A Review of Research on Optimal Scheduling of Smart Grids

Yuhan Ji
School of Intelligent Manufacturing, Nanyang Institute of Technology, Nanyang, Henan, China

Abstract: Against the background of energy structure transformation and the advancement of power system intellectualization, optimal scheduling has become a key technical means to ensure the safe, economical, and efficient operation of smart grids. This paper systematically combs the research status in the field of smart grid optimal scheduling, including the key technology system, classification of scheduling models, comparison of evaluation methods, existing challenges, research shortcomings, and future development directions. It is expected to provide references for relevant research and applications and contribute to the continuous development and engineering application of this technology.

Keyword: Smart Grid; Optimal Scheduling; Review

1. Introduction

A global consensus on sustainable development has been formed, and the power system is transforming towards intellectualization and greenization. As a core component, the smart grid greatly improves the operation efficiency, stability, and flexibility of the power system by integrating advanced information and communication technologies (ICT) and power electronic devices. As its core link, optimal scheduling plays a crucial role in coordinating new energy and traditional energy. Traditional scheduling can hardly adapt to the new situation of large-scale integration of new energy and diversified load demands. The optimal scheduling technology of smart grids can realize real-time perception of grid status, efficient processing of massive data, and achieve real-time optimal control of all links. This not only reduces the operation cost of the power grid and improves energy utilization efficiency but also effectively addresses the problems caused by the intermittency and volatility of new energy, enhancing the anti-interference ability of the power system. In conclusion, in-depth research on the optimal scheduling technology of smart grids is of great practical significance for promoting the progress of the power industry and facilitating the achievement of the "dual carbon" goals.

2. Key Technology System Supporting Smart Grid Scheduling

The realization of smart grid optimal scheduling requires the support of multi-level technologies, forming a complete technology chain from physical perception to data processing and then to decision execution.

2.1 Physical Perception Layer Technology

The physical perception layer is the "nerve endings" for the smart grid to obtain its operation status, providing data support for scheduling decisions. The technology at this layer directly determines the smart grid's perception of its own operation status.

2.1.1 Advanced metering infrastructure (AMI, PMU)

The Advanced Metering Infrastructure (AMI) is an integrated system that combines data collection and two-way communication. Wu Tao et al. [1] pointed out that AMI is an essential component in the planning and construction of smart grids, enabling the collection and interaction of user electricity consumption information. Power companies can obtain real-time user electricity consumption data through AMI, provide electricity consumption suggestions based on electricity price signals or scheduling instructions, guide users to adjust their electricity consumption behavior, and promote demand-side response management. The Phasor Measurement Unit (PMU) monitors grid data with microsecond-level accuracy and is a core device for ensuring grid stability. Zhang Lun et al. [2] proposed that equipping power systems with PMU edge computing control devices and combining relevant algorithms can accurately measure and record data, and compress data locally at the edge side, providing data support for real-time scheduling and improving the smart grid's ability to respond to sudden disturbances. In the event of a grid fault, the PMU can upload fault information within milliseconds, helping dispatchers quickly locate the fault location and gain time for fault isolation and grid recovery.

2.1.2 Communication and perception technologies (5G/6G, CPS)

5G/6G technologies, with their characteristics of low latency and high bandwidth, can meet the real-time communication needs of distributed energy sources and edge nodes. Zeng Qi et al. [3] proposed that the "source-grid-load-storage" collaborative control in the new-type power system has strict requirements for information transmission, and 5G/6G communication technologies can effectively meet the requirements of low latency, high reliability, and large connectivity. With the widespread integration of distributed energy into the power grid, 5G/6G can achieve millisecond-level communication time difference between distributed energy sources and the scheduling center, ensuring timely data upload and instruction issuance and enhancing the controllability of the power grid. Moreover, 5G slicing technology can divide mutually isolated communication networks to serve different services, ensuring the quality and security of data transmission. The Cyber-Physical System (CPS) integrates physical devices and information systems to realize dynamic perception and closed-loop control of the power grid. By combining the physical devices of the power grid with the information processing platform, real-time collection of equipment operation parameters is conducted, and the information system analyzes the parameters to control the equipment based on feedback, forming a closed-loop control system and improving the anti-interference ability of the power system.

2.2 Data Processing and Computing Support Layer

The data processing and computing support layer is the "brain" of the smart grid for information processing. The efficient processing and security of massive data are prerequisites for scheduling. The technologies at this layer mainly extract valuable information from redundant data and ensure the security of data during transmission, storage, and use.

2.2.1 Big data and cloud-edge collaborative computing

The massive data generated during grid operation needs to be screened and analyzed through big data technologies. Relevant studies have shown that in-depth analysis of power data through a big data analysis platform can establish a high-precision load forecasting model and improve the accuracy of data forecasting. Cloud-edge collaborative computing combines the large-scale computing power of the cloud with the real-time processing capability of edge nodes, which not only meets the needs of global optimization but also reduces the pressure of data transmission. The edge side quickly analyzes local data and uploads key information to the cloud for further analysis and decision-making, realizing the efficiency and timeliness of data processing.

2.2.2 Federated learning and data security technologies

Federated learning enables multi-agent data sharing on the premise of protecting user privacy and data security through the method of "transmitting models instead of data", which to a certain extent solves the contradiction between data silos and security risks in scheduling. During cross-regional grid scheduling, it is difficult to directly share data among power grids in different regions. However, by using federated learning technology, power grids in various regions can jointly train a unified model for communication without exchanging original data [4]. Data security is a prerequisite for the operation of smart grids. During transmission, encrypted transmission technologies (such as SSL/TLS protocols) can be used to prevent data from being stolen or tampered with; during storage, access control policies can be implemented, allowing only authorized personnel to access sensitive data, and backups can be made simultaneously to prevent data loss; during use, data desensitization technologies (anonymization processing) can be used to remove personal information and protect user privacy.

2.3 Decision Control Layer Technology

The decision control layer is the "execution center" that determines the operation mode of the smart grid and is the core execution link for achieving the goal of optimal scheduling. Based on the results of data processing and analysis, scientific and reasonable scheduling strategies are formulated and implemented to ensure the safe, economical, and efficient operation of the power grid.

2.3.1 Distributed energy management and coordinated control

Distributed energy management and coordinated control are the core of "source-grid-load-storage" collaboration: the former, as the "decision center", formulates scheduling plans for cost reduction, absorption improvement, and carbon reduction through multi-time-scale forecasting and optimization algorithms, combined with the characteristics of Distributed Energy Resources (DER), load demands, and grid constraints; the latter, as the "execution carrier", converts the plans into real-time actions of DER through hierarchical architecture and strategies such as droop control and multi-agent collaboration, suppressing fluctuations, eliminating supply-demand deviations, and collaboratively responding to grid peak shaving and frequency modulation to ensure the safe, efficient, and low-carbon operation of the power grid [5].

2.3.2 Demand-side response and virtual power plant integration

Demand-side response guides users to adjust their electricity consumption behavior (peak-shifting electricity consumption) through price signals or incentive mechanisms. Relevant studies have shown that in cities implementing demand-side response projects, through a series of operations, a large number of users reduce electricity consumption during peak hours, reducing the peak-valley difference of the load and alleviating the pressure of power supply during grid peak periods [6]. A Virtual Power Plant (VPP) aggregates scattered demand-side resources and distributed energy sources to participate in grid scheduling [7]. A virtual power plant project in Zhongshan City integrated distributed energy sources, energy storage facilities, and some interruptible load users in the region. Through advanced information and communication technologies and an intelligent control platform, it realized the unified scheduling and management of these scattered resources, providing backup capacity for the power grid during peak periods and improving the stability of the power system.

3. Research Progress on Classification of Optimal Scheduling Models and Comparison and Shortcomings of Evaluation Technologies

The core of smart grid optimal scheduling lies in realizing efficient resource allocation and stable system operation through scientific model design and evaluation. The research on optimal scheduling models serves as a bridge between key technologies and practical applications.

3.1 Model Classification

The classification of smart grid optimal scheduling models needs to be combined with the time dimension, goal orientation, and architectural characteristics of actual scheduling requirements to form a multi-dimensional classification system, providing a basic framework for subsequent method selection and scenario adaptation.

According to the time scale, scheduling models are divided into long-term, short-term, and real-time scheduling: long-term scheduling takes years/months as the cycle, focusing on strategic aspects such as power source planning; short-term scheduling is based on days; real-time scheduling responds on a minute-level to cope with scenarios such as sudden load fluctuations. According to the optimization goal, they are divided into single-objective and multi-objective optimization: single-objective optimization focuses on a single indicator, with a simple model that is easy to solve (suitable for scenarios with clear goals); multi-objective optimization needs to balance multiple factors, such as the collaborative optimization of "cost-carbon emission-power supply reliability [8]", and requires weight allocation to handle goal conflicts. According to the grid architecture, they are divided into centralized and distributed scheduling: centralized scheduling is uniformly processed by a central controller, suitable for traditional simple power grids but with high communication pressure and poor flexibility; distributed scheduling allows each region/entity to make independent decisions and achieve local coordination, suitable for distribution networks with a large number of distributed energy sources but may have local optimization problems [28].

3.2 Existing Model Evaluation Technologies

The evaluation of smart grid optimal scheduling models relies on a scientific method system. Existing technologies are divided into two categories: mathematical methods and artificial intelligence, each with its own focus.

Mathematical methods are based on rigorous theories and include two types: deterministic methods and methods for addressing uncertainties. Among deterministic methods, linear programming is suitable for scenarios with linear objective functions and constraints (economic dispatch of traditional units), nonlinear programming can handle the nonlinear problems of new energy output (but the solution complexity increases with the increase of variable dimensions), and mixed-integer programming is used for scheduling involving discrete variables (unit start-stop). Among methods for addressing uncertainties, dynamic programming decomposes multi-stage problems (charging and discharging strategies for new energy storage), and stochastic optimization models uncertainties such as wind and solar forecasting errors (using scenario generation technology to quantify impacts on new energy power grids). Artificial intelligence methods, relying on the advantages of data-driven approaches, are of great value in complex scenarios: deep learning (such as LSTM, CNN) explores the mapping relationship between historical data and future states, improving the forecasting accuracy of load and wind-solar output; reinforcement learning enables agents to learn optimal strategies through interaction with the environment (for microgrid power balance, but sample efficiency and convergence need to be improved); multi-agent systems and game theory simulate multi-agent decision-making and achieve interest coordination through Nash equilibrium (for virtual power plant aggregation and demand-side response)[25].

Comparisons show that mathematical methods have high accuracy but low efficiency in handling high-dimensional nonlinear problems, while artificial intelligence methods have strong adaptability but rely on data quality and have insufficient interpretability. The integrated evaluation of the two is an important direction to balance accuracy and efficiency; at the same time, there is no unified standard for existing evaluations, and the comparison of different models needs to be comprehensively judged based on the requirements of specific scenarios [26].

3.3 Typical Scenarios and Method Progress

In large-scale data-driven grid analysis task scheduling, the widespread deployment of AMI and PMU has led to a significant increase in the data volume of data analysis tasks, resulting in low efficiency of traditional scheduling calculations. To address this problem, Document [9] proposed a data volume-aware ICCTS scheme, taking a regional power grid with massive monitoring data as the research object; the scheduling model in this scenario belongs to short-term scheduling (hour-level periodic tasks) and has the characteristics of centralized scheduling (the central controller uniformly coordinates task allocation and transmission paths), with the goal of minimizing task completion time. Its core is to model the grid data analysis task as a DWDAG (Directed Weighted DAG), distinguish between internal data transmission within the same device and external data transmission across devices, and quantify the time difference. The evaluation combines mathematical optimization and simulation comparison: a CTM-ICCTSP mathematical model aiming at "minimizing task completion time" is constructed, which is adapted to the B&C algorithm; the TABC algorithm is proposed and compared with traditional methods such as random scheduling. The results show that the ICCTS scheme shortens the average task completion time by 15%-25% compared with traditional methods; the limitation of this method is that it assumes uniform communication channel bandwidth and does not consider the dynamic congestion of actual grid communication links [27].

In the scenario of collaborative scheduling of Electric Vehicle Charging Stations (EVCS) with distributed energy sources, EVCS serves as a bridge between the power grid and the transportation network, and its optimal operation needs to take into account the uncertainty of distributed energy sources and the dynamic changes of traffic flow. Document [10] takes an IEEE 34-node distribution network with 4 EVCS and a 12-node transportation network as a case to construct a three-level collaborative scheduling framework; the model in this scenario belongs to short-term-real-time hybrid scheduling and is a multi-objective optimization and distributed scheduling. Its core is hierarchical modeling to connect the power grid and transportation: the transportation layer forecasts the arrival volume of electric vehicles (EV), the charging station layer optimizes the local distributed energy scheduling, and the power grid layer balances the power of the entire network. The evaluation adopts scenario analysis and multi-index verification: 150 Monte Carlo scenarios of photovoltaic output are generated (reduced to 5 scenarios by the SCENRED tool), and deterministic models and stochastic models are compared; indicators such as "net profit" and "voltage deviation" are used to compare economy and security. The results show that scenarios considering uncertainty increase the electricity sales volume of EVCS by 28.1%, increase net profit by 32.6%, and reduce the load peak-valley difference by 12%; however, the problem is that it does not consider users' subjective preferences, and the framework has high iterative communication costs, which may lead to delay accumulation[20].

In the scenario of distribution network state estimation under incomplete measurements, the high penetration rate of distributed energy sources leads to incomplete measurement data and severe noise interference, making it difficult for traditional Weighted Least Squares (WLS) methods to meet accuracy requirements. To address this problem, Document [11] proposed a state estimation method based on Bayesian optimized CNN-LSTM, which was verified in IEEE 33-node and 123-node distribution networks; the model in this scenario belongs to real-time scheduling, with the single objective of "improving estimation accuracy when measurements are missing", integrating data-driven models and physical constraints. Its core is to supplement missing data through GAN (Generative Adversarial Network), then use CNN to extract spatial features and LSTM to capture temporal dynamics, and finally adjust hyperparameters through Bayesian optimization. The evaluation focuses on accuracy and efficiency comparison: the "Mean Absolute Error (MAE)" is used as the core indicator to compare the proposed method with WLS and other methods; robustness is verified in scenarios with 1%-3% Gaussian noise. The results show that in the IEEE 33-node test, the voltage amplitude MAE of the proposed method is 0.59×10^{-3} p.u., which is 53.9% lower than that of WLS, and the calculation time is shortened by 10.8%; however, the problem is that the physical consistency of GAN-generated samples depends on the accuracy of power flow verification, which may have deviations in complex distribution networks, and the model training requires a large amount of historical data, making it difficult to promote in areas with weak measurement infrastructure[21].

4. Key Challenges and Research Gaps

Against the background of high-proportion new energy integration and multi-agent participation, the smart grid optimal scheduling technology still faces many challenges. Existing research has significant research gaps in uncertainty management and multi-agent collaboration, and breakthrough technologies are needed to promote the implementation of research results[22].

4.1 Dilemma of Uncertainty Management and Balance between Robustness and Economy

With the integration of high-proportion intermittent energy sources such as wind and solar energy into smart grids, the uncertainty of "source-load-storage" has become a core challenge in scheduling optimization. Existing wind and solar output forecasting models have accuracy bottlenecks when dealing with complex working conditions: relevant studies point out that under extreme weather or complex terrain, the 24-hour forecasting error of mainstream models such as deep learning-based LSTM and physics-driven models reaches more than 20%; taking wind power as an example, when the forecasting error exceeds 15%, the traditional unit commitment model faces insufficient reserve capacity or a sharp increase in wind curtailment rate [12]. It is difficult to balance model conservatism and economy: stochastic optimization can quantify uncertainties through scenario generation, but the calculation time increases by approximately 3-5 times for every 10-fold increase in the number of scenarios; although robust optimization ensures the operational feasibility of the "worst-case scenario", it increases the operating cost by more than 20% due to excessive reserve capacity reservation [13].

Overall, current research lacks an integrated framework for stable and fast solution, making it difficult to determine the impact of uncertainties on scheduling results while achieving a balance between "risk controllability and cost optimization"[24].

4.2 Difficulties in Interest Game and Privacy Protection in Multi-Agent Collaboration

After multi-agents such as distributed energy owners and virtual power plants participate in grid scheduling, the optimization process shifts from "single-objective decision-making" to "multi-party collaboration", resulting in the following challenges: in terms of fairness of benefit distribution, centralized scheduling is difficult to take into account the private objectives of each agent, and non-cooperative games in distributed scheduling lead to the "prisoner's dilemma"; although existing cooperative game models achieve collaboration through Nash equilibrium, when the number of agents exceeds 10, the fairness index of the solution (such as Shapley value calculation error) exceeds 5%, and the calculation efficiency decreases [14]. The contradiction between data privacy and information sharing is prominent: multi-agent collaboration requires data interaction, but direct sharing will leak confidential information; although federated learning can "transmit models without moving data", it still has vulnerabilities in sensitive information protection, and the model convergence speed decreases linearly with the increase in the number of agents [15]. There are numerous barriers to cross-regional scheduling: power grid market mechanisms (electricity prices) vary across different regions.

These problems highlight the complexity of interest coordination and privacy protection in multi-agent collaborative scheduling, which has become a key bottleneck restricting the operation of smart grids.

5. Future Research Directions

The development of smart grid optimal scheduling needs to keep up with technological innovation and policy guidance. Combined with current research progress and practical needs, future research can focus on the following directions[23].

5.1 Technical Aspects

The integration of digital twin and real-time simulation technologies realizes real-time mapping and dynamic deduction of grid operation status by constructing a virtual mirror highly consistent with the physical power grid. Its specific application in the optimal scheduling of smart grids has become an important research direction, mainly including: establishing a high-fidelity grid digital twin model, integrating multi-source perception data to build a real-time fault diagnosis and self-healing model with predictive capabilities; using the digital twin platform to pre-verify scheduling strategies, simulating the economy, security, and carbon emissions of different schemes in a virtual environment to provide support for practical decision-making, thereby reducing trial-and-error costs and improving the reliability and economy of decisions [16]. Currently, some related projects have been implemented. For example, during the "14th Five-Year Plan" period, China Southern Power Grid has built a digital twin of the 110kV and above main power grid, forming a demonstration of the digital main grid framework for the new-type power system.

Due to the integration of renewable energy and changes in load characteristics, modern power systems have complex computing needs such as real-time monitoring and dynamic security analysis, and traditional computing efficiency is insufficient. Quantum computing, with the characteristics of superposition and entanglement, has advantages in handling high-dimensional and multi-objective grid scheduling computing problems and is an important direction to address the computing challenges of power systems. Key algorithms: HHL algorithm, quantum annealing, QAOA (Quantum Approximate Optimization Algorithm), QAE (Quantum Amplitude Estimation). Main challenges: poor stability of qubits; error correction protocols require a large number of high-quality qubits, which is difficult to achieve with existing equipment; insufficient algorithm scalability; low data encoding efficiency; and shortage of professional talents [17]. The quantum annealing algorithm is expected to be applied to efficiently solve mixed-integer models to address the uncertainty scheduling problems caused by the current high-proportion new energy integration; QAOA can be used to balance and solve multi-objective optimization problems. Nima Nikmehr used QAOA to solve the unit commitment problem in microgrid scenarios in Document [18]. Dr. Wang Baonan published a patent titled "Microgrid Power Generation Optimal Scheduling Method Based on Quantum Annealing Algorithm" in 2024. These all indicate that research on quantum computing is of great significance to the field of smart grid optimal scheduling.

5.2 Policy and Market Aspects

Scheduling strategies under the carbon neutrality goal need to achieve a balance between the economy and low carbon. Existing scheduling models mostly take cost minimization as the goal, while the carbon neutrality goal requires integrating carbon emissions into the optimization framework to form a dual-objective system of "cost and carbon emission reduction". Future research can combine the "dual carbon" policy to build a new power system, such as cross-regional power allocation (west-to-east power transmission), collaboration between new energy and the power grid, and AI intelligent regulation [19]. Building a new-type power system with new energy as the main body is a major step towards achieving carbon neutrality, which requires the joint improvement of technological innovation and policy-market mechanisms. On this basis, future policy formulation can focus on the following directions: designing a dynamic pricing mechanism based on carbon trading, including carbon costs in electricity prices, and guiding users' power generation and consumption behaviors through price signals. For example, exploring the establishment of an electricity price fluctuation mechanism linked to real-time carbon intensity, reducing electricity prices during peak output periods of renewable energy to promote absorption, and increasing electricity prices during high-carbon emission periods to curb user electricity consumption; improving the cross-provincial carbon market and electricity trading mechanism, breaking market barriers, and promoting collaborative optimal scheduling between western energy bases and eastern load centers. Introducing policies to encourage virtual power plants (VPP) and distributed energy aggregation to participate in system regulation, such as capacity subsidies and frequency modulation service compensation, to stimulate the potential of multi-agents. Finally, promoting data interconnection and mechanism collaboration between the power market and the carbon market, and building an "electricity-carbon" joint optimal scheduling model is a key path to realize the unification of economy and low carbon.

6. Conclusion

The field of smart grid optimal scheduling has evolved in a progressive manner, from technical support to model practice, and from single-objective to multi-agent collaboration. The key technology system provides technical boundaries for scheduling models; optimal scheduling models realize the transformation from theory to practice based on multi-dimensional classification and evaluation combining mathematical and artificial intelligence technologies. Currently, smart grid optimal scheduling faces two core challenges: one is uncertainty management; the other is limitations in multi-agent collaboration. In the future, it is necessary to make efforts in both technology and policy-market aspects: technically, exploring the application of digital twin and quantum computing; in terms of policy-market, constructing scheduling strategies and dynamic electricity price mechanisms under the carbon neutrality goal.

In general, breakthroughs in smart grid optimal scheduling require the coordinated advancement of policies and technologies. The implementation of results needs to focus on solving problems such as equipment compatibility, costs, and benefit distribution, and finally realize the closed loop from theoretical innovation to practical application, providing guarantees for the safe, efficient, and low-carbon operation of the power grid under high-proportion new energy integration.

References

[1] Wu T, Wu B H, Wang F J. Understanding and Implications of Advanced Metering Infrastructure (AMI) in Smart Grids [J]. Central China Electric Power, 2010, 23(06): 4-7.

[2] Zhang L, Xu K J, Xu H R, et al. Research on Synchronous Phasor Measurement Technology for Power Systems Based on Edge Computing [J]. Electric Machines & Control Application, 2025, 52(6): 125-132.

[3] Zeng Q, Liu Y B, Li Z W, et al. Design and Analysis of 5G/6G High-Reliability and Low-Latency Power Internet of Things Communication Supporting New-Type Power Systems [J]. Proceedings of the CSEE (Chinese Society for Electrical Engineering), 2024, 44(21): 8435-8443.

[4] Huang Y Q, Liu D. Research on Secure Sharing of Multi-Source Data in Smart Grid Networks Based on Federated Learning [J]. Intelligent IoT Technology, 2025, 57(02): 98-101.

[5] Liu C, Gu S T. Distributed Energy Management and Optimization Strategies in Smart Grids [C]//China Electric Power Equipment Management Association. Proceedings of the National Green Digital Intelligent Power Equipment Technology Innovation Achievement Exhibition (VII). State Grid Hebei Electric Power Co., Ltd. Xinle Power Supply Branch, 2024: 32-34.

[6] Li Y, Wang B B, Song H K. Demand Response and Its Application [J]. Power Demand Side Management, 2008, 10(6): 13-15.

[7] Zhong H W, Xia Q, He J B, et al. Concept and Application Prospects of Virtual Power Plants [J]. Automation of Electric Power Systems, 2016, 40(13): 198-205.

[8] Y. Chen, C. Ma, Y. Sun and B. Wang, "Low Carbon Economic Dispatch of Integrated Energy System Considering Demand Response and Carbon Capture Under Stepped Carbon Trading," 2024 IEEE PES 16th Asia-Pacific Power and Energy Engineering Conference (APPEEC), Nanjing, China, 2024, pp. 1-5.

[9] Guo B, Li H, Yan Y, et al. Data Volume-aware Computation Task Scheduling for Smart Grid Data Analytic Applications [C]//2023 IEEE International Conference on Communications (ICC). IEEE, 2023.

[10] Affolabi L, Shahidehpour M, Rahimi F, et al. Optimal Operation of Electric Vehicle Charging Stations with Variable Distributed Energy Resources in Constrained Electricity and Transportation Networks [C]//2023 IEEE Vehicle Power and Propulsion Conference (VPPC). IEEE, 2023: 1-6.

[11] Li P, Zu W J, Liu Y X, et al. State Estimation Method for Distribution Networks Based on Incomplete Measurement Data [J]. Electric Power, 2025, 58(5): 1-10.

[12] Xinxin W, Xiaopan S, Xueyi A, Shijia L. Short-term wind speed forecasting based on a hybrid model of ICEEMDAN, MFE, LSTM and informer [J]. PLoS ONE, 2023, 18(9): e0289161.

[13] A. Li, Y. Liu and J. Wu, "A Robust Stochastic Optimization for Locally Ideal Unit Commitment Considering Renewable Energy Sources," 2021 International Conference on Intelligent Technology and Embedded Systems (ICITES), Chengdu, China, 2021, pp. 184-189.

[14] Diego Jiménez, Alejandro Angulo, Alexandre Street, Fernando Mancilla-David. A closed-loop data-driven optimization framework for the unit commitment problem: A Q-learning approach under real-time operation [J]. Applied Energy, 2023, Volume 330, Part B: 120348.

[15] Amin Mohammadpour Shotorbani, Sevda Zeinal-Kheiri, Gyan Chhipi-Shrestha, Behnam Mohammadi-Ivatloo, Rehan Sadiq, Kasun Hewage. Enhanced real-time scheduling algorithm for energy management in a renewable-integrated microgrid [J]. Applied Energy, 2021, Volume 304: 117658.

[16] Han D. Application Analysis of Digital Twin Technology in Smart Grids [J]. Science & Technology Information, 2025, 23(09): 43-45.

[17] P. A. Ganeshamurthy, K. Ghosh, C. O'Meara, G. Cortiana, J. Schiefelbein-Lach and A. Monti, "Next Generation Power System Planning and Operation With Quantum Computation," in IEEE Access, vol. 12, pp. 182673-182692, 2024.

[18] NIMA NIKMEHR, PENG ZHANG, MIKHAIL A. BRAGIN. Quantum Distributed Unit Commitment: An Application in Microgrids [J]. IEEE Transactions on Power Systems: A Publication of the Power Engineering Society, 2022, 37(5): 3592-3603.

[19] Huang F P. Construction of New-Type Power Systems and Low-Carbon Energy Transition Paths Under the Carbon Neutrality Goal [J]. Electrical Technology and Economy, 2025, (06): 131-134.

[20] Dong K C, Xu D L, Pan Z, et al. Research on the Application of Advanced Metering Infrastructure (AMI) [J]. Heilongjiang Electric Power, 2023, 45(02): 143-146.

[21] Lü C M, Xiong W. Overall Framework Design of Smart Grids Based on 5G Slicing and MEC Technology [J]. Electric Power Information and Communication Technology, 2020, 18(08): 54-60.

[22] Li C, Xia B S, Lin B, et al. Overhead Transmission Line Icing Monitoring Technology Based on Multi-Dimensional Parameter Distributed Optical Fiber Sensing [J]. Optoelectronic Technology, 2024, 44(01): 38-46.

[23] Xu Y, Zhu Q, Wang C F. Classification and Collection of Electricity Consumption Information Data Based on Advanced Metering Infrastructure [J]. Industrial Innovation Research, 2025, (10): 72-74.

[24] Hu J J, Zhou H Y R, Li Y. Real-Time Scheduling Strategy for Suppressing Photovoltaic Fluctuations by Cluster Electric Vehicles [J]. Power System Technology, 2019, 43(07): 2552-2560.

[25] Yu B, Ding J W. Integration of Virtual Power Plants and Optimization Analysis of Scheduling Strategies [J]. Electronic Technology, 2024, 53(09): 296-297.
[26] Wang S, Yang C S. Research on Power Scheduling Optimization Strategies in Smart Grids [C]//China Electric Power Equipment Management Association. Proceedings of the National Green Digital Intelligent Power Equipment Technology Innovation Achievement Exhibition (VII). State Grid Baoding Power Supply Company; State Grid Handan Power Supply Company, 2024: 274-276.
[27] B. Qu, Z. Wang, B. Shen, H. Dong and D. Peng, "Adaptive Decentralized State Estimation for Multimachine Power Grids Under Measurement Noises with Unknown Statistics," in IEEE Transactions on Industrial Informatics, vol. 21, no. 2, pp. 1655-1664, Feb. 2025.
[28] Orumwense, E. F., & Abo-Al-Ez, K. (2023). An Optimal Scheduling Technique for Smart Grid Communications over 5G Networks. Applied Sciences, 13(20), 11470.

