J. Electrical Systems 20-10s (2024): 690-707

[1]Jinyu Li

Cloud computing-Based Grid-Connected Scheduling Technology for New Energy Distributed Power Generation

Journal of Electrical Systems

Abstract: - With the continuous development of new energy distributed power generation, the optimization of grid-connected scheduling technology becomes particularly important. This paper introduces the basic architecture of cloud computing platform and its application in new energy grid-connected scheduling. It discusses the design of distributed storage for data collection and transmission and microgrid big data. By virtue of the virtual power plant objective function and its constraints, such as power balance, generating unit operation, and wind and light abandonment and storage operation, an efficient new energy distributed generation grid-connected scheduling technique is realized. The results show that through this technique, the operating frequency of the microgrid is strictly controlled within a safe range, in which the maximum value of the frequency is less than 50.5 Hz and the minimum value is higher than 49.8 Hz, which ensures the stability of the power grid. In the economic analysis, at the 13:00 moment of the peak power demand, the output of unit 1 and unit 2 reached 397.5kW and 312.7kW respectively by the method of this study. cloud computing not only improves the efficiency of energy utilization, but also significantly improves the economic efficiency of the grid, and provides a new direction for the grid-connected scheduling of new energy distributed generation.

Keywords: cloud computing; distributed generation; grid-connected scheduling; virtual power plant objective function; distributed storage

1. Introduction

With the increasing severity of global climate change and the rising awareness of environmental protection, new energy distributed power generation has become an important development direction in today's energy field [1]. The extensive use of renewable energy sources, such as wind and solar, not only helps to reduce greenhouse gas emissions, but also promotes the optimization and transformation of energy structure [2-3]. However, the high intermittency and uncertainty of new energy sources bring new technical challenges to the grid-connected scheduling of power systems. The traditional power scheduling methods often appear to be incompetent in the face of the volatility and unpredictability of new energy generation, and innovative technical means are urgently needed to cope with it [4]. In this context, cloud computing technology provides a new solution for the grid-connected scheduling of new energy distributed generation with its powerful data processing capability, high flexibility and scalability. The cloud computing platform can collect, store and analyze a large amount of power data in real time, which provides strong support for the stable operation of the power system [5]. Through

[1] [1] *The School of Engineering, The University of Manchester, Manchester, M13 9PL, UK. Email: jinyurain@126.com

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cloud computing, accurate prediction of new energy generation can be realized, and the grid-connected scheduling strategy can be optimized, thus improving the stability and economy of the power system [6].

The current power generation grid-connected scheduling technology is in a stage of rapid development, how to improve the stability, reliability and economy of the power system has become the focus of research. Existing grid-connected scheduling technologies have achieved certain results, and many researchers have proposed innovative solutions. For example, Jing, Y et al. propose an optimal scheduling strategy based on hybrid energy storage system and demand-side response to further promote the grid integration of distributed generation. The model achieves economic and efficient operation of the microgrid by integrating hybrid energy storage system and demand-side response to ensure the stability and security of the power system, while maximizing the benefits of utilizing new energy sources by using the implementation of demand-side response [7]. Liu, Y proposed a low-carbon economic dispatch strategy based on meteorological classification, where meteorological conditions are first classified to get the predicted value of the output of wind power. Each microgrid contains different renewable energy generation units, and the optimized operation of low-carbon economic dispatch is accomplished through a reasonable dispatch strategy for wind and solar power [8]. Shen, H studied a two-stage robust economic dispatch model for enhancing the energy distribution of microgrids. The model first considers wind, solar and power load uncertainty, uses neural network model to predict carbon emissions, integrates the prediction results into the economic dispatch model, and realizes economic dispatch also completes the control of carbon emissions [9]. Xu, H et al. mainly explored optimal scheduling strategies for electric-heat-gas coupled microgrids, and researched a coupled microgrid containing three systems: electric power, thermal power and gas. Utilizing and distributing different forms of energy, a mixed-integer linear programming model containing multiple constraints and optimization objectives was developed to improve the energy utilization efficiency and satisfy the consumers' demand [10].

The application of cloud computing technology in new energy distributed power generation grid-connected scheduling is also getting more and more attention, Wei, H et al. proposed a cloud computing Anycast service combing algorithm based on wireless communication network. The algorithm prioritizes single-path transmission to reduce the number of new optical paths and working components, and is able to minimize transmission energy consumption when encountering traffic congestion. In addition, the algorithm introduces a spectrum reservation-based traffic grooming strategy to reduce the protection bandwidth and the cost of optical transceivers. Simulation results show that it is able to significantly reduce network energy consumption, avoid excessive increase in traffic congestion rate and achieve network load balancing compared to traditional energy efficient routing algorithms [11]. Gaikwad, A. D et al. conducted a comparative study on load balancing algorithms with respect to energy and tasks in cloud computing. Preservation was done by constructing new structures and measuring the effects in cloud data centers for potential use. Several different load balancing algorithms were also compared and the performance of these algorithms in terms of energy consumption and task completion time was evaluated with experimental data [12]. Su, W. and Shi, Y.j proposed a distributed energy sharing algorithm to optimize energy allocation and management within a microgrid by using cloud computing technology. The resource dynamic management data is used to interact with the cloud computing platform API to obtain the latest resource status information. Based on the execution of workflow and resource demand, cloud computing resources are dynamically requested or released to maximize the utilization of resources and complete the effective scheduling between different energy sources within the microgrid [13]. Alarifi,A et al. proposed a hybrid framework for cloud computing energy efficiency.The hybrid framework for cloud computing energy efficiency combines the request scheduling and server consolidation methods based on the time and power of the customer request demands are ordered and then scheduled. This ordered scheduling mechanism can make the management of cloud computing resources more efficient and helps to reduce energy wastage [14].

The above literature for distributed generation grid scheduling technology and cloud computing have been studied in depth, providing a strong reference for the power system. This paper first introduces the basic architecture of the cloud computing platform, and clarifies the complex business requirements of new energy distributed power generation and grid scheduling. Then, the platform data collection and transmission design and microgrid big data distributed storage design are designed. Taking the maximum net return of VPP as the objective function and taking into account the necessary constraints such as output plan constraints, unit operation constraints, unit start/stop constraints, and energy storage operation constraints, a system optimization operation model is established. The optimal economic dispatch robust optimization model is established by formulating game strategies and payments. Through the research in this paper, it is expected to provide a new and efficient solution for the grid-connected scheduling of new energy distributed power generation, in order to promote the development of sustainable energy, and to contribute to the stable operation of the power system and the improvement of economic benefits.

2. Basic Architecture of Cloud Computing Platform

The basic architecture of the cloud computing platform demonstrates a high degree of modularity and hierarchy, a design that enables it to flexibly respond to the complex business requirements of grid-connected scheduling of new energy distributed power generation. The platform is subdivided from top to bottom into a Web front-end and back-end interaction layer, a business application layer, a data analysis layer, a data computation layer, a data storage layer, and a data collection layer, each of which carries specific functions that together constitute this powerful cloud computing processing system. The basic architecture of the cloud computing platform is shown in Figure 1. The platform design is divided from top to bottom into Web front-end and back-end interaction layer, business application layer, data analysis layer, data calculation layer, data storage layer and data collection layer.

The data collection layer consists of Sqoop relational database collection cluster, Netty high-performance NIO communication framework, open source Flume log collection tool, in which Sqoop is used to import the existing existing microgrid database, Netty high-performance NIO communication framework is used for real-time data collection between the constructed multi-microgrids and the platform, Flume can be customized in the data transmission process of various types of Data sending and receiving. The data storage layer consists of HBase, HDFS, and MySQL, in which the HBase cluster stores the massive historical operation data of the microgrid, and the HBase data search speed can be improved by the secondary indexing scheme. In addition to storing structured microgrid data in HDFS, unstructured data can also be stored, and the MySQL database is used for multiple microgeographic information, equipment hardware status, real-time monitoring data and other information. The data computation layer relies on mainstream big data processing frameworks, such as Hadoop and Spark, to perform fast data analysis and computation, so as to satisfy the high requirements of grid-connected scheduling for real-time and accuracy [15]. The data analysis layer analyzes and calculates according to the needs of the business application layer, and the user can be based on specific business applications. Firstly, it is necessary to perform ETL data cleaning operation on power balance data, generator set operation data, wind and light abandonment and energy storage operation data of microgrid operation, and secondly, perform modeling to parallelize the prediction algorithm, and then submit this task to perform the offline calculation operation of the data calculation layer.

Web front-end and back-end interaction layer to achieve the platform's visualization and business logic functions, Web front-end SVG for visualizing the electrical components of the microgrid, and combined with front-end and back-end communication Ajax technology to achieve real-time operation and monitoring of the microgrid, through the enhancement of the diversity of the front-end interaction, combined with the open source visualization libraries for the display of the data relationship based on the timeline and the display of the multi-latitude data. the Web backend integration of the Spring, Spring MVC, MyBatis to build the Web back-end server, BoneCP database connection pool can complete the data collection layer in the Netty server to complete concurrent persistence operations, Spring and MyBatis can complete the Web back-end to read the database and persistence operations, Spring MVC to achieve the platform front-end page request and Spring MVC realizes the platform front-end page request and jump operation. This innovative design not only improves data availability and real-time, but also provides more comprehensive and accurate data support for grid-connected scheduling.

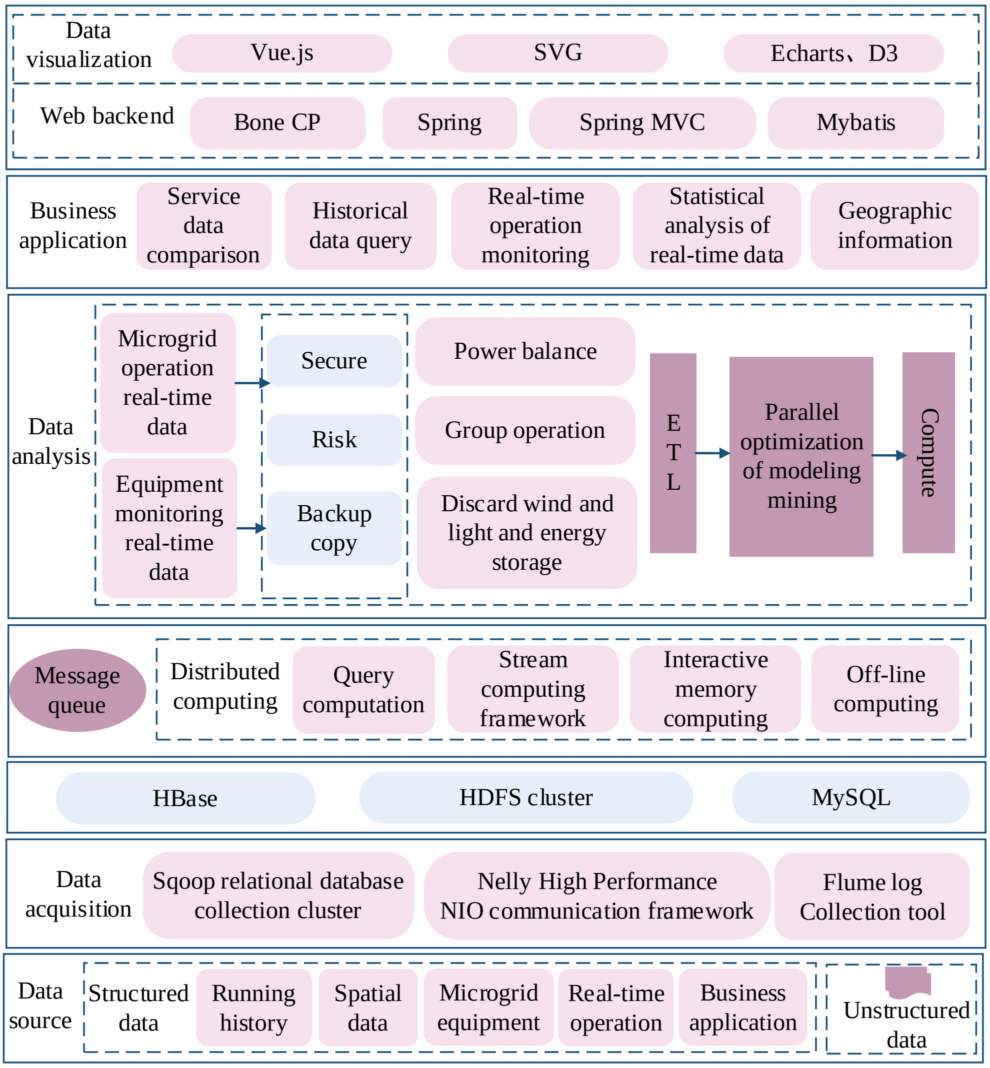

Figure 1 Overall design of cloud computing data platform

3. Data management and analysis

3.1 Platform data acquisition and transmission design

Microgrid real-time data collection is the key to the realization of remote real-time monitoring function, but also an important data source of the platform. In order to solve the phenomenon of microgrid information island, the real-time data collection of the platform draws on the idea of Flume distributed log collection tool. The host of the microgrid monitoring center needs to store the data collected by the online monitoring system in a directory at regular intervals, and it is saved in the log format overlay. When the client monitors the setting of the specified directory file changes, that is, there is new data to the log file, the new data will be read and sent to the server.Netty's network communication design is divided into server-side and client-side, the two in the existing network communication connectivity technology on the basis of secondary development. Figure 2 shows the implementation box of Netty client, firstly, register the monitored file directory as well as modify and save events on the platform. When a modification or save registration event occurs, i.e., when the microgrid host is monitored to override writing to a file in a specified directory, the monitoring thread changes the signal volume to notify the data sending thread to read the latest updated microgrid data using a byte stream first. Then it sends the data through the client's server based on the encoding of the electrical device model class using Protobuf encoding. When the server successfully receives the data, the client can proceed to read the information returned by the server [16].

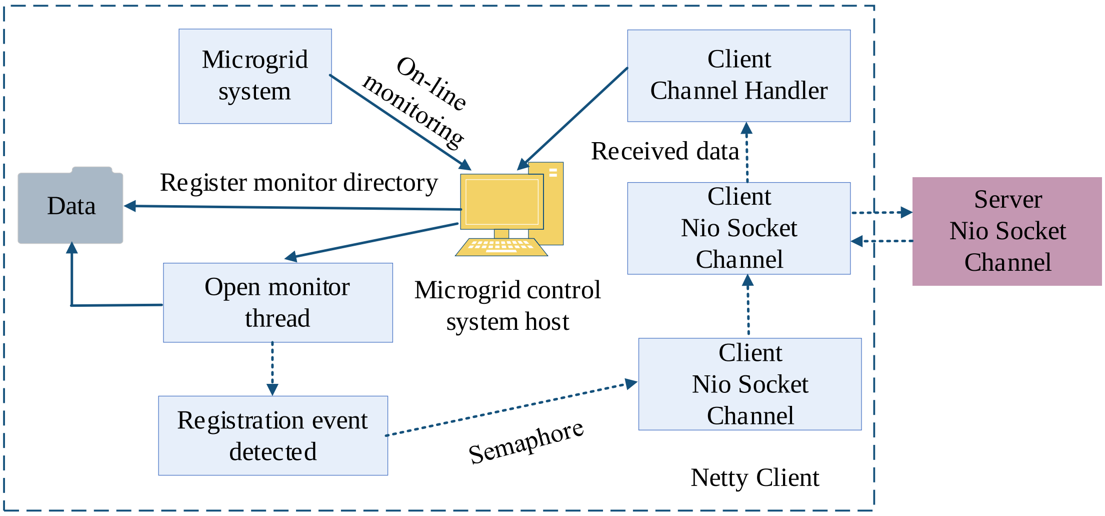

Figure 2 Netty client

3.2 Distributed storage design for microgrid big data

For the microgrid big data distributed computing and analysis platform, to meet the demand for massive microgrid data storage and management, the distributed storage system of the platform is inevitably required to have good scalability, high reliability, and easy management [17]. The current mainstream open source big data distributed storage system is represented by HDFS, and the distributed database HBase realized on the basis of HDFS technology has many advantages such as high reliability and powerful performance. Therefore, the platform takes HDFS as the basic technology and adopts HBase as the distributed database for microgrid big data storage [18]. Figure 3 shows the HBase secondary index structure, in setting the number of column families in each table between 1-3.HBase is applied by most distributed systems because it has many advantages such as high scalability, high concurrency, stability and high data security. However, because the data query performance of non-relational databases is not friendly compared to relational databases, when users need to query the data, they can only get it by prefix fuzzy through the row key, and then further filter the data through the filter. In the design of the row key, in order to avoid the HBas read and write requests concentrated in a very small number of regions, resulting in the hot spot phenomenon of regional servers to handle the sudden increase in the amount of requests, you can consider the use of hashed row keys to make the data stored in the HBase balanced. By setting the secondary index of HBase database to establish the mapping relationship between each column value and the row key, it can be queried according to the query conditions and improve the query performance [19].

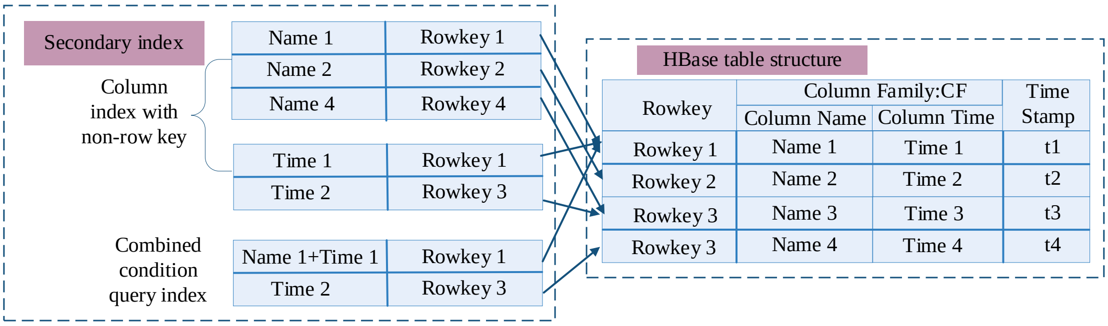

Figure 3 HBase secondary index structure

4. Cloud-based grid-connected scheduling

4.1 VPP objective function

The objective function of the optimal economic dispatch model of the virtual power plant, VPP for short, is to maximize the comprehensive operating revenue of the system during the dispatch time. This revenue mainly comes from the tariff revenue and renewable energy generation subsidies obtained from the VPP supplying electricity to the power system, and subtracts the VPP operating costs including the operating costs of the generating units, the environmental discounting costs, the starting and stopping costs of the generating units, and the operation and maintenance costs of the wind and photovoltaic units [20]. The objective function is:

$$\max f = E_{GRID} + E_{DG} - C_G - C_{OM} - C_{EN} - C_{DP} \tag{1}$$

Where: f is the objective function, E_{GRID} is the revenue gained by the VPP from exchanging power with the power system, E_{DG} is the renewable power generation subsidy received by the VPP, C_G is the operating cost of the thermal unit, C_{OM} is the cost of operating and maintaining the equipment, C_{EN} is the cost of environmental protection depreciation, and C_{DP} is the cost of depreciation of the equipment.The revenue gained by the VPP from exchanging power with the power system:

$$E_{GRID} = \sum_{t=1}^{T} P_{GRID}(t)\, p(t) \tag{2}$$

VPP receives subsidies for renewable energy generation:

$$E_{DG} = F_{WT}\left[P_{WT}(t) - P_{AB,WT}(t)\right] + F_{PV}\left[P_{PV}(t) - P_{AB,PV}(t)\right] \tag{3}$$

Thermal power unit operating costs:

$$C_G = \sum_{t=1}^{T} \sum_{i=1}^{N_g} \left\{ (u_i) tf \left[P_i^g(t) \right] + S_i(t) u_i(t) \left[1 - u_i(t-1) \right] \right\} \tag{4}$$

Where: $P_{GRID}(t)$ is the power exchanged between VPP and the power system in time period t, which is greater than zero when VPP generates electricity to the power system, and $p(t)$ is the system time-sharing price in time period t. $P_{WT}(t)$ is the wind power output in time period t, $P_{PV}(t)$ is the PV output in time period t, $P_{AB,WT}(t)$ and $P_{AB,PV}(t)$ are the abandoned wind power and abandoned light power in time period t, F_{PV} and F_{WT} are the subsidized price of PV and the government subsidy price for wind power and T is the number of scheduling hours of the virtual power plant. N_g is the number of generating units, $u_i(t)$ is the generation status of the i th generating unit in the t th hour, $u_i(t)=1$ is the generation status, $u_i(t)=0$ is the shutdown status, $P_i^g(t)$ is the generation output of the i nd generating unit in the t rd hour. $S_i(t)u_i(t)\left[1-u_i(t-1)\right]$ represents the startup and shutdown cost of the i th genset in the t th time period [21]. The fuel cost equation is as follows:

$$f\left[P_i^g(t)\right] = a_i P_i^g(t)^2 + b_i P_i^g(t) + c_i \tag{5}$$

where a_i, b_i, c_i is the fuel cost factor obtained for the i nd generating unit:

$$S_i(t) = \begin{cases} C_{HSi}, T_i^{off} \le X_i^{off} \le T_i^{off} + T_{CSi} \\ C_{CSi}, X_i^{off} > T_i^{off} + T_{CSi} \end{cases} \tag{6}$$

T_{CSi} is the start-up time of the i nd generating unit, C_{HSi}, C_{CSi} is the hot start-up cost and cold start-up cost of the i th generating unit, respectively, T_i^{off} is the minimum allowable shutdown time of the i th generating unit, and X_i^{off} is the number of continuous operation periods of the i th generating unit to obtain the equipment operation and maintenance cost and for environmental protection discounted cost [22]. The calculation expression is as follows:

$$C_{OM} = \sum_{t=1}^{T} \sum_{i \in M} k_{om,i} \left(\left| P_i(t) \right| \right) \tag{7}$$

$$C_{EN}=\sum_{t=1}^{T}\sum_{i=1}^{N_g}\sum_{\theta=1}^{N}\lambda_{G,i}^{\theta}c^{\theta}P_i^g\left(t\right) \quad (8)$$

M is the set of VPP equipment, $k_{om,i}$ is the O&M cost coefficient for the i rd unit, $P_i\left(t\right)$ is the power of the i th unit in the t time period, θ is the pollutant category, and N is the number of pollutant types. $\lambda_{G,i}^{\theta}$ is the emission factor of the i th generating unit for the θ th pollutant category, c^{θ} is the environmental discounted cost factor for the θ th category, and the equipment depreciation cost equation is as follows:

$$C_{DP}=\sum_{i\in M}^{M}\sum_{t=1}^{T}\frac{C_{az,i}}{k_i}\cdot\frac{r\left(1+r\right)^{n_i}}{\left(1+r\right)^{n_i}-1}\left|P_i\left(t\right)\right| \quad (9)$$

where $C_{az,i}$ is the installed cost factor for the i nd unit, k_i is the capacity factor for the i th unit, r is the annual interest rate on social capital, and n_i is the expected economic life of the i th unit.

4.2 Constraints

4.2.1 Power balance constraints

$$\sum_{i=1}^{N_g}P_i^g\left(t\right)+P_{WT}-P_{AB,_{WT}}\left(t\right)+P_{PV}\left(t\right)-P_{AB,PV}\left(t\right)+P_{ESS}\left(t\right)-P_{loss}\left(t\right)=P_{VPP}\left(t\right) \quad (10)$$

$$P_{loss}\left(t\right)=\sum_{k=1}^{K}\frac{P_k^2\left(t\right)+Q_k^2\left(t\right)}{U_k^2\left(t\right)}R_k \quad (11)$$

Where: $P_{ESS}\left(t\right)$ is the storage charging and discharging power in time period t, which is greater than zero for discharging. $P_{loss}\left(t\right)$ is the network loss power in time period t, $P_{loss}\left(t\right)$ is the output power allocated to VPP by the power system energy management center in time period t. $P_k\left(t\right),Q_k\left(t\right)$ are the active and reactive power of the feeder k in time period t, respectively, and K is the number of feeders. R_k is the feeder k resistance, and $U_k\left(t\right)$ is the t time period feeder k voltage magnitude.

4.2.2 Generating unit operating constraints

The constraints include unit start/stop constraints, unit creep rate constraints, and unit output constraints:

$$\begin{cases}\left[X_i^{on}(t-1)-T_i^{on}\right]\left[u_i(t)-u_i(t-1)\right]\geq 0\\ \left[X_i^{off}(t-1)-T_i^{off}\right]\left[u_i(t)-u_i(t-1)\right]\geq 0\\ DR_i\times\Delta T\leq P_{i(j+1)}^g-P_{ij}^g\leq UR_i\times\Delta T\\ P_{i,\min}^g\leq u_i^t P_i^g(t)\leq P_{i,\max}^g\end{cases} \tag{12}$$

Where: $X_i^{on}(t-1), X_i^{off}(t-1)$ is the continuous startup and shutdown time of the i nd unit up to $t-1$ the time period, UR_i, DR_i is the output ramp-up and ramp-down rates of the i th unit, and $P_{i,\min}^g, P_{i,\max}^g$ is the minimum operating output and maximum allowable output of the i th unit, respectively.

4.2.3 Wind and Light Abandonment and Energy Storage Operation Constraints

After calculating the generating unit operation constraints, the wind and energy storage operations are then constrained as follows:

$$\begin{cases}0\leq P_{AB,WT}(t)\leq P_{WT}(t)\\ 0\leq P_{AB,PV}(t)\leq P_{PV}(t)\end{cases} \tag{13}$$

$$\begin{cases}-P_{ESS}^{\max}\leq P_{ESS}(t)\leq P_{ESS}^{\max}\\ E_{ESS,t}=E_{ESS}(t-1)+\mu_{ch}P_{ESS}(t)\eta_{ch}\Delta t-\mu_{dis}\dfrac{P_{ESS}(t)}{\eta_{dis}}\Delta t\\ r_{ESS,\min}Q_{ESS}\leq E_{ESS}(t)\leq r_{ESS,\max}Q_{ESS}\end{cases} \tag{14}$$

Where: μ_{ch} and μ_{dis} are the energy storage state coefficients, μ_{ch} is 1 and μ_{dis} is 0 for charging, and μ_{ch} is 0 and μ_{dis} is 1 for discharging. $P_{ESS}^{\max}$ is the maximum charging and discharging power, Q_{ESS} is the energy storage capacity, η_{ch}、η_{dis} is the energy storage charging and discharging efficiencies, respectively, and $r_{ESS,\min}$、$r_{ESS,\max}$ is the energy storage minimum discharging depth and maximum charging depth, respectively [23].

4.3 VPP Robust Optimized Economic Dispatch

Optimization problems containing uncertainty are explored in depth in a cloud computing environment using powerful computational capabilities and data storage. The interval uncertainty description method is adopted to deal with the uncertainty of PV and wind power output. The PV and wind power outputs can be described by the uncertainty in interval form, which is formulated as follows:

$$\begin{cases} \bar{P}_{PV}(t) = \bar{\bar{P}}_{PV}(t) + \hat{P}_{PV}(t) \\ \bar{P}_{WT}(t) = \bar{\bar{P}}_{WT}(t) + \hat{P}_{WT}(t) \\ \hat{P}_{PV}(t) \in \left[\hat{P}_{PV,\min}(t), \hat{P}_{PV,\max}(t) \right] \\ \hat{P}_{WT}(t) \in \left[\hat{P}_{WT,\min}(t), \hat{P}_{WT,\max}(t) \right] \end{cases} \tag{15}$$

Where: $\bar{\bar{P}}_{PV}(t)$ and $\bar{\bar{P}}_{WT}(t)$ are the predicted power of PV and wind power in the t time period, $\hat{P}_{PV}(t)$ and $\hat{P}_{WT}(t)$ are the deviation of actual power and predicted power of PV and wind power in the t time period. $\hat{P}_{PV,\min}(t)$ and $\hat{P}_{PV,\max}(t)$ are the minimum and maximum values of the deviation between the actual power and the predicted power for PV in the t time period, and $\hat{P}_{WT,\min}(t)$ and $\hat{P}_{WT,\max}(t)$ are the minimum and maximum values of the deviation between the actual power and the predicted power for wind power in the t time period, respectively [24]. In the cloud computing environment, the historical data can be deeply mined using big data analytics and machine learning techniques to more accurately predict and define the intervals of these deviations. The energy management center of the VPP is considered as the system decision maker, while the uncertainty of wind and PV output in the VPP is considered as the natural decision maker. The game process between these two can be efficiently simulated through a cloud computing platform in order to find the optimal operation scenario of the VPP under the most unfavorable conditions. Considering the game between the system decision maker and the natural decision maker, the optimal economic dispatch model of VPP based on robust optimization is constructed:

$$\begin{cases} \min\limits_{u_1}(u_1, u_2), \max\limits_{u_2}(u_1, u_2) \\ s.t. \quad h(u_1, u_2) \le 0 \\ u_1 \in U_1 \\ u_2 \in U_2 \end{cases} \tag{16}$$

With the output of Eq. (16), a strategy is needed to minimize this cost for the system decision maker, and a strategy is needed to maximize this cost for the natural decision maker. u_1 is the control variables for the system decision maker, including the unit start/stop schedule, unit output schedule, storage charging/discharging schedule and power system exchange power schedule, and U_2 is the control variables for the natural decision maker, including the wind power output and PV output that satisfy the interval uncertainty. The cloud computing environment provides a powerful computational capability that makes it possible to solve this complex optimization problem quickly. The existence of a saddle point solution or Nash equilibrium (u_1^*, u_2^*) for this robust optimization model implies that at this equilibrium point neither the system decision maker nor the natural decision maker can further optimize their objective functions by changing their strategies, i.e., for $\forall\left(u_1,u_2\right)$, then $\min_{u_1} f\left(u_1,u_2^*\right) \geq \max_{u_1} f\left(u_1^*,u_2^*\right)$ and $\min_{u_2} f\left(u_1^*,u_2\right) \geq \max_{u_2} f\left(u_1^*,u_2^*\right)$ hold.

Through cloud computing, not only large-scale data can be processed, but also parallel computing technology can be utilized to accelerate the optimization process, thus providing a more accurate and efficient solution for economic scheduling of VPP.

5. Analysis of grid-connected scheduling of power generation based on cloud computing

This experiment adopts the constructed cloud computing platform, which has powerful data processing capability and efficient computing resources, providing a solid foundation for new energy distributed power generation grid-connected scheduling. The experimental dataset includes a variety of new energy generation data, such as wind power, photovoltaic, grid load data, and generator set operation data. The evaluation indexes mainly include the stability of the grid-connected frequency, the start-stop efficiency of the units, the economy of the system, and the utilization rate of renewable energy.

5.1 Unit Output and Energy Storage Scheduling Strategies

The unit output and energy storage charging and discharging plan is shown in Fig. 4. In the 1st-4th time periods, the VPP requires the output level to be in the low valley, and the VPP arranges the G2 power generation, which has relatively low fuel cost, to satisfy the VPP output curve, and at the same time, stores the excess power through the energy storage equipment, so as to be ready for the subsequent discharging process. During periods 5-16, the VPP requires a higher level of output, and the VPP can basically meet the requirements of the VPP output curve mainly through the output of G2 combined with the output of renewable energy generation. During the peak hours of the phase, VPP controls the energy storage devices to be in a discharged state in order to regulate the output curve. When individual renewable energy output and G2 cannot meet the VPP output requirements, VPP has to open additional G1 and arrange for G1 to have more continuous and concentrated generation periods as much as possible, thus reducing the unit portfolio cost. During hours 17-23, when the outside power system reaches peak load, the outgoing power required for VPP is further increased. During this time period, distributed wind and distributed PV output is low, and the VPP operates G2 with an additional G1 and discharges the energy storage to meet the output requirements. G2, which has relatively low fuel cost, is in full power state, while G1 and energy storage effectively regulate the VPP power curve, and there is no wind and light abandonment in the process.VPP makes reasonable arrangements for the combination plan and power plan of the units in the system through the cloud computing platform, and this intelligent scheduling not only ensures stable operation of the power system, but also optimizes the operation cost.

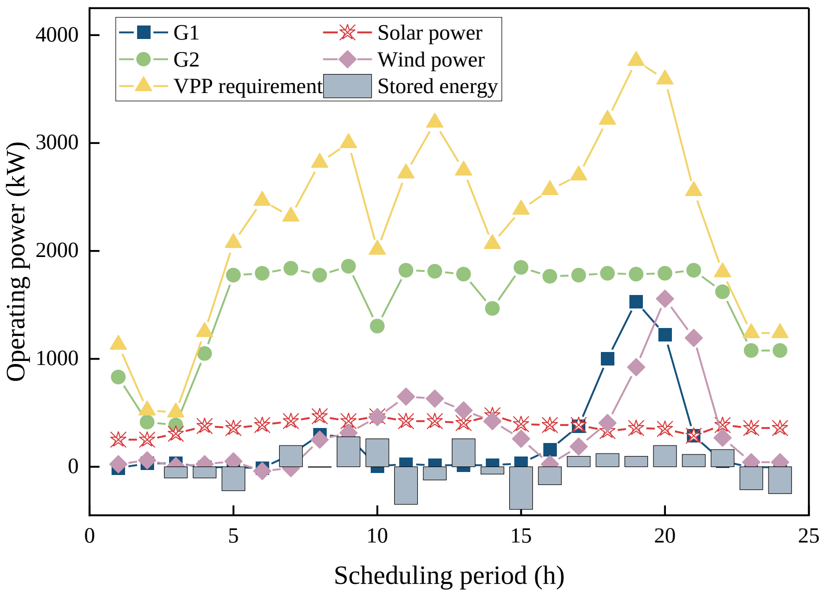

Figure 4 Unit output and energy storage charge and discharge plan

Figure 5 shows the unit start-stop plan, which is empowered by cloud computing, presenting the advanced and practicality of the new energy distributed generation grid-connected scheduling technology. The start-stop status of the two generating units, G1 and G2, can be clearly seen, switching in an orderly manner during different time periods to meet the dynamic demand of the power system. The cooperative work of cloud G1 and G2 is a direct reflection of the precise scheduling of cloud computing technology, showing the trend of intelligent and efficient grid-connected scheduling of new energy generation. Through this advanced scheduling method, limited energy resources can be better utilized.

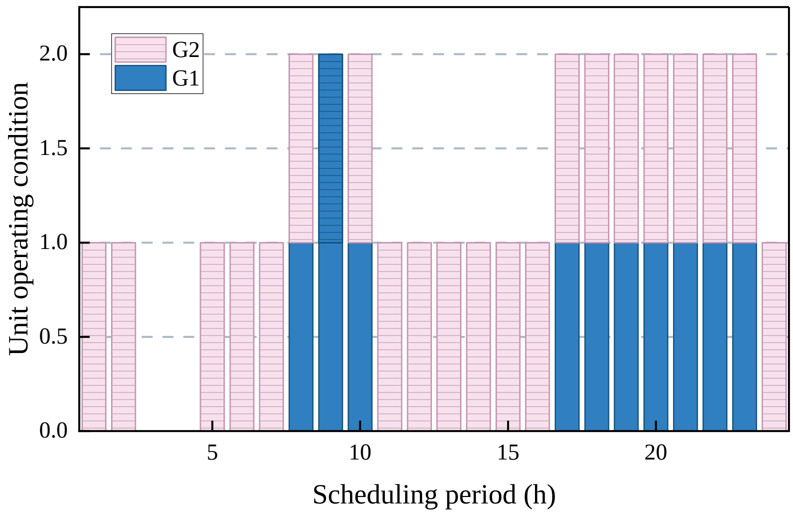

Figure 5 Start-stop plan of the unit

5.2 Evaluation of frequency stability and grid integration effect

The frequency fluctuation of the new energy distributed generation grid is shown in Fig. 6, and the operating frequency of the microgrid is strictly controlled within the safety range, in which the maximum value of the frequency is less than 50.5 Hz, the minimum value is higher than 49.8 Hz, and the frequency change rate is not more than 1.3 Hz/s. This setting not only ensures the economic operation of the microgrid, but also fully takes into account the frequency safety.

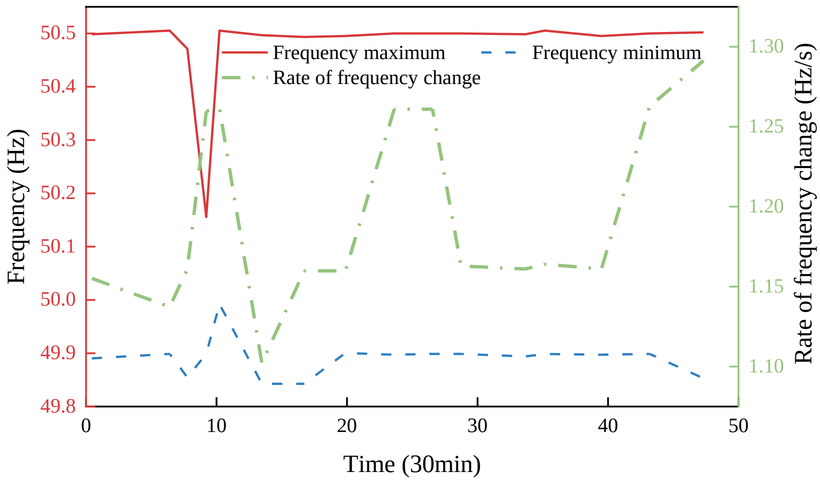

Figure 6 Frequency fluctuation of grid-connected new energy distributed generation

Figure 7 shows the scheduling results of the new energy generation platform, which chooses to perform grid-connection operation at the near-shore end during specific time periods, such as 0:00-14:30, 17:00-19:00, and 21:30-24:00. And during the time periods 15:00-16:30 and 19:30-21:00, it shifts to capture wave energy at the far shore end. This flexible grid-connection and energy capture strategy is made possible by the application of cloud computing in the new energy distributed generation grid-connection scheduling technology. Through cloud computing's data processing capabilities and intelligent scheduling algorithms, the platform is able to accurately predict and plan the optimal timing of grid integration and wave energy capture, ensuring that there is no impact on the microgrid frequency during the transfer process or operation at the far shore end, thus enhancing the operational security of the microgrid. At the same time, the cloud computing technology also optimizes the management of the energy storage battery, with the battery charge reaching 80.74kw at 42 hours, which improves the utilization rate of the battery and further enhances the economic efficiency and environmental performance of the whole system.

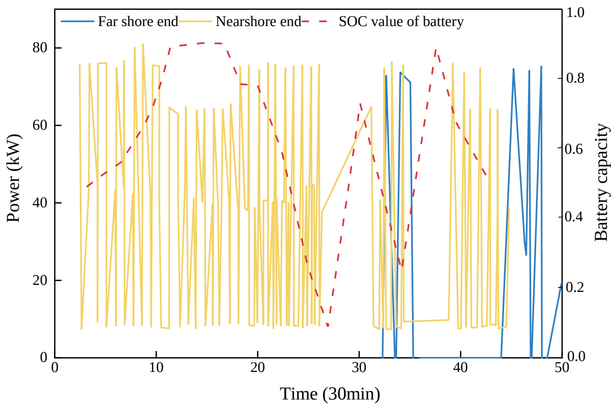

Figure 7 Scheduling results of power generation platform

Figure 8 shows the output waveform of the distributed generation system. During the grid-connected switching at 0.02s, the system voltage waveform is always stable, thanks to the real-time data analysis and precise control provided by cloud computing technology. Before switching, the current waveform has serious aberrations, but after the grid-connected switching, the current waveform is significantly improved, and the seamless switching of voltage and current is exactly the intuitive display of the cloud computing optimized scheduling strategy. In addition, the significant increase in the active power output of the system from -0.12P(Mw) to 0.21P(Mw) after grid-connection and the small fluctuation of reactive power are effectively controlled under the intelligent monitoring and scheduling of cloud computing. It is worth noting that the change of DC bus voltage before and after grid-connected switching is also smoothly transitioned under the accurate prediction and management of cloud computing, keeping at 1160Vdc(V)-1180Vdc(V). Meanwhile, the stabilization of system short-time wind speed and light intensity also maintains the system power output at 0.15wr (pu)-1.22wr (pu) with smoothness.

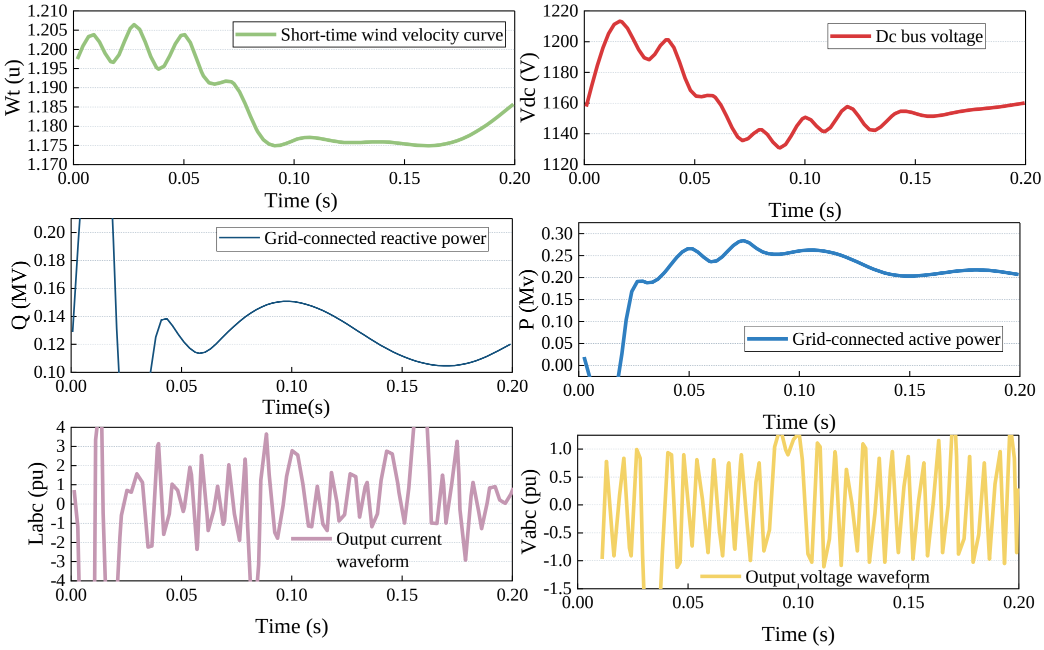

Figure 8 Output of distributed generation system

5.3 Economic analysis and comparison of algorithms

The new energy distributed generation grid-connected scheduling technology proposed in this paper, supported by a cloud computing platform, realizes the efficient optimization of the output of multiple units. By comparing the performance of different algorithms in the economically optimal output situation, it is found that the optimization method designed in this study can effectively improve the efficiency of unit output at all times. Table 1 shows the comparison of the economically optimal output case, where the cloud computing optimization improves the output case compared to the output case based on the improved genetic algorithm and the improved PSO algorithm for each time period from 7:00 am to 7:00 pm. For example, at the 13:00 hour of peak demand, through the fast data processing and parallel computing capability of the cloud computing platform, this research method provides 397.5kW and 312.7kW of output for Unit 1 (1) and Unit 2 (1), respectively, which better meets the power demand at that time compared to the other two algorithms. At the same time, the method of this study can also intelligently adjust the unit output during the hours of lower power demand, such as 7 a.m. and after 7 p.m., avoiding energy waste and improving economic efficiency. The new energy distributed generation grid-connected scheduling technology through cloud computing not only monitors and adjusts the output of each unit in real time, but also carries out prospective scheduling based on historical data and prediction models, thus maximizing the economic benefits and energy utilization efficiency while ensuring the stable operation of the power grid.

Table 1 Comparison of economically optimal output conditions

Time	Based on improved genetic algorithm /kW		Based on improved PSO algorithm /kW		Cloud optimized output /kW	
Set	Unit 1 (1)	Unit 2 (1)	Unit 1 (2)	Unit 2 (2)	Unit 1 (3)	Unit 2 (3)
7:00	162.2	411.7	212.6	344.2	381.8	495.7
9:00	212.5	398.4	254.4	313.9	379.9	481.8
11:00	244.4	365.3	250.2	364.1	375.5	491.2
13:00	397.5	312.7	266.7	380.7	382.6	497.3
15:00	215.2	289.2	247.8	331.0	378.2	486.3
17:00	149.4	256.8	235.2	331.7	385.8	492.9
19:00	105.8	212.4	264.4	316.3	375.4	489.4

6. Conclusion

In this paper, the efficient management and analysis of new energy generation data and the optimization of grid-connected scheduling are achieved by constructing a cloud computing platform, and the following conclusions are obtained:

(1) In terms of unit output and energy storage scheduling strategy, VPP opens additional G1 on the basis of G2 operation and makes energy storage discharge to meet the output requirements, and the cloud computing platform can switch the start and stop status of both G1 and G2 generating units in an orderly manner in different time periods.

(2) Frequency stability and grid-connected effect, the operating frequency of the microgrid is in has been in the frequency stability range, the maximum value of the frequency is lower than 50.5Hz, the minimum value is greater than 49.8Hz, the frequency rate of change is not more than 1.3Hz/s. The battery charge reaches a maximum of 80.74kw, which improves the utilization rate of the battery, and the grid-connected system outputs a significant increase in the active power from the original - 0.12P(Mw) to 0.21P(Mw).

(3) In terms of economic analysis. This research method provides 397.5kW and 312.7kW of output for Unit 1 (1) and Unit 2 (1), respectively, which significantly improves the economic efficiency compared to the improved genetic algorithm with the improved PSO algorithm.

In this study, the robust optimization economic dispatch model is constructed through the cloud computing platform to achieve the optimization of the efficient utilization of new energy generation and grid-connected dispatch, which provides certain data support for promoting the development of green energy.

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About the Author

Jinyu Li was born in Chengdu，Sichuan, China, in 1998. She obtained a BEng degree from The University of Manchester, UK, in 2022. Her main research direction is new energy distribution power generation and grid connection technology.

E-mail: jinyurain@126.com