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Application of Robust Optimization Algorithms to Wind Power Systems

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Abstract: In the current context of global energy structure transformation and climate change response, the development and utilisation of wind power, as a kind of clean and renewable energy, has received extensive attention. However, the intermittency and uncertainty associated with wind power present challenges to its stability and reliability in power system scheduling. This paper provides an in-depth analysis of the application of robust optimization algorithms in wind power systems, focusing on how these algorithms can enhance the efficiency and stability of wind power within power systems. This paper discusses the specific methods of robust optimisation algorithms for solving problems in wind power systems from various perspectives. For example, by constructing a robust optimisation model that takes into account the uncertainty of wind power output, the scheduling flexibility and economy of the wind power system can be effectively improved. At the same time, the application of robust optimisation algorithms is analysed in terms of improving the anti-interference capability of wind power systems, optimising the combination of wind turbines, grid integration and wind farm planning, and improving the accuracy of wind power forecasts. The effectiveness of the algorithms in solving the problems encountered in the scheduling of wind power systems is analysed, and the challenges and opportunities for future development are discussed.

Keywords: Robust Optimisation, Wind Power Systems, Power System Scheduling

1. Introduction

In the new energy era, promoting the upgrade of wind power systems can greatly promote the development of new power systems. Due to the inherent volatility and intermittency of wind power, traditional deterministic data-based optimization methods often fall short in meeting the needs of wind power systems [1, 2]. Thus, there is a pressing need to establish optimal scheduling and operational methods that can handle uncertain wind power conditions. Currently, the problem research methods for uncertain wind power systems mainly include stochastic optimisation and robust optimisation [3-6]. The former optimises the expected value of an objective based on a known probability distribution. Stochastic optimisation is able to deal with probabilistic information more directly and generate possible solutions in multiple scenarios, but requires a more accurate knowledge of the probability distribution of the uncertain parameters, which may lead to unreliable decisions if the probability distribution is not estimated accurately. The robust optimisation algorithm, on the other hand, does not require precise information about the probability distribution.

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Instead, it defines a set of uncertainties, making it highly effective for wind power systems where data is incomplete or probability distributions are difficult to obtain. Robust optimisation methods are further divided into classical robust optimisation and distributional robust optimisation. In current wind power systems, robust optimisation algorithms are mostly applied to design optimisation models that can adapt to multiple uncertain scenarios and develop hybrid algorithms that combine other optimisation techniques for better balancing. In addition, researchers are exploring the use of robust optimization for frequency regulation and voltage control in wind power systems, aiming to maintain power quality amidst fluctuations in wind power. This paper introduces the basic concepts of robust optimisation algorithms and their principles of application in power system scheduling, especially their advantages in dealing with wind power output uncertainty. Through a comprehensive analysis of the existing literature, this paper summarises including its application cases in the combination of wind turbines, planning and designing of wind farms, as well as the grid-connected operation of wind power. The results of this paper are of great help to users in terms of cost and rational use of resources.

2. Basic concepts of robust algorithms

Robust optimization is a methodology designed to address model parameter uncertainty by creating a strategy to maintain system performance within acceptable limits despite parameter variations. This property is particularly important in wind power systems, where the uncertainty of the wind power output poses a significant challenge to the stability and economy of the grid.

Its basic architecture consists of four core components: establishing the uncertainty range, setting the objective function, specifying the constraints, and selecting the optimisation strategy. The uncertainty set defines the potential magnitude of model parameter variations, which is the core building block of robust optimisation. The objective function plays a central role in the optimisation problem, and its main goal can be to reduce costs, improve efficiency or maximise revenue. By defining a well-defined objective function, it is possible to systematically search for the most optimal solution under given constraints. This function usually needs to be designed precisely according to the characteristics of the problem, to ensure that the solution meets both functional and operational requirements. The constraints ensure the feasibility of the optimised solution [7].

Since there is no definite model for robust optimisation algorithms, the model is generally determined based on the actual situation. In the power system robust optimisation problem, the model can be expressed as the following equation:

$$\min \mathrm{J} = \mathrm{f}(\mathrm{x}, \mathrm{y}) \tag{1}$$

$$\mathrm{s.t.g(x)} \leqslant 0 \tag{2}$$

$$h(\mathrm{x}, \mathrm{y}) \leq 0 \tag{3}$$

Where: $\mathrm{f}(\mathrm{x}, \mathrm{y})$ is the optimisation objective of the problem; for $\mathrm{x} \in \mathrm{R}_{\mathrm{n}}$ are uncertainty-independent decision variables, which can also be called structural variables, e.g., start-stop variables in the model; for $\mathrm{y} \in \mathrm{R}_{\mathrm{m}}$ are control variables that need to be adjusted according to the specific situation of the uncertain variables, e.g., the output value of the generating unit.

The constraint functions are defined as:

$$\mathrm{g(x)} = [\mathrm{g1(x)}, \mathrm{g2(x)}, \ldots, \mathrm{gI(x)}]\mathrm{T} \tag{4}$$

$$h(\mathrm{x}, \mathrm{y}) = [h1(\mathrm{x}, \mathrm{y}), h2(\mathrm{x}, \mathrm{y}), \ldots, h\mathrm{J}(\mathrm{x}, \mathrm{y})]\mathrm{T} \text{ with } h(\mathrm{x}, \mathrm{y}) = [h1(\mathrm{x}, \mathrm{y}), h2(\mathrm{x}, \mathrm{y}), \ldots, h\mathrm{J}(\mathrm{x}, \mathrm{y})]\mathrm{T} \ \ldots, \mathrm{gI(x)}]\mathrm{T} \text{ and } h(\mathrm{x}, \mathrm{y}) = [h1(\mathrm{x}, \mathrm{y}), h2(\mathrm{x}, \mathrm{y}), \ldots, h\mathrm{J}(\mathrm{x}, \mathrm{y})]\mathrm{T} \tag{5}$$

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Because the decision variables are divided into two kinds of structural variables and control variables, the constraints should be distinguished accordingly.

Equation (2) represents the structural constraint, where the coefficients are fixed and invariant, independent of the perturbation factors; and equation (3) represents the control constraint, where the coefficients are affected by the perturbation factors [8].

3. Uncertainty in wind power systems

Wind power systems, as a key component of the renewable energy sector, are playing an increasingly vital role in the global drive to transform the energy mix. Compared with traditional thermal and nuclear power generation modes, the distinguishing feature of wind power systems is the unpredictability of their output [9].

Firstly, wind speed, as an important factor in the uncertainty of wind power systems, has a direct and significant impact on their stability and efficiency. Wind systems utilise wind energy to drive generators to produce electricity. However, wind speed exhibits significant temporal and spatial fluctuations, which makes its accurate prediction challenging. Variations in wind speed are influenced by a variety of factors, including natural climatic phenomena, geomorphological features, and seasonal changes. Therefore, optimizing for uncertain parameters has become a primary concern in this field, which in turn has an impact on the stability of the power grid [10]. In the case of low wind speed, if the generation is not enough to meet the demand, it may lead to grid frequency instability, which in turn leads to the risk of power outage [11]. When high wind speed conditions are encountered, it may be necessary to temporarily deactivate the wind turbines in order to ensure the safety of the equipment, which may cause a temporary shortage of power supply. Secondly, the uncertainties associated with wind power technologies significantly affect the layout and operational efficiency of the grid. The intermittent nature of wind power can lead to grid instability and disrupt the continuous power supply, increasing the need for backup energy sources to handle fluctuations in wind generation. When large wind turbines are connected to the grid, the energy system must be able to flexibly adjust other generation resources (e.g., thermal and hydropower) to compensate for power shortages caused by wind energy fluctuations. Thus, the uncertainty of wind grid access increases the complexity of system deployment and requires greater flexibility and control of the energy system. In addition, the unpredictability of electricity demand further increases the complexity of wind turbine operations. As the share of wind power in the energy mix increases, there is a growing need for accurate load forecasting in power networks to effectively cope with the uncertainty of wind energy output. However, the high variability in power demand, combined with the stochastic nature of wind generation, significantly amplifies the complexity of power system operations.

3.1. Wind scheduling and host combinations

When exploring the scope of application of robust optimisation algorithms in wind power systems, the optimisation problem of wind turbine combinations indeed occupies a central position [12]. Robust optimisation algorithms show their unique advantages when facing the challenges of uncertainty, such as wind speed variations and prediction errors, which are unique to wind power systems.

Specifically, the main objective of introducing robust optimisation algorithms into the optimisation process of wind turbines is to cope with the challenges posed by forecast uncertainty. The use of robust optimisation algorithms allows for the design of more stable and adaptive control strategies, ensuring efficient and reliable operation of wind turbine generators (WTGs) despite potential errors and fluctuations in future wind speed forecasts. Robust optimisation algorithms aim to provide a decision-making framework for WTGs that can withstand the effects of external uncertainties, thus improving the stability and economy of overall energy production. In Robust optimisation (RO) scheduling models, the uncertainty of wind power output is usually described as a bounded closed set. Unlike stochastic optimisation models, which require information about the probability distribution of the wind power output, classical robust optimisation only requires information about the boundaries of the wind power output, i.e., the upper and lower limits of the uncertainty parameters. A typical two-stage RO model that takes into account the uncertainty of the wind power output during the optimal operation and dispatch of the power system is constructed as follows:

$$\begin{cases} \min(f_1(x) + \max[\min f_2(y,x,\xi)]) \\ \quad\quad \text{s.t.} \quad h(x) \leqslant 0 \\ \quad\quad\quad g(y,x,\ \xi\ )] \end{cases} \tag{6}$$

where: x is the decision variable; ξ is the uncertain random variable; U is the variation interval of the wind power uncertain variable, $U \in [u_{min}, u_{max}]$; $f_1(x)$ and $f_2(y,x,\xi)$ are the objective functions of the two stages, respectively; $h(x)$ and $g(y,x,\xi)$ are the constraints containing the decision variable of the first stage and the constraints of the second stage containing the random variable, respectively [13]. In short, applying robust optimisation algorithms to wind turbine combination optimisation enhances the stability and profitability of wind power generation systems while providing effective technical support for large-scale grid integration. As wind power technology advances and new optimisation algorithms emerge, the application of robust optimisation strategies in wind turbines is expected to demonstrate unprecedented potential and value.

3.2. Wind power grid integration planning

The fluctuating and intermittent nature of wind power generation poses a challenge to the stability and peak performance of the grid [14]. Robust optimisation techniques provide an effective strategy to cope with this difficulty. Yuan Shuang et al proposed a methodology that takes into account wind power time-dependent polyhedral uncertainty modelling and robust unit combination optimisation, which ensures system reliability and economy under grid-connected wind power [15]. Specifically, given the volatility and unpredictability of wind resources, the use of robust optimisation algorithms ensures the stable operation and economic efficiency of the power system, even in the face of a variety of potential operating scenarios and environmental changes. For example, a multilevel model that integrates wind speed prediction biases enables the identification and development of optimal planning scenarios for a wide range of wind conditions. This strategy not only takes into account the existing wind resource in real time, but also anticipates possible future changes in order to maximise the efficiency of the wind energy use, while ensuring the safety of the system operation. In addition, the robust optimisation algorithm can be flexibly adapted to specific needs, which significantly improves the system's adaptability and responsiveness. By adjusting the energy supply head, the robust optimisation algorithm reduces the carbon footprint of the system and significantly increases the proportion of renewable energy used.

3.3. Application of wind farm planning and design

In the field of wind farm planning and design, robust optimisation algorithms have demonstrated their unique advantages and non-negligible value [16, 17]. Such algorithms are able to provide robust solutions in environments with high uncertainty, ensuring that wind farms remain efficiently operated and economical in the face of various potential risks and variations. By taking into account factors such as wind speed variations, equipment failure rates, and power market fluctuations, robust optimisation algorithms are able to generate adaptable design solutions that can effectively improve the reliability and profitability of wind farms. Robust optimisation algorithms play a crucial role in improving the stability and efficiency of power allocation in wind farms. They select the optimal turbine model and configuration for varying wind conditions, optimising the overall performance of the wind farm. The algorithm not only considers the original purchase cost of the fan, but also analyses its operating cost and power generation efficiency. Further, the robust optimisation algorithm supports the layout and positioning of wind farms. By analysing multiple factors, such as terrain characteristics and climate patterns, the algorithm provides solid scientific guidance for the selection of ideal locations for wind farms. In this process, the algorithm not only takes into account the diversity of wind energy resources, but also evaluates grid access and environmental impacts to ensure the sustainability and green development of wind power projects.

4. Challenges of robust optimisation algorithms

Not to be neglected when discussing robustness analysis of wind power systems and the challenges they face is the application and outlook of robust optimisation algorithms. Although these algorithms provide effective solutions to the uncertainties and volatilities inherent in wind power systems, several practical challenges remain.

4.1. Computational complexity issues

A major problem is the computational complexity of the robust optimisation algorithm. Due to the nonlinear characteristics of wind power systems and the variability of environmental conditions, the models constructed are often large in scale and have many variables, resulting in a time-consuming solution process and difficulty in real-time optimisation. In addition, the conservatism of the algorithms is an issue that cannot be ignored. Robust optimisation aims to ensure an acceptable solution in all possible scenarios, however, this conservatism often comes at the expense of economy, limiting its efficiency in practical applications.

4.2. Calculation accuracy issues

Another key challenge is the improvement of prediction accuracy. The output power of a wind power system is affected by a variety of factors such as wind speed, temperature, and humidity, with prediction errors in these factors directly impacting the effectiveness of robust optimisation models. Although existing techniques have been able to provide accurate predictions to a certain extent, the accuracy of predictions still needs to be improved under certain extreme weather conditions, such as thunderstorms [18]. Meanwhile, the physical constraints and operational limitations in wind power systems also put higher requirements on robust optimisation algorithms. For example, the starting and stopping of wind turbines and the transmission capacity limitations of the power network need to be handled appropriately in the model. Balancing these complex constraints while maintaining algorithm robustness is a significant area of current research.

4.3. Impact of new energy technology development on wind power systems

In addition, with the continuous advancement of renewable energy technologies and the addition of new types of loads such as electric vehicles, wind power systems are becoming more and more complex [19]. This not only increases the uncertainty of the system, but also poses new challenges to robust optimisation algorithms. How to adapt to these changes and design algorithms that can deal with traditional problems as well as adapt to emerging challenges is the key to future research. Finally, from the perspective of practical applications, the popularity and application of robust optimisation algorithms also face the problems of cost and technology transfer. The development of efficient and low-cost algorithms, as well as the promotion of knowledge transfer between academia and industry, are important for promoting the application of robust optimisation algorithms in wind power systems. Future research needs to further explore how to overcome these challenges in order to achieve efficient, stable and economic operation of wind power systems.

5. Conclusion

By studying the application of robust optimisation algorithms in wind power systems, several critical issues need to be addressed, including the uncertainty of wind power generation, wind scheduling and unit combinations, grid-connected wind power planning, wind farm planning, the arrival of new energy development and the accuracy of the calculations. This paper elucidates not only the challenges it faces but also their potential. In particular, researchers must focus on developing algorithms that can respond to wind fluctuations in real time while maintaining a balance between economics and sustainability. Future research should explore the integration of robust optimisation with artificial intelligence techniques, aiming to significantly improve the accuracy of forecasting models and the intelligence of decision support systems. In the technical area, researchers need to explore more efficient computational strategies to address the challenges of computational difficulty and complexity in building and optimising large-scale wind power systems. For example, distributed computing and parallel processing techniques can be applied to accelerate the optimisation process and significantly improve the performance of real-time solutions.

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