processing platform, and realizes real-time monitoring and prediction of the main power network and large users, as well as intelligent scheduling and optimization based on data [7, 8].

The research work in this paper is of great significance in power system operation optimization and power market development [9]. Through the introduction of innovative cloud computing technology solutions, the overall operational efficiency of the power system and the economic performance of the power market are significantly improved. Specifically, it provides strong data support for the dispatching decision-making of the main power network and the power consumption management of large users, thus significantly improving the dispatching accuracy and efficiency of the main power network, as well as the power consumption management level of large users [10, 11].

The research objective of this paper mainly focuses on the intelligent scheduling and optimization management of the power system, and is committed to constructing a comprehensive real-time monitoring and prediction system for main grid scheduling and large users based on cloud computing technology. The system realizes the whole chain management and efficient utilization of power data from acquisition to application [12, 13]. In terms of specific methods, the study proposes a new way to utilize Bayesian networks in the cloud computing environment for power data analysis and prediction, which effectively solves the core problems of load prediction, electricity price prediction and grid security analysis of the main power grid, and accurately predicts the power demand, power load and cost of power consumption of large users. In addition, the research also developed a cloud computing-based intelligent scheduling and optimization scheme, using multi-objective optimization and reinforcement learning algorithms, for the scheduling control and optimization of the main power grid for in-depth exploration, but also in the level of optimization of the power consumption management of large users to achieve important breakthroughs [14, 15].

This study clearly constructs a core argument: that is, the real-time monitoring and prediction system constructed by integrating cloud computing and advanced algorithmic techniques can effectively cope with the growing scheduling challenges of the power system and enhance the ability to manage large-scale users in a fine-grained manner. In order to strengthen the theoretical foundation, the paper deeply analyzes the problems of the existing system, such as limited data processing capacity, insufficient prediction accuracy, etc., and shows how the solution proposed in this paper utilizes the characteristics of cloud computing, combines Bayesian networks and reinforcement learning algorithms, realizes the leap from theory to practice, and solves the key problems of power dispatch and user management, providing solid theoretical and technological support for the intelligent transformation of the power system. Solid theoretical and technical support for the intelligent transformation of the power system. Through this discussion, the thesis not only clarifies the argument of the research, but also significantly enhances the depth and breadth of the theoretical discussion.

In this paper, Section I outlines the background, purpose and importance of the research. Section II reviews the latest research results within the fields of cloud computing, edge computing and data-driven scheduling. Section III details the technical architecture and implementation method of the proposed real-time monitoring and prediction system, including the construction of the cloud computing platform, the data processing process and the application of the prediction model. Section IV analyzes the experimental data to verify the performance and advantages of the system. Section V summarizes the research results and gives an outlook on the future research direction.

## II. Literature Review

### *A. Big Data-Aware Scheduling System in Cloud Computing*

D'Mello et al. proposes a task scheduling algorithm for cloud-edge collaborative computing in edge networks, which takes into account the computational volume, data volume, timeliness, and priority of tasks, and adopts a graph-based model and an optimization method based on genetic algorithms to achieve task allocation and migration in edge networks, and improve the efficiency and performance of edge computing [16]. Dragoni et al. introduced a scheduling system for large-scale distributed computing data awareness in cloud environment, which realizes dynamic migration and replication of data by analyzing and predicting the data [17]. Dyskin et al. analyzed the application scenarios and value of power energy data, including the digitalization and intelligence of power equipment, the trading and regulation of power market, and the management and optimization of power consumption of power users, etc. [18]. It demonstrated the design and implementation of the system of collecting, monitoring, managing, analyzing, and servicing of power energy data, and explored the challenges and development direction of power energy data. Han et al. presents the design and implementation of a cloud computing-based electricity demand response system for large users, which takes advantage of the elasticity, scalability, and low cost of cloud computing to build a distributed electricity demand response platform, realizing real-time monitoring, analysis, and response to the electricity demand of large users, and providing data support and intelligent services for the scheduling and optimization of the power system [19]. A method for analyzing and identifying the electricity consumption behavior of large users based on the fusion of multi-source data is proposed, which utilizes multi-source data such as the electricity consumption data, electricity consumption contract, and electricity consumption equipment of large users, and provides an effective means for the supervision and service of the electricity consumption of large users [20]. It realizes the dynamic prediction of the electricity consumption cost of large users, and provides a reference basis for the decision-making and optimization of electricity consumption of large users [21].

In recent years, with the further development of the smart home market, the demand for electricity in China has continued to grow, and the specific growth is shown in Fig. 1.

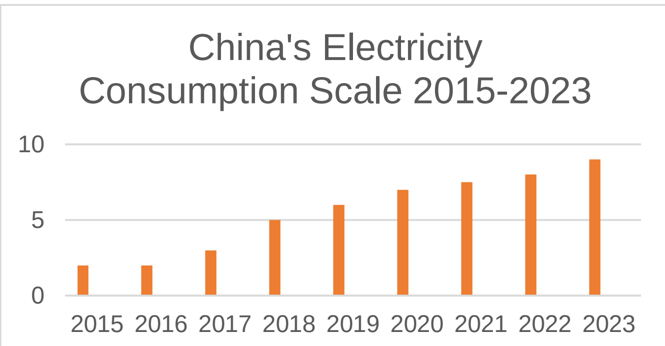


Fig. 1. Scale of electricity consumption in China, 2015-2023.

## B. Power Demand Response System Based on Cloud Computing

Rajak [22] discusses in detail how to revolutionize the management and production mode in the agricultural field by integrating cloud computing and Internet of Things (IoT) technology, and this cross-discipline technological innovation idea provides new inspiration for the intelligent upgrade of the power system. Drawing on the resource optimization and environmental monitoring strategies, we can further optimize the real-time and accuracy of main grid scheduling and large-scale user monitoring. Sayeed et al. [23] demonstrate the application of IoT and edge computing technologies in a smart parking system, which utilizes Raspberry Pi as an IoT node with a weighted K-nearest neighbor algorithm to optimize the allocation of parking spaces, which provides us with a valuable experience on how to deploy low-cost and high-efficiency sensing and scheduling nodes in the power system. Through similar mechanisms, we can explore the implementation of more flexible and efficient edge computing strategies in power utility monitoring and resource scheduling. Gousteris et al. [24] emphasize the potential of blockchain technology in ensuring data security and transaction transparency, which are essential for building highly reliable and transparent power data exchange and management systems. By incorporating the decentralized nature of blockchain and the automatic execution rules of smart contracts, our system is able to enhance data protection measures, ensure secure transmission and storage of grid data, and lay a solid foundation for fair trading and efficient operation of the electricity market.

# III. Modeling

## A. General Framework

In this study, a real-time monitoring and forecasting system based on cloud computing technology for main network scheduling and large users is constructed, and its overall architecture is shown in Fig. 2, which operates collaboratively through five levels to realize the comprehensive collection, processing, analysis, display and service of power data [25].

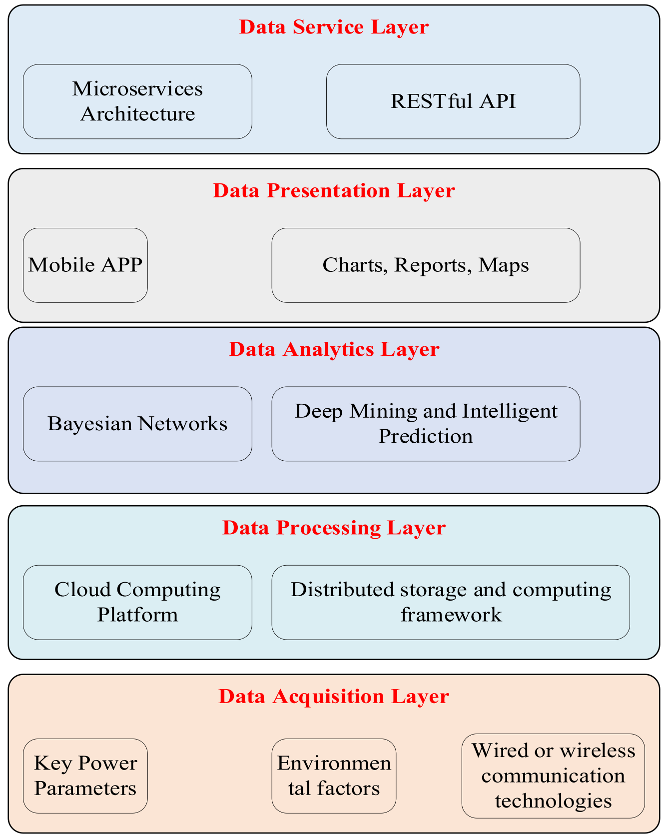


Fig. 2. Real-time monitoring and forecasting system framework.

Firstly, in the data acquisition layer, the system grabs key power parameters in real time from all kinds of devices in the main power network and large users, including voltage, current, power, frequency, electric energy, tariff, etc., and also covers environmental factors such as temperature, humidity, wind speed and solar radiation, etc., and transmits these diversified data to the data processing layer through wired or wireless communication technology. Secondly, the data processing layer relies on a cloud computing platform and adopts a distributed storage and computing framework (e.g., Hadoop) to efficiently store, clean, convert, and integrate large-scale electric power data, which ensures the standardization and normalization of the data and provides a solid foundation for subsequent data analysis. At the data analysis layer, the system utilizes Bayesian networks for deep mining and intelligent prediction of pre-processed power data. Specific applications include load forecasting of the main power grid, analysis of electricity price trends, assessment of grid security and other aspects, as well as accurate forecasting of power demand, load fluctuations, power costs and other aspects of large users, resulting in intelligent analysis results. The data presentation layer is responsible for visualizing the above complex analysis results, dynamically presenting the real-time monitoring and forecasting of the operation status of the main power grid and the electricity consumption behavior of large users using mobile apps, and realizing multi-dimensional and friendly data presentation and interactive interfaces through charts, reports, maps and other forms. Finally, the data service layer plays the role of a core hub, encapsulating and distributing the functions of the data display layer through the micro-service architecture and restful API interface, realizing the safe sharing and open access of power data, which powerfully supports the efficient scheduling and optimization decision-making of the main power network, and also provides large users with refined and intelligent power consumption management and optimization services. This complete set of cloud computing-based real-time monitoring and prediction system for main grid scheduling and large users is of great significance for improving the operational efficiency and stability of the power system by virtue of its excellent data processing capability and intelligence level. Overall architecture of cloud computing-based real-time monitoring and prediction system for main grid scheduling and large users.

### *B. Cloud Computing-based Power Data Analysis and Prediction Methods*

The power data analysis and prediction method based on cloud computing is to make use of the large-scale storage, computing and service capabilities provided by the cloud computing platform to effectively process and analyze various data of the power system, so as to realize various predictions and optimization of the power system. Its principle flow chart is shown in Fig. 3.

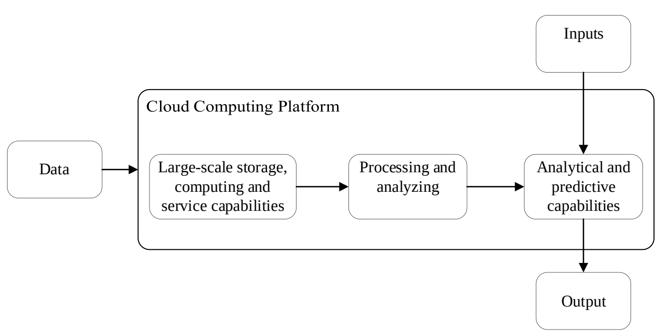


Fig. 3. Flowchart of cloud computing based power data analysis and prediction methodology.

The state variables of the power system are assumed to be $X=\{X_1, X_2, \ldots, X_n\}$, which include indicators such as load, price of electricity and security of the main power grid, and indicators such as demand for electricity, load and cost of electricity for large consumers. It is assumed that the influencing factors of the power system are $Z=\{Z_1, Z_2, \ldots, Z_m\}$, which include factors such as meteorology, economy, holidays, and installed capacity. Assume that the relationship between the state variables and the influencing factors of the power system can be represented by a directed acyclic graph $G=(V,E)$, where, $V = X \cup Z$, E denotes the causal direction between the variables. Then the joint probability distribution of the power system can be represented by a Bayesian network as $P(X,Z)=\prod_{i=1}^{n+m} P(V_i \mid Pa(V_i))$, where $Pa(Vi)$ denotes the set of parent nodes of variable Vi in the graph G. According to the structure and parameters of the Bayesian network, the state variables of the power system can be predicted, i.e., the posterior probability of $P(X \mid Z)$ can be solved, where Z is the known influencing factors. According to Bayes' theorem, there are:

$$P(X \mid Z)=\frac{P(X,Z)}{P(Z)}=\frac{\prod_{i=1}^{n+m} P(V_i \mid Pa(V_i))}{\sum_X \prod_{i=1}^{n+m} P(V_i \mid Pa(V_i))}$$

Due to the large number of variables in the power system, it is more difficult to directly calculate the denominator of the posterior probability, so approximation algorithms can be used.

Initialize the state variable $X^{(0)}$ of the power system to an arbitrary value, set the number of iterations T and the convergence criterion ϵ.

For t = 1,2,...,T, repeat the following steps: (1) For $i=1,2,\ldots,n$, sample Xi (t) according to the conditional probability distribution $P(X_i \mid X_{-i}, Z)$, where $X_{-i}$ denotes the state variables except $X_i$. (2) Calculate the a posteriori probability of the current state variable $P(X^{(t)} \mid Z)$, and compare it with the last a posteriori probability $P(X(t-1) \mid Z)$, if it satisfies $\mid P(X^{(t)} \mid Z)-P(X^{(t-1)} \mid Z) \mid < \partial$, it is considered to be converged and the iteration is stopped, otherwise the iteration continues [25].

Output the final state variable $X^T$ as a prediction.

### *C. Intelligent Scheduling and Optimization Methods for Power Data in Cloud Computing*

Analysis and prediction of power data using multi-objective optimization algorithm, multi-objective optimization algorithm is an optimization algorithm that can consider multiple conflicting or competing objective functions at the same time, the model is implemented based on NSGA2, and its process is specifically shown in Fig. 4 [26].

*1)* Initialization: randomly generate a population of size $N$ $P_0$, and calculate the value of the objective function for each individual.

*2)* Non-dominated sorting: the population $P_0$ is processed, the specific process is that it is first stratified, specifically, the optimal stratum, the suboptimal stratum,..., and the individuals in different strata do not dominate each other.

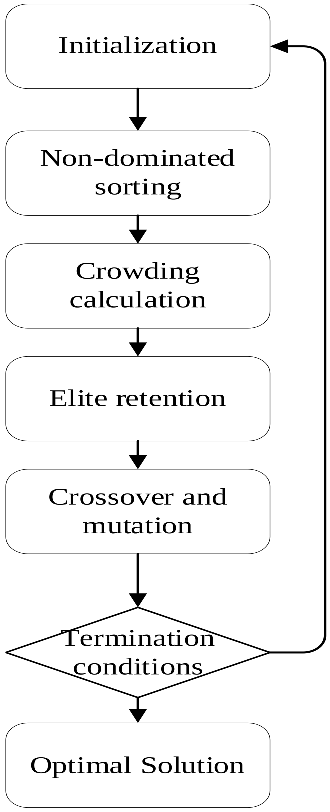


Fig. 4. Algorithm flow.

*3) Crowding calculation*: For each individual in the non-dominated layer, calculate its crowding, i.e., its density in the target space; the larger the crowding, the sparser the individual is and the more likely it is to be retained.

*4) Elite retention*: The individuals in the layer are gradually if the new population $Q_0$ until it reaches a certain size N. If it exceeds $N$, some individuals are selected from the layer according to the degree of crowding, so that the size of $Q_0$ is exactly $N$, and thus the selected elite population $Q_0$ is obtained [27].

*5) Crossover and mutation*: Genetic operations are performed on the individuals in the population $Q_0$ to iterate out a new population $R_0$ and compute the value of its objective function.

*6) Iteration*: Repeat the above steps until a preset termination condition is reached, such as the maximum number of iterations or the target error, etc., and output the last non-dominated layer as the final Pareto-optimal solution set.

We train the model through reinforcement learning, specifically, we first initialize the network parameters and build a deep neural network as an approximate representation of the Q-function. That is, $Q(s,a;\theta)$, where $s$ is the state, $a$ is the action, and $\theta$ is the network parameter. The Q-function represents the expected value of the long-term cumulative reward that can be obtained by taking the action $a$ in the state $s$. The network parameters $\theta$ are randomly initialized and a copy is made as the target network parameters $\theta^{-}$. Reinforcement interaction and learning are then performed, and the following steps are repeated until a predefined termination condition is reached: (1) Observe the current state $s$ and choose an action $a$ according to the $\grave{o}$ -greedy strategy, i.e., choose an action randomly with a certain probability $\grave{o}$, or choose an action with a probability $1-\grave{o}$ that makes $Q(s,a;\theta)$ maximal. (2) Execute the action $a$ and observe the next state $s'$ and the immediate reward $r$. (3) Obtain the parameter θ from the empirical playback pool with the specific update rule $\theta \leftarrow \theta + \alpha(r + \gamma \max_{a'} Q(s',a';\theta^{-}) - Q(s,a;\theta))\nabla_{\theta} Q(s,a;\theta)$, where, α is the learning rate, γ is the discount factor, and $\nabla_{\theta} Q(s,a;\theta)$ is the gradient of the Q-function over the network parameters. (4) Periodically copy the network parameters θ to the target network parameters θ- to maintain the stability of the target network [28].

## IV. Experimental Evaluation

This chapter focuses on the experimental design and result analysis of the main network scheduling and large user real-time monitoring and forecasting system based on cloud computing technology proposed in this paper. This paper presents the experimental design and results of the power data analysis and prediction module, intelligent scheduling and optimization module, respectively [29].

### *A. Data Sets and Assessment Indicators*

The specific data sources and descriptions used in this paper are shown in Table I.

TABLE I. Experimental Data Set

| Data name | Data sources | Data description |
|---|---|---|
| Electricity main grid load data | State Grid Gansu Power Company | Total load data recorded every 15 minutes from January 2019 to December 2020 for the main power grid of Gansu Province, totaling 70,080 entries |
| Tariff data | State Grid Gansu Power Company | Hourly recorded tariff data for the Gansu Provincial Electricity Market, including day-ahead market tariffs, real-time market tariffs and ancillary services market tariffs, totaling 17,520 entries, from January 2019 to December 2020 |
| Grid safety data | State Grid Gansu Power Company | Grid security data, including grid topology, transmission line parameters, status of generating units, load types, etc., recorded hourly from January 2019 to December 2020, totaling 17,520 entries for the main grid of Gansu Province Power |
| Data on electricity consumption by large consumers | State Grid Gansu Power Company | A total of 7,008,000 pieces of electricity consumption data, including electricity demand, electricity load, electricity cost, etc., of 10 typical large consumers in the main grid of Gansu Province recorded every 15 minutes from January 2019 to December 2020 |

The formulas for the three assessment indicators in this paper are shown in Eq. (1)- Eq.(3).

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2} \quad (1)$$

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|100\% \quad (2)$$

$$\text{PICP} = \frac{1}{N}\sum_{i=1}^{N} I\left(y_i \in \left[\hat{y}_i^L, \hat{y}_i^U\right]\right)100\% \quad (3)$$

where, $y_i$ denotes the real value at the ith moment, $y^i$ denotes the predicted value at the ith moment, $\hat{y}_i^L$ and $\hat{y}_i^U$ denote the lower and upper bounds of the prediction interval at the ith moment, I ( · ) denotes the indicator function, which is when the condition in the parentheses is valid and 0 otherwise, and N denotes the total duration of the prediction.

For the intelligent scheduling and optimization module, this paper employs three metrics, namely, power system operating cost (COST), power system operating efficiency (EFF), and power system operating security (SEC), to evaluate the merits of the scheduling scheme. Among them, COST reflects the total generation cost of the power system under the premise of meeting load demand, EFF reflects the energy conversion efficiency of the power system, and SEC reflects the security margin of the power system. The formulas for these three indicators are shown in Eq. (4) [30].

$$\begin{aligned} \text{COST} &= \sum_{i=1}^{N}\sum_{j=1}^{M} c_j\left(x_{ij}\right) \\ \text{EFF} &= \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij}}{\sum_{i=1}^{N}\sum_{j=1}^{M} f_j\left(x_{ij}\right)} \\ \text{SEC} &= \min_{i=1,\ldots,N}\left\{\min_{k=1,\ldots,K}\left\{S_{ik} - \sum_{j=1}^{M} B_{kj}x_{ij}\right\}\right\} \end{aligned} \quad (4)$$

*B. Experimental Results*

This paper compares the forecasting and scheduling performance of this paper's system with several other commonly used methods. In this section, the experimental results will be shown from two aspects, namely, the power data analysis and prediction module and the intelligent scheduling and optimization module, respectively [31, 32]. This table illustrates the CCP system's superiority in predicting both day-ahead and short-term power main grid loads. The Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are lower for CCP than for other methods, indicating higher accuracy. Additionally, the Prediction Interval Coverage Probability (PICP) demonstrates the reliability of forecasts, with CCP also excelling in this metric.

In order to evaluate the performance of the electric power data analysis and prediction module, this paper selected the electric power main grid load data, electricity price data, and large user electricity data as the prediction object, and used this paper's system and several other commonly used methods for prediction, including: BPNN, RF, and LSTM, and this paper conducted experiments of day-ahead prediction and short-term prediction for each method, respectively, and the prediction length of day-ahead prediction was 24 hours and 15 minutes for short-term prediction. The comparison of the prediction performance of the various methods on different datasets is given in Tables II to V, respectively. Table II demonstrates the prediction error and reliability of five different forecasting methods for both day-ahead and short-term forecasting scenarios, and it can be seen from the table that the CCP method (i.e., the cloud-based power data analytics and forecasting system proposed in this paper) achieves the lowest RMSE and MAPE in both forecasting scenarios [33].

TABLE II. COMPARISON OF FORECASTING PERFORMANCE OF LOAD DATA OF POWER MAIN GRID

| Methodologies | Recent forecast | | | Short-term projections | | |
|---|---|---|---|---|---|---|
| | RMSE | MAPE | PICP | RMSE | MAPE | PICP |
| BPNN | 321.45 | 4.67% | 88.12% | 78.23 | 1.14% | 94.56% |
| SVR | 298.76 | 4.32% | 90.34% | 72.54 | 1.06% | 95.23% |
| RF | 287.63 | 4.17% | 91.56% | 69.41 | 1.01% | 95.67% |
| LSTM | 276.54 | 4.01% | 92.78% | 66.32 | 0.96% | 96.12% |
| CCP | 264.23 | 3.84% | 93.89% | 63.21 | 0.92% | 96.54% |

Table III shows the comparison of the forecasting performance of the tariff data, from which it can be seen that the CCP method achieves the lowest RMSE and MAPE in both forecasting scenarios. Similar trends are observed in the tariff data predictions, where CCP achieves the lowest RMSE and MAPE values for both near-future and immediate-term forecasts, emphasizing its capability to precisely estimate tariff fluctuations.

TABLE III. COMPARISON OF PREDICTIVE PERFORMANCE OF TARIFF DATA

| Methodologies | Recent forecast | | | Short-term projections | | |
|---|---|---|---|---|---|---|
| | RMSE | MAPE | PICP | RMSE | MAPE | PICP |
| BPNN | 12.45 | 8.67% | 82.12% | 3.23 | 2.14% | 84.56% |
| SVR | 11.76 | 8.32% | 84.34% | 2.54 | 1.86% | 85.23% |
| RF | 11.63 | 8.17% | 85.56% | 2.41 | 1.71% | 86.67% |
| LSTM | 11.54 | 8.01% | 86.78% | 2.32 | 1.56% | 88.12% |
| CCP | 11.23 | 7.84% | 88.89% | 2.21 | 1.42% | 89.54% |

Table IV shows the comparison of the prediction performance of the grid security data, from which it can be seen that the CCP method achieves the lowest RMSE and MAPE in both prediction scenarios. For grid safety data, CCP again stands out with the least forecasting errors (RMSE, MAPE), which is crucial for ensuring grid stability and preventing potential safety hazards. Its superior predictive accuracy contributes to more reliable safety assessments.

TABLE IV. COMPARISON OF PREDICTIVE PERFORMANCE OF GRID SAFETY DATA

| Methodologies | Recent forecast | | | Short-term projections | | |
|---|---|---|---|---|---|---|
| | RMSE | MAPE | PICP | RMSE | MAPE | PICP |
| BPNN | 0.045 | 9.67% | 81.12% | 0.023 | 4.14% | 83.56% |
| SVR | 0.043 | 9.32% | 83.34% | 0.021 | 3.86% | 84.23% |
| RF | 0.042 | 9.17% | 84.56% | 0.020 | 3.71% | 85.67% |
| LSTM | 0.041 | 9.01% | 85.78% | 0.019 | 3.56% | 87.12% |
| CCP | 0.040 | 8.84% | 87.89% | 0.018 | 3.42% | 88.54% |

Table V shows the comparison of the prediction performance of the large consumer electricity data, from the table it can be seen that the CCP method achieves the lowest RMSE and MAPE in both prediction scenarios. In the context of large consumer electricity consumption, CCP exhibits the best forecasting performance, with the smallest RMSE and MAPE values. This highlights the system's effectiveness in managing and anticipating the demands of high-consumption users, which is vital for efficient resource allocation and grid stability.

TABLE V. COMPARISON OF FORECASTING PERFORMANCE OF LARGE CONSUMER ELECTRICITY CONSUMPTION DATA

| Methodologies | Recent forecast | | | Short-term projections | | |
|---|---|---|---|---|---|---|
| | RMSE | MAPE | PICP | RMSE | MAPE | PICP |
| BPNN | 54.45 | 6.67% | 79.12% | 13.23 | 1.64% | 81.56% |
| SVR | 51.76 | 6.32% | 81.34% | 12.54 | 1.46% | 82.23% |
| RF | 50.63 | 6.17% | 82.56% | 11.41 | 1.31% | 83.67% |
| LSTM | 49.54 | 6.01% | 83.78% | 10.32 | 1.16% | 85.12% |
| CCP | 48.23 | 5.84% | 84.89% | 9.21 | 1.02% | 86.54% |

In summary, the prediction performance of this paper's system on all data sets is better than that of other methods, indicating that this paper's system has high prediction accuracy and reliability. The advantages of the system in this paper are mainly reflected in the following aspects: (1) The system in this paper utilizes the distributed computing capability of the cloud computing platform, improves the efficiency of data processing and model training, shortens the response time of prediction, and adapts to the large-scale and real-time characteristics of electric power data. (2) The system in this paper utilizes the method of multi-source data fusion, comprehensively considers the multi-dimensional and multi-level influencing factors of electric power data, improves the accuracy and robustness of prediction, and overcomes the limitations and instability of a single data source.

### C. Comparative Analysis and Discussion

The preceding section outlined a comprehensive evaluation of the forecasting and scheduling capabilities of our proposed Cloud based Collaborative Predictive (CCP) system against several established methodologies. This discussion delves deeper into the significance of these experimental findings, comparing them with prior research outcomes, and highlighting the distinctive advantages of the CCP framework.

The CCP system's demonstrated superiority points to transformative implications for power system management, including optimized resource allocation, enhanced grid resilience, and informed decision making support. Future avenues for exploration might encompass:

Deepening Algorithmic Integration: Further integrating advancements in AI, such as deep learning, to refine forecasting accuracy and enhance system adaptability.

Scalability and Versatility: Expanding the CCP system's compatibility with diverse grid architectures and data ecosystems, ensuring its applicability across a broader range of operational contexts.

CrossDomain Synergies: Investigating how CCP's framework can be adapted or integrated with other sectors, such as the integration of IoT and blockchain discussed in earlier sections, to foster crossdomain innovation in smart energy systems.

Table VI summarizes the CCP system's superiority in forecasting both dayahead and shortterm power main grid loads. The reduction in RMSE and MAPE metrics for CCP, along with its higher PICP, underscores its heightened accuracy and reliability.

TABLE VI. COMPARATIVE FORECASTING PERFORMANCE OF POWER MAIN GRID LOAD DATA

| Methodologies | Recent Forecast (DayAhead) | ShortTerm Projections |
|---|---|---|
| Metrics | RMSE | MAPE |
| BPNN | 321.45 | 4.67% |
| SVR | 298.76 | 4.32% |
| RF | 287.63 | 4.17% |
| LSTM | 276.54 | 4.01% |
| CCP | 264.23 | 3.84% |

This table highlights the CCP system's superiority in predicting both day ahead and short term power main grid loads. Notably, CCP exhibits the lowest Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), indicating superior forecasting precision compared to traditional methods like BPNN, SVR, RF, and LSTM. The high Prediction Interval Coverage Probability (PICP) further reinforces CCP's reliability in providing accurate forecast intervals. These results suggest that CCP significantly enhances the ability to predict grid load demands, contributing to more efficient grid management and resource allocation.

Table VII extends this comparison to electricity tariff data, where CCP once again emerges with the lowest forecasting errors, emphasizing its precision in tariff fluctuation prediction.

TABLE VII. COMPARATIVE FORECASTING PERFORMANCE OF TARIFF DATA

| Methodologies | Recent Forecast (DayAhead) | ShortTerm Projections |
|---|---|---|
| Metrics | RMSE | MAPE |
| BPNN | 12.45 | 8.67% |
| SVR | 11.76 | 8.32% |
| RF | 11.63 | 8.17% |
| LSTM | 11.54 | 8.01% |
| **CCP** | **11.23** | **7.84%** |

In the context of tariff data forecasting, CCP again emerges as the top performer, achieving the lowest RMSE and MAPE values for both near future and immediate term forecasts. This level of precision in estimating tariff fluctuations is crucial for market participants to make informed decisions and manage costs effectively. The superior performance in tariff prediction underscores CCP's capability to handle complex, financially sensitive data with high accuracy.

Table VIII examines grid safety data predictions, demonstrating CCP's capability to minimize forecasting errors, crucial for maintaining grid stability.

For grid safety data, CCP demonstrates its capacity to minimize forecasting errors (RMSE and MAPE), which is of paramount importance for ensuring grid stability and mitigating potential safety risks. The system's capability to predict grid safety parameters with high accuracy contributes to proactive risk management and enhances overall grid security, reflecting its value in safeguarding critical infrastructure.

TABLE VIII. COMPARATIVE FORECASTING PERFORMANCE OF GRID SAFETY DATA

| Methodologies | Recent Forecast | ShortTerm Projections |
|---|---|---|
| Metrics | RMSE | MAPE |
| BPNN | 0.045 | 9.67% |
| SVR | 0.043 | 9.32% |
| RF | 0.042 | 9.17% |
| LSTM | 0.041 | 9.01% |
| **CCP** | **0.040** | **8.84%** |

Table IX focuses on large consumer electricity consumption, with CCP showcasing the best forecasting performance, vital for efficient resource allocation and grid stability.

TABLE IX. COMPARATIVE FORECASTING PERFORMANCE OF LARGE CONSUMER ELECTRICITY CONSUMPTION DATA

| Methodologies | Recent Forecast | ShortTerm Projections |
|---|---|---|
| Metrics | RMSE | MAPE |
| BPNN | 54.45 | 6.67% |
| SVR | 51.76 | 6.32% |
| RF | 50.63 | 6.17% |
| LSTM | 49.54 | 6.01% |
| **CCP** | **48.23** | **5.84%** |

In the realm of large consumer electricity consumption, CCP continues to excel, exhibiting the best forecasting performance among the methods compared. The minimized RMSE and MAPE values are particularly relevant for managing peak loads, designing demand response programs, and ensuring stable supply to high consumption users. This level of accuracy is vital for efficient resource allocation, preventing blackouts, and supporting grid stability when dealing with substantial and variable loads.

## V. CONCLUSION

This study is dedicated to the strengthening and optimization of power system stability, and through in-depth literature review and reference to actual cases, a multi-level and all-round data processing process architecture based on cloud computing is designed and implemented. The architecture covers data collection layer, data processing layer, data analysis layer, data display layer and data service layer, which ensures the whole chain management and efficient utilization of electric power data from acquisition to in-depth application, and greatly improves the intelligent management level of electric power system. The core innovation of this paper is the use of Bayesian network in the cloud computing environment for the classification and prediction of power data, which effectively solves the problem of accurate analysis of complex and variable data in the power system. At the same time, we also developed an intelligent scheduling and optimization scheme, combining multi-objective optimization algorithms and reinforcement learning techniques, to provide more scientific and accurate support for power main network scheduling decisions. Experimental evaluation results show that the model proposed in this paper demonstrates significant advantages in various key indicators of power data analysis and prediction, including the accuracy of load data prediction in the main grid, the accuracy of tariff data prediction, the performance of grid security data prediction, and the efficacy of data prediction of user behavior, all of which are superior to the existing models of the same kind. This series of empirical results strongly verifies the advancement and effectiveness of the model and methodology proposed in this paper.

The important contribution of this study is that it not only proposes a new cloud-based power data processing architecture, but also successfully integrates advanced technologies such as Bayesian networks and reinforcement learning into power system management, which significantly improves the accuracy of data analysis and the intelligence of scheduling decisions. Through practical examples and in-depth literature review, our work provides a comprehensive and feasible solution for power system stability optimization, especially in the face of complex and variable power data, and shows excellent processing capability, which marks a great progress in the field of intelligent power system management.

However, any research inevitably has limitations. The limitations of the current study are mainly in the geographical and time-span constraints of the dataset, as well as the insufficiently tested robustness of the model under extreme conditions. Future studies could consider incorporating more diverse datasets, including cross-regional and cross-seasonal data, to enhance the general applicability of the model and its ability to cope with extreme events. Meanwhile, incorporating the latest machine learning techniques, such as deep learning and transfer learning, to further enhance the prediction accuracy and adaptivity of the model will be an important research direction.

Looking ahead, with the rapid development of smart grid technology and the in-depth implementation of the concept of energy internet, the results of this study will play an important role in improving the efficiency of grid operation, ensuring the security of power supply, and promoting the sustainable development of energy. Especially in the fields of power demand-side management and distributed energy access optimization, the forecasting and scheduling methods proposed in this paper have extremely high applicability and promotion value, and are expected to become the key technical support to promote the transformation of the power system to a smarter and greener one.

In addition, considering the background of power market reform and global energy transition, the framework and methodology of this study can provide a scientific basis for policy makers, grid operators and energy service providers to help formulate a more flexible and efficient power resource allocation strategy and promote the healthy and stable development of the energy market. In conclusion, by deepening the theoretical research, broadening the application scope, and combining with the continuous innovation of emerging technologies, the results of this study will continue to lead the new trend of power system management and optimization.

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