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Research on Power Grid Dispatching Based on Particle Swarm Optimization

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Abstract: The optimization and dispatching of microgrids is the main issue in achieving efficient operation of smart grids. In recent years, various optimization algorithms have been widely used in microgrid dispatching. This paper systematically reviews the research progress that has made in this field and compares the advantages and disadvantages of different optimization methods. First, the classic intelligent optimization algorithms, such as particle swarm optimization, genetic algorithm, and differential evolution are introduced, and in this essay, their applications and improvement strategies in microgrid dispatching are discussed. Secondly, the optimization methods based on reinforcement learning, including deep reinforcement learning (DRL), deep deterministic policy gradient (DDPG), and proximal policy optimization (PPO), are analyzed, focusing on their advantages in dealing with high-dimensional, nonlinear, and real-time dispatching problems. Additionally, the 'prediction plus optimization' combination strategy, such as Bayesian optimization, metaheuristic optimization, and multi-scenario optimization methods based on machine learning, is discussed to deal with the uncertainty and robustness problems of microgrids. These three aspects represent three kinds of most popular research on microgrid optimization. Finally, this paper summarizes the applicability of different optimization methods and looks forward to future development trends. Comprehensive analysis shows hybrid optimization strategies (such as PSO +GOA) are also worthy of further study in improving robustness.

Keywords: Power grid, Microgrid, Optimization, Reinforcement Learning

1. Introduction

The global energy system is undergoing a transformation, with microgrids emerging as a key component of the future smart grid. By integrating renewable energy sources (e.g., photovoltaic and wind power), energy storage systems, and intelligent scheduling, microgrids enhance energy efficiency, reduce carbon emissions, and improve overall grid resilience. A notable example is the microgrid deployment in Aomori Prefecture, Japan, where engineers achieved a 57.3% reduction in energy consumption and a 47.8% decrease in carbon emissions by dynamically managing power fluctuations and renewable energy integration.

A typical microgrid consists of distributed energy resources (DERs), energy storage systems (ESS), load management, and an energy management system (EMS). DERs supply primary power, while ESS stabilizes fluctuations through charge-discharge strategies. Load management optimizes demand-side consumption, and EMS leverages optimization algorithms to coordinate energy dispatch, storage, and grid interactions. Microgrids operate in two modes, the first one is Grid-connected mode,

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where power can be exchanged with the main grid. Another one is Island mode, which ensures autonomous operation during grid failures, maintaining power for critical loads.

Despite their advantages, microgrids also face some major challenges, including renewable energy uncertainty, such as PV and wind output exhibiting large fluctuations. Besides, the supply-demand balance is also a tricky problem, requiring real-time adjustments to load and storage. Finally, multi-objective optimization involves trade-offs between economic cost, environmental impact, and reliability.

Various optimization algorithms have been proposed to address these issues. Classical swarm and evolutionary algorithms (PSO, GA, NSGA-II) provide robust solutions for multi-objective tasks but can struggle with parameter tuning or high computational overhead. Reinforcement learning methods (DRL, PPO, SAC) excel in handling dynamic, high-dimensional scheduling but demand extensive training data and face generalization hurdles. Hybrid prediction-plus-optimization frameworks further improve system performance by integrating forecasting models (e.g., LSTM) with scheduling optimization. Despite these advances, a comprehensive, comparative review of these methods—covering algorithmic features, trade-offs, and real-time constraints—remains lacking. Thus, this paper aims to review recent advancements in microgrid optimization scheduling and classify and compare commonly used optimization techniques, analyzing the strengths, limitations, and applicability of different methods. Identify research trends and future directions for microgrid scheduling optimization. With the increasing demand for intelligent, adaptive, and robust scheduling, methods such as reinforcement learning + optimization and multi-objective evolutionary algorithms (MOPSO, NSGA-II) have gained significant attention. A systematic review of these approaches will contribute to advancing smarter, more efficient, and sustainable microgrids [1].

2. Current progress in algorithms

2.1. Classical intelligent algorithms

At present, traditional algorithms such as PSO are still widely used, mainly due to their fast convergence speed and wide search range. Although many other algorithms can be combined for improvement, the actual power grid dispatching situation is much more complicated and usually involves multi-objective optimization. In traditional algorithms, even if PSO is improved to the MOPSO algorithm, the performance of MOPSO/PSO is still not as good as the NSGA algorithm in some problems with conflicting optimization objectives. P. Mundra et al. constructed a smart grid model with a single utility and multiple consumers, in which demand-side management is identified as the core of multi-objective optimization problems. Finally, it is proved that the NSGA-II algorithm is applicable and robust in processing mixed integer programs [2]. Although the NSGA-II algorithm has been upgraded to the NSGA-III algorithm, it adds a set of well-distributed reference points for adaptive update, reduces the complexity of NSGA [3], and has been verified in a typical multi-energy integration system in Etuoke Economic Development Zone of Inner Mongolia. However, the performance of these traditional optimization algorithms is greatly affected by parameter selection, and achieving automatic parameter adjustment is still an urgent problem to be solved. Moreover, most of the existing research on traditional algorithms is tested in offline optimization scenarios, while in real-time applications, the computational efficiency of these methods may be insufficient.

2.2. Reinforcement learning approaches

In recent years, the application of deep reinforcement learning (DRL) in microgrid scheduling has attracted widespread attention, especially methods such as SAC have been used to solve high-dimensional dynamic scheduling problems. To be specific, Weng Cheng Liu et al. studied and proposed an information-enhanced DRL method (IE-DRL), which considers the predicted future load

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and photovoltaic power generation in the state space, thereby improving the robustness of scheduling decisions. On this basis, the proposed method was tested using microgrid data from Shandong Province, China. The final experimental results show that the four baseline DRL algorithms (IE-DDPG, IE-SAC, IE-TD3, and IE-PPO) achieved a reduction in operating costs, especially the IE-SAC algorithm, which achieved a 12.85% reduction in operating costs, verifying the effectiveness of the proposed method [4]. However, the DRL method requires a large amount of training data, resulting in a high threshold for practical application. In addition, different microgrid architectures and load patterns vary greatly, and training can only be performed offline, resulting in poor adaptability of the trained DRL strategy in the new environment.

2.3. Hybrid approaches and future directions

Due to the uncertainty of renewable energy generation, in recent years, a new wave of approaches combines machine learning prediction (e.g., LSTM, Transformer) with optimization (PSO, GA, DRL) to improve the stability and robustness of scheduling. The experiments conducted by S. S. Shuvo et al. combined LSTM with the GA algorithm and PSO algorithm respectively, showing that the trained LSTM network achieved an accuracy of more than 95% in predicting future loads and the PSO algorithm in this combination achieved a lower analysis cost [5]. However, the prediction accuracy of this method is highly dependent on the optimization algorithm. Specifically, the prediction error affects the optimization scheduling effect. Most existing studies assume that the prediction model is accurate enough. In practical applications, the prediction error may affect the actual effect of scheduling optimization [6].

3. Microgrid optimization algorithms

3.1. Microgrid model overview

This study is based on a microgrid structure that includes photovoltaic power generation (PV), micro gas turbines (MT), and energy storage devices (BA). The goal is to optimize the scheduling strategy of each power source while meeting the load demand to reduce operating costs and improve the robustness of the system. Due to the volatility of renewable energy (photovoltaic) power generation, this study uses the Weibull distribution + Monte Carlo simulation method to predict photovoltaic power and sets three scheduling schemes (Optimistic, mean, and Pessimistic) based on a 95% confidence interval. Usually, a typical microgrid architecture includes a 1-5kW micro gas turbine, and a 200kWh energy storage system with a maximum discharge of 150kW/charge of 100kW and considers a variety of uncertainty scenarios. Weibull distribution can be applied to fit photovoltaic radiation, combined with Monte Carlo simulation to generate multi-scenario data.

3.2. PSO optimization algorithm and enhancements

3.2.1. Classical PSO constraints

Particle swarm optimization (PSO) is an optimization algorithm based on swarm intelligence, which has a fast convergence speed in high-dimensional optimization problems. However, in practical applications, standard PSO has several limitations. PSO can Easily fall into local optimality, as it relies on the historical optimal solution, which may lead to early convergence to the local optimal solution and fail to further explore the global solution. It also suffers from reduced population diversity in the iteration proceeds, when the particles gradually converge to a certain solution, resulting in a limited search space. Moreover, PSO is sensitive to parameters. Inertia weight ω

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learning factor $c1$, c 2, c 2 will directly affect the optimization performance, and improper parameter selection may lead to optimization failure.

The standard update formula of PSO is as follows:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(p_i^k - x_i^k\right) + c_2 r_2 (p_g^k - x_i^k)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}$$

Among them, v_i^kdenotes the velocity of the ith particle in the kth generation; x_i^k is the position of the ith particle; p_i^k is the historical optimal position of the particle; p_g^k is the global optimal position; c_1, c_2 are the learning factors of the individual and the group respectively; r_1, r_2 are random numbers between [0,1]; ω is the inertia weight. Since the inertia weight ω affects the search range, a larger ω is suitable for global search, and a smaller ω is conducive to local convergence. How to adaptively adjust ω is an important direction of PSO optimization.

3.2.2. Improved PSO with MOPSO+SA+gaussian mutation+NSGA-II

To overcome the limitations of standard PSO, this paper proposes an improved method based on multi-objective particle swarm optimization (MOPSO), combining simulated annealing (SA), Gaussian mutation, and NSGA-II screening to improve the algorithm's global exploration ability and convergence speed.

Improved PSO applies simulated annealing (SA) to avoid local optimality

Simulated annealing (SA) uses a temperature drop mechanism to control the search range and avoid premature convergence of PSO:

$$T_{new} = T_{old} \times \alpha$$

$$X_{new} = X_{old} + \delta$$

$$P = \begin{cases} 1, & if\ f(x_{new}) < f(x_{old}) \\ \exp\left(\frac{-\Delta f}{T}\right), & if f(x_{new}) \geq f(x_{old}) \end{cases}$$

Among them,T_{old} denotes current temperature; α is the cooling coefficient; By comparing the fitness difference between the new and old solutions, we determine whether to accept the new solution under the certain probability, either 1 or $\exp\left(\frac{-\Delta f}{T}\right)$.

Gaussian mutation can enhance the population diversity. At each particle update, the velocity v_i^k is Gaussian mutated, which can be calculated through the following equation:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(p_i^k - v_i^k\right) + c_2 r_2 \left(p_g^k - x_i^k\right) + N(0, \sigma^2)$$

Among them, $N(0, \sigma^2)$is the Gaussian noise with mean 0, and variance is used to improve the search capability.

NSGA-II uses non-dominated sorting and crowding distance methods to screen the optimal Pareto solution set and ensure that the solutions of multi-objective optimization are evenly distributed. Integrating these approaches outperforms standard PSO in terms of solution quality and stability for multi-objective microgrid tasks. However, computational complexity grows with population size and objective count.

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4. Discussion

This review indicates that classical swarm/evolutionary algorithms (PSO, GA, NSGA-II) retain a prominent role in microgrid scheduling due to their simplicity and proven performance, especially in offline or less dynamic contexts. By analyzing the research on microgrid optimization scheduling in recent years, the following main conclusions can be drawn. Intelligent optimization algorithms such as particle swarm optimization (PSO), genetic algorithm (GA), and non-dominated sorting genetic algorithm (NSGA-II) are still widely used in microgrid scheduling. Studies have shown that MOPSO is suitable for multi-objective scheduling optimization, especially when considering the economy, renewable energy utilization, and carbon emissions. NSGA-II is superior to other evolutionary algorithms in terms of the diversity of Pareto optimal solutions, but its computational complexity is high, and it is difficult to meet the needs of real-time optimization. Hybrid optimization methods, such as PSO+GOA, have shown good solution capabilities in some studies, and the optimization effect is improved compared with a single algorithm [7]. From this point of view, intelligent optimization algorithms combined with traditional optimization algorithms still occupy an important position in microgrid scheduling, especially hybrid optimization strategies are becoming a trend.

DRL-based scheduling has demonstrated advantages in addressing dynamic and high-dimensional tasks. In recent years, deep reinforcement learning (DRL) has been widely studied in microgrid scheduling, especially in high-dimensional, nonlinear, and real-time scheduling problems. Hybrid methods that integrate advanced prediction (LSTM, Transformer) to reduce uncertainties are shown to enhance scheduling robustness. In particular, the SAC algorithm can be applied to the optimization of real-time scheduling and high-dimensional problems, showing the characteristics of strong applicability and online learning ability. However, they depend significantly on the reliability of predictive models. Its unstable convergence, large training data, and the need to be constrained by data transmission speed are often criticized.

At present, a considerable number of researchers have also devoted their attention to the fusion method of machine learning prediction + optimization scheduling to cope with the uncertainty caused by fluctuations in renewable energy output. In this way, while retaining the advantages of the original optimization algorithm, it can be applied to scenarios with large fluctuations and long-term scheduling needs. This can reduce the impact of uncertainty and improve the adaptability of the algorithm. Nevertheless, parameter tuning and limited real-time adaptability hamper their full potential. The core of this algorithm lies in the prediction of LSTM, so the prediction result largely determines the effect of optimization.

5. Limitations and future prospects

5.1. Limitations

Although the existing methods have made significant progress in microgrid optimization scheduling, there are still the following limitations, such as computational complexity and real-time constraints, generalization and adaptability, forecasting reliability, as well as multi-object balancing. Specifically, the traditional optimization method has low solution efficiency in large-scale microgrid environments, and the DRL method has a long training time and is difficult to deploy quickly. Secondly, the generalization ability of the model is limited. The reinforcement learning method has poor adaptability under different microgrid architectures or load modes and lacks universality. The third is strong data dependence. Its main feature is that the prediction + optimization method relies on high-quality historical data. If the quality of the input data decreases, the scheduling optimization effect may be affected. Finally, there is the problem of balance in multi-objective optimization. The existing methods are still not perfect in the trade-off between economy, environmental friendliness, and power supply reliability, especially in the face of extreme weather or sudden load changes. The robustness of the scheduling strategy is insufficient.

In general, these limitations show that microgrid optimization scheduling still requires further theoretical breakthroughs and practical improvements to improve the reliability and applicability of the algorithm.

5.2. Potential developments

To overcome the limitations of existing research, future research on microgrid optimization scheduling can be carried out from the following directions: "Development of adaptive hybrid optimization methods", "Application of efficient training and transfer learning in reinforcement learning scheduling", "Development of prediction-optimization integrated methods", and "Research on robustness and security of microgrid optimization".

5.2.1. Adaptive hybrid optimization

In the development of adaptive hybrid optimization methods, it is necessary to improve the current situation that most optimization methods are algorithms with fixed parameters. In the future, an adaptive hybrid optimization framework can be developed. For example, by combining reinforcement learning and evolutionary algorithms, the optimization parameters can be dynamically adjusted during the training process to improve scheduling flexibility. The Bayesian optimization tuning intelligent algorithm can also be integrated into the traditional optimization algorithm to automatically adjust the algorithm parameters to adapt to different load modes. This can improve the versatility of the optimization method and make it applicable to different microgrid structures and load modes.

5.2.2. Application of efficient training and transfer learning

In terms of the application of efficient training and transfer learning in reinforcement learning scheduling, the current DRL method has a long training time and poor generalization ability in new environments. In the future, the Meta-Learning method can be used to enable the DRL model to quickly adapt to new tasks with less training data [8]. Transfer Learning can be studied to enable the trained reinforcement learning model to migrate between different microgrid architectures to improve applicability. This can reduce the model training cost and improve the application value of DRL in different microgrid environments.

5.2.3. Prediction-optimization integrated methods

In the development of integrated prediction-optimization methods, existing prediction, and optimization are usually two independent modules. In the future, we can explore end-to-end prediction optimization frameworks, such as combining LSTM with optimization, using stronger time series modeling capabilities to improve load prediction accuracy, and directly guiding scheduling optimization decisions. The method of combining reinforcement learning with adaptive prediction is adopted to continuously correct the load prediction error through the DRL training process to make the optimization scheduling more robust. This method reduces the impact of prediction errors on optimization results and improves the accuracy of microgrid scheduling.

5.2.4. Robustness and security

Finally, with the increasing application of microgrids in critical infrastructure, future research needs to focus on the robustness and safety of optimized scheduling, to deal with extreme weather or emergencies. Robust optimization makes the scheduling strategy more flexible. After such improvements, the stability of microgrid scheduling can be improved, making it suitable for more practical application scenarios.

6. Conclusion

This review systematically analyzes the research progress of microgrid optimization scheduling and compares the applicability of traditional intelligent optimization algorithms, deep reinforcement learning (DRL) methods, and prediction + optimization hybrid methods. It is not difficult to draw the following conclusions from the existing major studies. First, traditional optimization algorithms, such as MOPSO and NSGA-II, have good stability when solving multi-objective optimization problems, but it is difficult to meet the real-time scheduling requirements. Secondly, deep reinforcement learning, such as SCA, can handle dynamic scheduling problems, but generalization ability and computational cost are still the main challenges. Finally, optimization methods combined with load forecasting, such as LSTM+ optimization, can improve the robustness of microgrid scheduling, but prediction errors may affect the final scheduling results.

Overall, the study shows that a single optimization method is difficult to fully meet the needs of microgrid scheduling. The focus of future research will be the integration of multiple methods to improve the adaptability and robustness of the algorithm.

References

[1] *Zhanghua Zheng, Qian Ai. Present Situation of Research on Microgrid and Its Application Prospects in China[J]. Power System Technology,2008,(16):27-31+58.*

[2] *P. Mundra, A. Arya, S. Gawre and S. Mehroliya, "Independent Demand Side Management System Based on Energy Consumption Scheduling by NSGA-II for Futuristic Smart Grid," 2020 IEEE-HYDCON, Hyderabad, India, 2020, pp. 1-6, doi: 10.1109/HYDCON48903.2020.9242816.*

[3] *Yang, J.; Li, L. Micro-Energy Grid Energy Utilization Optimization with Electricity and Heat Storage Devices Based on NSGA-III Algorithm. Energies 2024, 17, 5563. doi: 10.3390/en17225563*

[4] *Weng Cheng Liu, Zhi Zhong Mao, Microgrid economic dispatch using Information-Enhanced Deep Reinforcement Learning with consideration of control periods, Electric Power Systems Research, Volume 239, 2025, 111244, doi: 10.1016/j.epsr.2024.111244.*

[5] *S. S. Shuvo and M. M. Islam, "Optimal Dispatch for A Microgrid with Distributed Generations and EV Charging Load," 2023 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, USA, 2023, pp. 1-5, doi: 10.1109/ISGT51731.2023.10066388.*

[6] *LI Jiawei, JU Yuntao, ZHANG Lu, LIU Wenwu, WANG Jie. Multi-time scale distributed robust optimal scheduling of microgrid based on model predictive control [J]. Electric Power Engineering Technology, 2024, 43(4):45-55*

[7] *Hassan, Q., Viktor, P., Al-Musawi, T.J., Ali, B.M., Algburi, S., Alzoubi, H.M., Al-Jiboory, A.K., Sameen, A.Z., Salman, H.M., Jaszczur, M.: The renewable energy role in the global energy transition. Renew. Energy Focus, 2024, 48, 100545. Doi: 10.1016/j.ref.2024.100545*

[8] *Shen, H.; Shen, X.; Chen, Y. Real-Time Microgrid Energy Scheduling Using Meta-Reinforcement Learning. Energies, 2024, 17, 2367. https://doi.org/10.3390/en17102367*