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Research on the Application of Joint Optimization Strategy of Energy Storage System and Demand Side Response Based on Tianqun Algorithm in Renewable Energy Grid

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Abstract: This article addresses the challenges of integrating high proportions of renewable energy into microgrids, focusing on optimization and research to manage the inherent uncertainty and volatility of renewable energy output. To ensure smooth operation of the renewable energy grid, the study employs energy storage systems and demand-side response technologies. Initially, the paper provides a comprehensive overview of the research background, significance, and current status of renewable energy integration both domestically and internationally, along with the associated impacts and existing solutions.The study then analyzes the characteristics of various microgrid components, including wind power systems, photovoltaic arrays, and energy storage systems, and develops relevant models for demand-side response. It introduces a two-layer optimization model for active distribution network planning, aiming to minimize costs related to investment, operation, demand-side response, and annual network losses. The improved beetle swarm algorithm, enhanced by combining it with particle swarm optimization, is used to solve this bi-level programming model. The case studies demonstrate that joint programming effectively enhances economic benefits.To address the economic costs, improve reliability, and increase renewable energy utilization in islanded microgrids, the paper presents a multi-objective optimization model and an optimization scheduling method that accounts for islanded operation and renewable output uncertainty. Monte Carlo sampling is applied to forecast wind and photovoltaic outputs, while linear programming is used to develop frequency regulation strategies for modulation power sources. The proposed methods are validated through case studies. Future research directions include exploring the uncertainties of demand-side response, improving prediction accuracy, and investigating additional energy storage technologies and shared energy storage solutions in integrated energy systems.

1. Introduction

To meet the urgent growing demand for sustainable development in the global community and address environmental challenges, the transition to renewable energy is becoming increasingly urgent. Although fossil fuels have driven economic growth throughout history, they have had serious impacts on ecosystems. In order to address climate change and ensure energy supply security, countries around the world are accelerating the adoption of clean renewable energy. In the United States, the use of wind, solar, and biofuels has significantly increased, and this change has become increasingly evident since then. According to the Energy Information Administration, from 2020 to 2023, the consumption of wind energy has increased from 1153 trillion British thermal units (Btu) to 1451 trillion Btu; Similarly, the usage of solar energy increased from a peak of 511 trillion Btu to 878 trillion Btu; The consumption of biofuels has also increased from 2136 trillion Btu to 2662 trillion Btu. Although these data demonstrate the widespread application of renewable energy, their promotion still faces technical and economic challenges. The variable nature of solar power results in a substantial rise in nergy, making energy storage systems essential for maintaining grid stability. These systems can store surplus electricity during periods of oversupply and discharge it when demand surpasses supply. At the same time, demand-side management (DSM) strategies have gaiened increasing importance, as they enhance energy efficiency by optimizing power usage, cutting costs, and improving grid reliability. In the United States, DSR strategy helps balance the supply of renewable energyThe aim of this study is to explore how to further integrate renewable energy into microgrids through efficient energy storage and demand side response technologies to address their fluctuations. A differentiated optimization model has been proposed for planning the upper level load reduction and backup system, wind energy investment, and demand side response costs of an active distribution network model, while the lower level is dedicated to reducing annual grid losses. In addition, a multi-objective optimization model was proposed to improve the economic efficiency of isolated microgrids, increase the utilization of renewable energy, and enhance the reliability of the system by applying improved swarm optimization algorithms (BAS) and particle swarm optimization (PSO). To cope with the uncertainty of renewable energy output, Monte Carlo simulation was used in the study, and the allocation and frequency regulation strategies were optimized through BAS algorithm. Future research should explore advanced backup technologies such as shared storage and delve into demand side response

2. Correlation theory

2.1 Challenges and optimization strategies faced by renewable energy grid connection

With the continuous expansion of renewable energy worldwide, although its proportion in total power generation has increased, the average penetration rate remains at around 8%. In 2023, the consumption of renewable energy in the United States reached a new high of 8.2 trillion kilowatt hours, mainly relying on solar power generation and biofuels. However, wind energy usage has decreased for the first time in 25 years, while coal consumption has dropped to 820 million British thermal units, the lowest level since 1900; Nuclear energy has slightly increased, reaching 810 million British thermal units. Meanwhile, driven by demand from the power industry, natural gas consumption has reached a historic high of 33.6 trillion British thermal units.

Faced with challenges such as transmission line congestion, insufficient backup capacity, and transient issues in the US power grid, including low inertia systems and deteriorating power quality, comprehensive measures need to be taken immediately. This includes optimizing energy storage technology[1], balancing grid supply and demand through expanding scale and intelligent scheduling; Deepen the demand side response strategy, use smart meters, time of use electricity prices and other means to guide users to change their electricity consumption behavior; At the same time, optimizing the design and planning of renewable energy systems[2], ensuring economic feasibility and operational safety through diversified energy combinations, enhancing grid infrastructure, and strengthening system resilience. In addition, increasing investment in technological innovation and research and development, promoting international cooperation and exchanges, as well as improving policies and regulations and strengthening regulatory efforts, are all key measures to promote the power grid's response to challenges and achieve sustainable development.

2.2 Optimization application of energy storage and demand side response in distribution network

As the United States confronts the escalating energy challenges, a harmonious blend of energy storage technologies and demand-side management (DSM) strategies [3]has emerged as a pivotal solution to safeguard grid stability. The rapid adoption of renewable energy sources, particularly wind power, while commendable for environmental gains, poses operational complexities due to their intermittent nature. This intermittency can disrupt grid frequency and voltage, posing a threat to the overall system's stability. To further address the challenges posed by renewable energy variability and enhance grid resilience, energy storage systems have emerged as crucial components, capable of mitigating fluctuations and improving the reliability of power supplies. However, the significant investment required for energy storage necessitates a strategic integration with demand-side management (DSM) mechanisms to maximize cost-effectiveness and flexibility. Researchers are increasingly focused on developing advanced optimization models that employ a comprehensive strategy, combining various energy sources, storage capabilities, and DSM techniques. This holistic approach aims to optimize storage usage in response to wind power variability, leveraging smart grid technologies and DSM strategies to efficiently manage renewable energy influxes.

Reflecting this trend, the United States has experienced a notable surge in renewable energy consumption, particularly in wind and solar power. As wind energy jumped from 1,153 trillion BTUs in 2020 to 1,451 trillion BTUs by 2023, and solar energy followed a similar upward trajectory, the importance of integrating energy storage systems and DSM practices becomes even more pronounced. This transformation underscores the need for innovative solutions to manage the influx of renewable energy effectively, ensuring grid stability amidst the ongoing energy transition.

3. Research method

3.1 Wind speed probability distribution model

The output power of wind turbines is affected by wind speed, and the randomness of wind speed leads to fluctuations in power generation. Therefore, during the construction of wind farms, it is necessary to study changes in wind speed and select appropriate probability distribution models. The commonly used wind speed distribution models [4] include two parameter and three parameter Weibull distributions, Gaussian distributions, and Rayleigh distributions, among which Weibull distribution is the most representative of actual wind speed changes.The probability density function for wind speed is expressed as:$f(v)=(k/c)(v/c)^{(k-1)}\exp(-(v/c)^k)$where C is the scale parameter, and k is the shape parameter. Once the wind speed distribution is defined, Monte Carlo sampling can be employed to generate actual wind speeds, which can then be applied to calculate the wind turbine's power output based on its characteristics. For photovoltaic power systems, the output depends on light intensity, which is commonly modeled using a Beta distribution. The probability density function for light intensity is:$f(e)=[\Gamma(\alpha+\beta)/\Gamma(\alpha)\Gamma(\beta)](e/e_{max})^{(\alpha-1)}(1-(e/e_{max}))^{(\beta-1)}$Photovoltaic power output is influenced by both light intensity and temperature. The output power is determined by the following equation: $P_{pv}(t)=(S(t)/S_{STC})Q_{STC}[1+\lambda_{PV}(T(t)-T_{STC})]$where $S(t)$is the light intensity, $T(t)$ is the temperature,

S_{STC} is the standard test condition light intensity, Q_{STC} is the rated power under standard conditions, and PV is the power temperature coefficient.

3.2 Energy storage system model

The energy storage system model [5] is a solution proposed to address the grid stability issues caused by the randomness and volatility of high proportion renewable energy integration into the grid. Traditional stable energy sources use micro gas turbines, while renewable energy sources have output fluctuations due to their susceptibility to natural factors. To manage the fluctuations in renewable energy output and ensure stable grid operation, the integration of energy storage systems is essential. These systems possess a dual role in the power grid, functioning both as a load and a power source. They can operate flexibly in both grid-connected and islanded modes, enhancing the grid's ability to accommodate clean energy.Energy storage systems are categorized into power-type and energy-type based on their functionalities. Power-type storage systems, such as flywheels and supercapacitors, are designed for rapid charging and discharging. In contrast, energy-type systems, including pumped storage, lead-acid batteries, sodium-sulfur batteries, lithium batteries, and compressed air energy storage, focus on longer-term energy storage.The primary functions of energy storage systems in the grid include smoothing out renewable energy output fluctuations, participating in frequency regulation, peak shaving, and maintaining supply-demand balance. These systems also contribute to improved system economics, reliability, and efficiency in utilizing new energy sources. The operational mode of an energy storage system—charging or discharging—is determined by the balance between power output and load demand. When the output surpasses the demand, the system charges; otherwise, it discharges.Additionally, demand-side response mechanisms play a crucial role in grid regulation by modifying electricity consumption patterns through pricing and incentives. When combined with energy storage systems, demand-side response enhances grid stability and performance.

3.3 Double layer optimization model

In order to optimize the joint strategy of energy storage system and demand side response, it is necessary to develop a reasonable operational plan, prioritize the planning of energy storage system, and then consider demand side response. The energy storage system controls the charging and discharging operations by smoothing out wind power fluctuations, ensuring that power fluctuations are within the set range; And demand side response reduces distribution network fluctuations by sorting and interrupting loads. The Tian Niu Qun Optimization Algorithm (BSS)[6] combined with Particle Swarm Optimization (PSO) is used to solve bi level programming problems. The simulation results show that the double-layer optimization scheme based on IEEE 33 nodes has the best economic benefits in the third scenario (simultaneously planning source, storage, and load), significantly reducing the investment costs and annual network loss expenses of wind power and energy storage. The wind power access nodes are 10 and 17, with a single unit capacity of 500kW and a wind speed fluctuation range of 4.3m/s to 7.5m/s. The rated capacity of the energy storage battery is 1000kWh, the maximum charging and discharging power is 500kW, the efficiency is 95%, the lifespan is 10 years, the investment cost is $500/kWh, and the annual operation and maintenance cost is $1000/kWh. Among the three simulation scenarios, scenario three has an energy storage capacity of 765kWh, an interruption of 977kWh, and a total economic cost of 166100 yuan; In contrast, scenario one has an energy storage capacity of 859kWh and a total cost of 250500 yuan, while scenario two has an energy storage capacity of 953kWh and a total cost of 397000 yuan. Scenario three achieved optimization of energy storage capacity while reducing economic costs. The BSS algorithm converges at the 210th generation, outperforming PSO (260th generation) and

BAS (400th generation), demonstrating its advantages in joint planning.

4. Results and discussion

4.1 Optimization and scheduling of source storage system

In the uncertainty model of the source-storage-load system, the outputs of wind turbines and photovoltaic arrays exhibit significant variability. Accurately predicting the actual output of wind power generation is a formidable task, resulting in discrepancies between forecasted and realized power production. To reduce the impact of variability in renewable energy sources on the autonomous microgrid, mathematical models are employed to represent the actual output of wind turbines, PWT(t), and photovoltaic (PV) systems, along with prediction error terms, ΔPWT(t) and ΔPPV(t), respectively. These errors, commonly modeled using Gaussian distributions, capture the uncertainty in renewable energy generation. When assessing the benefits of the microgrid, the model considers a wide array of factors, including initial investments, operational and maintenance costs, economic losses from unutilized renewable energy, and the financial gains from mitigating these losses through energy storage and demand-side management (DSM) strategies.

The optimization model for the microgrid aims to balance multiple objectives: minimizing power generation costs, improving system reliability, and enhancing energy efficiency. It utilizes objective functions tailored to economic feasibility, system stability, and optimal resource utilization. To accurately assess the performance of the grid under varying conditions, the model incorporates uncertainties in wind and PV output, employing sophisticated sampling techniques to evaluate the expected value and variability of system performance across diverse scenarios. This approach ensures that the microgrid operates optimally, even in the face of inherent variability in renewable energy sources.

4.2 Model experiment

This section focuses on an autonomous microgrid that incorporates a diverse energy mix, comprising wind turbines (with an upfront cost of 1000 yuan per kilowatt, operational and maintenance expenses of 50 yuan per kilowatt, and a cost-saving of 10 yuan per kilowatt due to reduced losses), photovoltaic (PV) panels (initially costing 800 yuan per kilowatt, with 40 yuan per kilowatt in maintenance and operation expenses, and an 8 yuan per kilowatt loss mitigation value), gas turbines for backup, energy storage units for balancing supply and demand, and controllable loads. The microgrid faces the challenge of managing the variability in renewable energy generation from wind and solar sources, while also balancing the financial aspects of investing in, operating, and maintaining this complex system. The potential cost savings achieved through efficient utilization of renewable energy sources provide a strong motivation for the microgrid's economic feasibility and sustainability. Energy storage systems, however, require a significantly higher investment of 2000 yuan per kilowatt hour, with maintenance and operational costs of 100 yuan per kilowatt hour.By reducing the losses caused by wind and solar power generation, 0.5 yuan can be saved per kilowatt hour..Gas turbines have an initial investment of 3000 yuan per kilowatt, and O&M costs of 150 yuan per kilowatt. The compensation cost for movable load in demand side response is 0.2 yuan per kilowatt hour, and the compensation for reduced load is 0.3 yuan per kilowatt hour. The economic objectives of optimizing the scheduling model include the aforementioned investment, operation and maintenance, and losses from wind and solar power curtailment, with a total cost of approximately 6000 yuan per cycle. The system reliability is measured by the amount of load shedding. If the load shedding power reaches 100 kilowatts and the duration of load shedding is 1 hour, the system exhibits low reliability. The energy utilization rate is improved by reducing the abandonment of wind and solar power, resulting in a decrease in energy utilization rate. The actual output of wind turbines and photovoltaics is 20 kW and 5 kW lower than the scheduling arrangement, respectively. To cope with the uncertainty of output, the model calculates the expected and variance of the objective function through multiple sampling. The mean of the 100 sampled samples is 5000 yuan, and the total variance is 100 yuan. The final optimization goal balances economy, reliability, and energy utilization.

4.3 Effect analysis

This chapter explores the optimization scheduling strategy of islanded microgrids, with a focus on the impact of renewable energy output uncertainty on scheduling. Four strategies were analyzed: basic power optimization and frequency modulation power linear programming without considering demand side response, basic power optimization and frequency modulation power linear programming considering demand side response, micro power scheduling without considering demand side response and output uncertainty, and scheduling considering demand side response but not output uncertainty. Taking an islanded microgrid with multiple distributed power sources as an example, the energy storage system has a capacity of 200 kW ·h, and the power parameters include a micro gas turbine of 100 kW, a wind turbine of 200 kW, a photovoltaic panel of 140 kW, and a battery of 50 kW. Wind power output is below 20 o'clock, photovoltaic output is concentrated at noon, and gas turbines generate electricity from 16:00 to 21:00. The multi-objective optimization weights areω=[0.476,0.319,0.205]\. When considering the uncertainty of renewable energy output, the economic cost is 1324.51 yuan, and when not considered, it is 1769.35 yuan; The utilization rates of renewable energy are 84.32 kWh and 206.74 kWh, respectively; The power generation is 1032.87 kWh and 1853.54 kWh. The results show that considering output uncertainty will increase economic costs, reduce the utilization rate of renewable energy, and decrease power supply reliability. The cost comparison of different frequency modulation schemes shows that the scheduling scheme considering demand side response has lower power generation costs, and the output analysis of the basic power source shows that demand side response optimization improves the utilization efficiency of wind and photovoltaic power, reduces gas turbine output, and improves economy. The mean of the scheduling plan is 0.556 with a variance of 1.01, while the mean without considering demand side response is 0.626 with a variance of 2.16. The analysis of system frequency fluctuations shows that considering output uncertainty improves system stability, especially when considering demand side response, the system's requirements for frequency fluctuations are met. Overall, the proposed optimization scheduling method has shown excellent performance in improving economy, reliability, and utilization of new energy.

5. Conclusion

This article explores the challenges and optimization techniques associated with integrating a high proportion of renewable energy into microgrids. The study then focuses on the characteristics of essential microgrid components, such as wind power systems, photovoltaic arrays, and energy storage systems, and develops models for demand-side response. It introduces a two-layer optimization model for active distribution network planning, which aims to optimize investment and operational costs, as well as demand-side response for energy storage and wind turbines, while minimizing annual network loss costs.To solve this bi-level programming model, the study employs an enhanced beetle swarm algorithm that combines beetle whisker and particle swarm optimization techniques. This approach improves both the speed of iteration and the efficiency of global search. The effectiveness of this integrated optimization method in boosting economic benefits is demonstrated through case studies..In order to reduce the economic cost, improve reliability and renewable energy utilization of islanded microgrids, this paper establishes a multi-objective optimization model [7] and proposes an optimization scheduling method considering islanded operation and renewable energy output uncertainty. The Monte Carlo method is used to sample wind and photovoltaic output, and the linear programming method is used to solve the frequency regulation strategy of the frequency modulation power source. The effectiveness of the proposed method is verified through case analysis. Future research can further consider the uncertainty of demand side response and other factors, improve prediction accuracy, and explore the application of more energy storage technologies and shared energy storage technologies in integrated energy systems.

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