The Application Progress of Artificial Intelligence Technology in The Optimal Dispatch of Smart Grids

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Abstract. With a high proportion of new energy sources connected to the power grid, the traditional dispatching model is facing severe challenges in dealing with uncertainties.To address this challenge, this article systematically reviews the progress of the application of artificial intelligence(AI) technology in the optimization scheduling of smart grids..The research focuses on three core methods: data-driven prediction, multi-objective optimization decision-making, and real-time perception diagnosis.Case studies have shown that artificial intelligence technology can systematically enhance the operational efficiency of power grids. In scenarios such as new energy grid connection, energy storage scheduling, and safety management, it has achieved significant reductions in the rate of wind power abandonment and a qualitative improvement in the efficiency of fault handling.The research has verified the crucial role of artificial intelligence technology in facilitating the transformation of power grid dispatching from "passive response" to "active optimization", and has provided a technical path and empirical basis for building an efficient and reliable new power system.

Keywords: Artificial Intelligence; Smart Grid; Optimal Dispatch; Energy storage scheduling; New energy consumption.

1. Introduction

As global attention to the issue of climate change continues to increase, carbon emission management has become a crucial path towards achieving the "dual carbon" goals. Power grid enterprises, as an important link in energy conversion and transmission, play a significant role in promoting the country's green and low-carbon transformation process [1]. Renewable energy sources such as wind power and solar power are experiencing a period of significant growth. However, because renewable energy resources, such as wind and solar power, are unpredictable, sophisticated forecasting methods are required [2]. It has brought severe challenges to traditional power grid dispatching, significantly increasing the difficulty of system operation.

AI technology has provided a new path for the intelligent transformation of the power grid. Based on the analysis of power grid dispatching data, the compatibility was examined. The results showed that the core technologies of AI are highly aligned with the dispatching requirements of the power grid. Additionally, in the interdisciplinary field of electrical engineering and AI, core optimization methods were summarized. These methods provide technical support for the construction of the new power system in practical applications. Although existing studies have explored the application of AI in the power system, there is still a gap in building a comprehensive "source-network-load-storage" collaborative scheduling system for all links [3]. This article focuses on this topic, conducting a systematic study on the application of artificial intelligence technology in the optimization scheduling of the smart grid, which has both significant theoretical value and practical significance.

This study will first analyze the compatibility between artificial intelligence technology and grid dispatching requirements, and focus on three core technologies: Data-driven precise prediction methods, multi-objective collaborative optimization decision-making methods, and Real-time perception-based intelligent diagnostic methods. Through empirical analysis of typical application cases, it will verify the optimization effect of artificial intelligence technology compared to traditional methods, providing theoretical references and a practical basis for promoting the construction of smart grids.

2. The Compatibility of Artificial Intelligence Technology with Power Grid Dispatching

2.1. Core technological advantages

AI technology has provided a new methodology for solving the problem of optimizing the dispatch of smart grids. Its core advantage lies in converting data into perception and decision-making capabilities. The core methods and applications as shown in Table 1:

Table 1. Core Methods and Applications of Artificial Intelligence in Grid Optimization Scheduling

Core method	Main function	Typical application scenarios
Machine Learning(ML)	Data Mining and Precise Prediction	Short-term load forecasting, prediction of new energy output
Deep Learning(DL)	Complex Pattern Recognition and Feature Extraction	Ultra-short-term power prediction, equipment image fault diagnosis
Reinforcement Learning(RL)	Sequential decision-making and strategy optimization	Energy storage system scheduling, real-time voltage control

Machine learning is based on statistical learning theory and is adept at extracting patterns from historical data. It is crucial for achieving precise prediction of short-term load and the output of new energy sources, providing a reliable input foundation for scheduling decisions.ML plays a crucial role in transforming grid management. For example, the LSTM-based RL model improved renewable energy integration and load balancing optimization in a smart grid with 92% accuracy as compared to other ML algorithms.

Deep learning takes it a step further, being particularly adept at handling high-dimensional, unstructured spatiotemporal data for complex pattern recognition and feature extraction. Models such as spatiotemporal graph neural networks can simultaneously capture the time series characteristics of power flow and the spatial correlations of power grid topology, thereby enabling ultra-short-term wind and solar power prediction and fault diagnosis of equipment images. This solves the complex perception problems that traditional methods struggle to handle.

The advantage of reinforcement learning lies in sequential decision-making and strategy optimization. The agent autonomously learns the optimal control strategy under uncertainty through continuous interaction with the power grid environment. For instance, the collaborative effect based on the deep deterministic policy gradient module significantly improves the accuracy and optimization effect of energy storage system scheduling and measurement. It demonstrates excellent adaptability in real-time voltage control and extreme weather scenarios. Meanwhile, it has good real-time and scalability, providing a reference for further research in the field of smart grids [4].

These three elements together form a complete intelligent technology stack: ML lays the foundation for prediction, providing accurate predictions, DL achieves deep perception, mining data correlations, and RL ultimately generates intelligent decision-making to drive the intelligence of scheduling, achieving a full-process optimization of "prediction-perception-decision-making".

2.2. The compatibility between artificial intelligence and scheduling requirements

AI technology is highly compatible with the requirements of power grid dispatching, mainly reflected in three aspects: Firstly, AI has the ability to respond in milliseconds, which can meet the real-time requirements of power grid dispatching; Secondly, AI can effectively deal with the volatility and uncertainty of new energy power generation; Finally, AI has deep perception capabilities, which can achieve pre-warning and intelligent decision-making, improving the reliability of power grid operation.

3. The Core Method of Enabling Scheduling Optimization through Artificial Intelligence

3.1. Data-driven precise prediction methods

Data-driven prediction methods are the key to supporting the optimal dispatch of smart grids. Current research mainly focuses on two core tasks: In short-term load forecasting, use machine learning algorithms like gradient boosting trees to improve accuracy. For the prediction of more variable renewable energy output, the academic focus is mostly on using advanced models such as spatio-temporal graph neural networks to simultaneously capture the correlation characteristics of their output in both time and space dimensions.

3.2. Multi-objective Collaborative Optimization Decision-making Methods

In response to the challenge of balancing multiple objectives such as economy, safety and the integration of new energy sources in power grid dispatching, current research mainly adopts a path that combines deep reinforcement learning (DRL) with multi-objective optimization algorithms. For instance, the introduction of technologies such as spatio-temporal graph neural networks have achieved significant results in the field of multi-region power load forecasting. Based on electricity load forecasting, energy transfer and energy coupling are respectively associated with natural gas demand forecasting and heat load forecasting, and then through energy complementarity and collaborative optimization, an integrated energy forecasting is formed to achieve joint forecasting of multiple energy systems, achieving breakthroughs in safety and compliance performance. The prediction accuracy has significantly improved, with the error fluctuation range reduced by 62.3% compared to the benchmark model. The communication efficiency and the single-round training time are shortened by 73% compared to centralized training time, as shown in Figure 1.

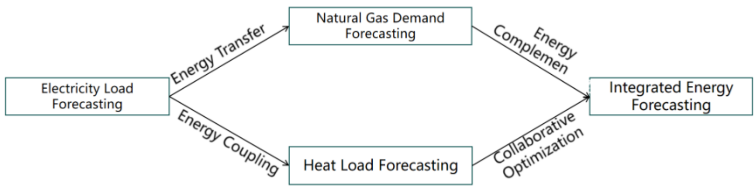

Fig. 1 Technical Roadmap of the Combined Prediction System for Electric, Gas, Thermal and Multi-energy Flows [5]

3.3. Real-time Perception-based Intelligent Diagnostic Methods

The intelligent diagnosis system builds a comprehensive monitoring network by deploying sensors at various nodes of the power grid. Based on multi-source data fusion and DL technology, it enables real-time perception of equipment status and precise fault diagnosis, which can simultaneously analyze equipment operation data, and complete early fault warning and precise location. Taking the smart grid as an example, by using RL algorithms to analyze real-time power grid operation data, it learns and optimizes power grid dispatch strategies, achieving efficient energy utilization and reducing energy consumption. It can reduce the energy consumption rate to less than 80%, significantly improving energy utilization efficiency [6].

4. Application Practice

4.1. Optimization of New Energy Grid Connection

In 2023, the installed capacity of renewable energy exceeded 1.5 billion kilowatts, accounting for more than 50% of the total installed capacity of power generation in the country. The newly added capacity exceeded 300 million kilowatts, accounting for 85% of all the newly added capacity [7]. However, the randomness and volatility of new energy sources far exceed those of traditional thermal power plants. This has significantly increased the difficulty of power prediction, and the prediction error is much higher than that of traditional energy sources.

The AI technology, based on the knowledge graph mining of the spatio-temporal synchronous graph convolutional network, has achieved a breakthrough in the utilization of new energy. Relying on the mechanism knowledge in the knowledge graph of new energy consumption as guidance for the model, it not only eliminates the complex mathematical modeling and solution steps, but also achieves a dual improvement in solution efficiency and prediction accuracy [8]. The source-grid-load-storage coordinated scheduling model driven by deep reinforcement learning algorithms enables the power grid to have adaptive optimization capabilities, significantly enhancing the flexibility and economy of system operation.

After the deployment of the AI scheduling system, compared with traditional methods, it has higher evaluation accuracy and speed. This transformation marks a fundamental breakthrough in the new energy consumption from "passive adaptation" to "active guidance". The value of AI technology not only lies in improving the consumption efficiency at the technical level, but also lies in redefining the operation logic and functional positioning of the power grid. The power grid is no longer merely a channel for energy transmission, but has evolved into a resource allocation platform that can actively sense, make intelligent decisions, and dynamically optimize. This transformation will profoundly affect the planning and construction of the power grid.

4.2. Energy Storage System Scheduling Optimization

The energy storage system utilizes specific technologies to store electrical energy and other forms of energy and release them on demand. It plays a crucial role in smart grids by enhancing the utilization of renewable energy. The operation mode of traditional energy storage systems has become inadequate to meet the operational requirements of smart grids. But the introduction of AI-powered smart grid technologies is revolutionizing energy transmission,and distribution [9].

The Enhanced Deep Reinforcement Learning Algorithm (E-DRL) is an intelligent decision-making technology that combines DRL. It is used for optimizing the storage capacity on the power grid side. This method builds a high-fidelity simulation model of the battery and embeds it into the optimization framework. Establishing a joint optimization model for capacity and operation that takes into account the full life cycle cost. This approach enables the energy storage system to effectively extend the service life of the storage system.

The improved E-DRL algorithm is applied to the optimization of grid-side energy storage. The core design: Firstly, a high-fidelity battery simulation model integrating physical and data-driven methods is constructed to match the state/action space mapping. Then, through the interaction between the agent and the simulation environment, the states, actions, and rewards are obtained. Finally, the value function is updated through TD error:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma \max_{a'} Q\left(s_{t+1}, a'\right) - Q(s_t, a_t) \right] \tag{1}$$

(α represents the learning rate, which is used to control the step size of updates; γ is the discount factor, which adjusts the weight of future rewards)

The experiment shows that the E-DRL algorithm outperforms both traditional DRL and benchmark methods. It can reduce the total life cycle cost of the system, extend the storage life by 22.55% and 37.36% and increase the new energy consumption rate to 92.3%, which is 8.7% higher than the traditional DRL method. It also significantly reduces the phenomenon of wind and solar energy waste [10]. Battery state of health is determined with a mean absolute error of 1.39% by using a simple ANN with a small amount of data. This helps optimize the operation and management of energy storage systems [11]. This technology will lead the field of energy storage management to undergo a paradigm shift from "system optimization" to "ecological synergy coordination".ultimately becoming the core pillar of the distributed intelligent energy network.

4.3. Power Grid Security and Stability Control

With the rapid development and complexity of the power grid, traditional power grid security management mainly relies on manual inspections and experience-based judgments, similar to "putting out fires after they occur". The traditional methods for fault diagnosis and handling have been unable to meet the current demands. The incorporation of AI technology presents unique potential for enhancing the performance and reliability of small-scale electric power infrastructures. By employing machine learning, predictive maintenance algorithms can evaluate past data, identify patterns, and anticipate equipment breakdowns before they happen.

To address this issue, the optimization algorithm based on DRL in AI technology offers a new solution. By using DL methods, the optimization strateg can be adaptively adjusted to optimize the safe and stable operation of the power grid. RL can adaptively adjust the optimization strategy through the interaction between the intelligent agent and the environment without fully knowing the system model. Therefore, it is more suitable for complex nonlinear systems like the power grid.

The method of minimizing the loss function for achieving joint training is as follows:

$$\begin{gathered} \mathrm{L}(\theta^{\mu}) = -E_{s\sim\rho^{\beta}}\left[Q\left(s,\mu\left(s \mid \theta^{\mu}\right) \mid \theta^{Q}\right)\right] \\ \mathrm{L}\left(\theta^{Q}\right) = E_{\left(s,a,r,s'\right)\sim D}\left[\left(\begin{matrix} Q\left(s,a \mid \theta^{Q}\right) - \\ \left(r+\gamma Q\left(s',\mu\left(s' \mid \theta^{\mu}\right) \mid \theta^{Q'}\right)\right) \end{matrix}\right)^{2}\right] \end{gathered} \tag{2}$$

ρ^{β} represents the state distribution under behavior strategy β, D is the experience replay buffer, and γ is the discount factor.Through continuous interaction, storing experiences and updating the network, the Actor network can eventually learn the optimal control strategy. This strategy not only effectively maintains the safety and stability of the power grid, but also performs well in terms of economy, with rapid convergence and good robustness.[12]

In the research and practice of grid security and stability control, we have deeply realized that the application of AI technology not only brings about the upgrading of technical means but also leads to a fundamental transformation of the security concept. AI has achieved a leap to active early warning, intelligent diagnosis and autonomous decision-making. Security is no longer merely the reliable operation of equipment,expanding to adaptability of the system in complex environments.

5. Challenges and Future Trends

5.1. Challenges

Although AI has performed well in power grid dispatching, its large-scale application still needs to overcome the practical bottlenecks in three dimensions: data, algorithms, and implementation. These challenges affect the efficiency of its promotion. Firstly, at the data level, the data formats and collection standards in various links of the power system are not unified, and the difficulty of cross-scenario data interoperability and sharing is significant. Secondly, at the algorithm level, in complex scenarios such as extreme weather and equipment failures, the generalization ability of AI algorithms and making it difficult to meet the trust requirements of the power industry. Finally, in the implementation level, the construction cost of AI dispatching systems is high, and there is poor compatibility with the protocols and interfaces of existing power equipment; the trial-and-error space for AI technology is limited, which delays the promotion pace.

5.2. Future Trends

The future development of smart grids will exhibit two major trends:The integration of multiple technologies, combining AI algorithms with the operational laws of the grid itself; AI is responsible for calculating the fluctuations in power generation from wind and solar energy and changes in user electricity consumption, while the grid ensures the safety and reliability of these calculated scheduling plans. AI enables the grid to achieve intelligent operation through self-sensing, self-decision-making, and self-evolution, gradually achieving a state with less human intervention and even autonomous operation. Standardized construction will become an important cornerstone for promoting industry development.

6. Conclusion

This paper systematically studies the innovative application of artificial intelligence technology in the optimization scheduling of the smart grid, and constructs a complete method system including Data-driven precise prediction,Multi-objective collaborative optimization decision-making, and Real-time perception-based intelligent diagnosis. The research shows that the new scheduling mode based on AI can significantly enhance the new energy consumption capacity, optimize the operation efficiency of the energy storage system, and strengthen the safety and stability level of the power grid. It provides solid support for the transformation of power grid scheduling from traditional experience-driven to modern data-intelligent-driven.

Looking ahead, with the continuous deepening of multi-technology integration and the increasingly refined standard system, the smart grid will rapidly develop in the direction of cloud collaboration and autonomous decision-making. AI technology will not only drive a profound transformation in the operation mode of the power system, but also effectively enhance the grid's ability to accommodate a high proportion of renewable energy, providing key technical support for building a clean, low-carbon, and safe, efficient new energy system, and ultimately contributing significantly to achieving the strategic goal of energy transformation.

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