Research on Robust Optimization Based Strategy for Enhancing Power Grid Consumption Capacity under Uncertain Wind Power Output

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2024 4th Power System and Green Energy Conference (PSGEC) | 979-8-3503-6557-3/24/$31.00 ©2024 IEEE | DOI: 10.1109/PSGEC62376.2024.10720956

***Abstract*—According to the uncertainty inherent in wind power output, robust optimization is employed to manage this variability. An uncertainty set is defined to represent wind power output, and a robust parameter is used to adjust the set's size. To simplify the calculation, the system's power flow equation is linearized. This involves approximating the cosine function, which relates voltage amplitude and phase angle to active and reactive power, using multiple linear segments for linearity. The wind power consumption model is established taking into account the system constraints impacting the absorption rate of wind power, and various factors influencing the capacity for wind power absorption are thoroughly investigated. The main factors affecting wind power consumption are the technical capabilities of grid connection, the system's peak regulation capacity, and the grid's transmission capacity. Finally, using the IEEE-39 system, a model is created with yalmip programming to analyze how the grid's transmission capacity limits wind power consumption rates.**

Keywords*—robust optimization; linearization of power flow equations; Wind power consumption model

I. Introduction

As a form of energy that may replace traditional fossil energy in the future, new energy is more economical and clean when converted into electricity. In recent years, significant advancements have been made in electricity generation technologies, with wind power and photovoltaic power leading the way in development and maintaining substantial growth potential. However, due to the randomness, intermittency, and volatility of new energy sources [1], the technical methods for predicting their output are not sufficiently advanced. Additionally, the uncertainty of user-end load significantly impacts the power grid's absorption capacity. Therefore, researching the output characteristics of new energy, the electricity consumption patterns of regional loads, and the grid structure and unit output characteristics is crucial for addressing the uncertain power consumption capacity of the grid caused by new energy output variability [2]. For wind power consumption research, researchers have explored optimization methods, focusing on three mainstream approaches: stochastic optimization, interval optimization, and robust optimization. However, robust optimization has better characteristics and has been favored by many researchers, especially in order to meet the requirements of different decision-makers, robust parameters have been proposed. The core idea is to transform the original problem into a convex optimization problem with polynomial computational complexity, achieving a certain degree of approximation. In reference [3], a method for solving nonlinear optimization models with random variables is proposed. The model is equivalent to the sum of optimization subproblems and run validation subproblems, and then the objective model is optimized and solved using genetic algorithm and robust optimization algorithm. Reference [4] proposes a data-driven method for constructing uncertain sets of renewable energy output prediction errors. Develop relevant electricity gas conversion plans based on the uncertainty of new energy output. Some literature has also developed models to optimize wind power utilization. Reference [5] introduces a method for addressing wind power output uncertainty using a chance constrained model. Construct a virtual power plant consisting of a microgrid that combines uncertain new energy output and deterministic loads. Based on the analysis of the working principles of carbon capture units and solar thermal power plants, reference [6] introduces a coordinated optimization scheduling model for virtual power plants. This model includes wind power, solar thermal, and carbon capture, while accounting for source load uncertainty. By applying fuzzy theory, the parameters for wind power and load are fuzzified, and deterministic system constraints are replaced with fuzzy chance constraints.

This paper treats wind power output as an uncertain set using robust optimization, where a robust parameter is adjusted to control the set's size. The power flow equation is linearized by incorporating the relationship between voltage and power, approximating the nonlinear term using piecewise and Taylor series expansions of the cosine function. This approach achieves the linearization of the power flow equation. Discuss the various constraints in the system and determine the constraints required for the study; Building upon these constraints, an optimization model is developed to enhance absorption capacity, taking into account the uncertainty in wind power output. The absorption model is then implemented using programming based on the IEEE-39 node system to validate the derived conclusions.

II. Wind Power Output Uncertainty Management and Power Flow Linearization

A. Use Robustness to Construct Wind Power Output Model

Wind power generation faces challenges due to its inherent uncertainty, which is crucial to address for effective grid integration. Robust optimization offers a method to construct a model that encompasses all scenarios of wind power output variability. Due to the unpredictable nature of wind, wind power output is represented as an uncertain set. The upper and lower bounds of this set are determined by the maximum and minimum wind magnitudes, which can be derived from historical data or predictions. To ensure robustness, the model must consider the worst-case wind scenario, accounting for uncertainty in wind energy fluctuations. This requires constructing a wind power output model that guarantees system safety under all conditions, ensuring secure integration of wind power into the network. Second, the designed model must be combined with the key factors influencing the optimization of the wind grid, which can simultaneously determine the location and capacity of the network to be incorporated. Ultimately, wind power generation and thermal power generation typically complement each other. In practice, the flexible adjustment capabilities of conventional units, such as thermal and hydropower plants, are often utilized to manage the random fluctuations in wind power output. Thermal power units perform peak regulation when wind power is integrated into the grid. It's essential for these units to maintain a sufficient peak regulation capacity to effectively manage the fluctuations in wind power output under all conditions; Secondly, the model also considers the ability to ramp up or down to accommodate changes in wind conditions. In summary, to manage fluctuations in wind power, the model incorporates the technical constraints of integrating conventional units to enhance wind power consumption. Generally speaking, in a typical scenario, the typical change of load size can be used to reflect the change of load in one day, and even represent the load change of a longer period of load, which is a reasonable representation of typical load.

Because there is great uncertainty and harsh conditions in wind power resources, the wind power output capacity that nodes are allowed to access has an upper bound, which is $\bar{C}_{wi}$; Secondly, due to the economic factors involved, there is a certain limit on the scale of wind farm investment, and there is also a limit on the number of wind farms that are allowed to be connected to the grid, which is N_W.

$$0 \le C_{wi} \le W_i \bullet \bar{C}_{wi} \tag{1}$$

$$\sum W_i = N_W \tag{2}$$

In the formula, the variable W_i is used to describe the node access situation. $W_i = 1$ means that the node is allowed to access the wind farm, and at that time, the node is not allowed to access the wind farm.

Since the accessible wind capacity of each node is a decision variable, it is difficult to describe the strength of the wind with a limited set. Therefore, it is first necessary to find its unit value according to the size of the grid-connected capacity, use historical data or predict the limit range of its maximum and minimum power, and use the scenario with wind power output as the limit as the actual wind power output within this limit range. For example, if the maximum active power of the wind farm connected to the node is 1.0 per unit (p.u.), and the minimum active power is 0 per unit (p.u.), then the random variable P_{wi}^s of wind power output will be randomly taken in the range from zero to its grid-connected capacity, and it is a random value. Therefore, the uncertainty in the randomness of wind power output is described by the following equation:

$$C_{wi} P_{wi}^{\min} \le P_{wi}^s \le C_{wi} P_{wi}^{\max}, i = I_w \tag{3}$$

In the formula, the superscript S represents the wind power output scenario corresponding to the typical load mode S, reflecting the seasonal characteristics of wind power.

Additionally, accounting for the stochastic deviation of wind power from its predicted output, the random variable P_{wi}^s of wind power output is equivalent to the sum of fluctuating power ΔP_{wi}^s and wind power output prediction $P_{wi}^{s,AVG}$. Among them, the predicted wind power output is derived from historical measurements or current forecast data, serving as a fixed parameter in the analysis; Fluctuating power is employed to quantify deviations from the predicted range of wind power generation, serving as a stochastic parameter in the analysis. This constraint can be expressed as follows:

$$P_{wi}^s = C_{wi}(P_{wi}^{s,AVG} + \Delta P_{wi}^s), i = I_w \tag{4}$$

Through substitution, an uncertainty set can delineate both the upper and lower bounds of the stochastic variations in wind power generation:

$$-\beta_i P_{wi}^{s,AVG} \le \Delta P_{wi}^s \le \beta_i P_{wi}^{s,AVG}, i = I_w \tag{5}$$

$$0 \le \beta_i \le 1 \tag{6}$$

Among them, β_i is the robust parameter for fluctuations in wind power output.

In the uncertain range of wind power output, an adjustable robustness parameter is introduced to limit the fluctuating power of wind power to a variation range. The reasonable values of different robust parameters can obtain models with different degrees of randomness, and realize the scaling of the value range of random parameters. Based on the above, the uncertainty in wind power output can be represented as:

$$0 \le P_{wi}^{s} + \Delta P_{wi}^{s} \le P_{wi}^{s,AVG} \tag{7}$$

B. Linearization of Power Flow Equations

The AC system bus and line equation is as follows:

$$P_i = \sum\nolimits_{j}^{i \neq j} P_{ij} \tag{8}$$

$$Q_i = \sum\nolimits_{j}^{i \neq j} Q_{ij} \tag{9}$$

$$\begin{aligned} P_{ij} &= \left|\tilde{v}_i\right|^2 g_{ij} - \left|\tilde{v}_i\right|\left|\tilde{v}_j\right| g_{ij} \cos(\theta_i^0 - \theta_j^0) \\ &- \left|\tilde{v}_i\right|\left|\tilde{v}_j\right| b_{ij} \sin(\theta_i^0 - \theta_j^0) \end{aligned} \tag{10}$$

$$\begin{aligned} Q_{ij} &= -\left|\tilde{v}_i\right|^2 b_{ij} + \left|\tilde{v}_i\right|\left|\tilde{v}_j\right| b_{ij} \cos(\theta_i^0 - \theta_j^0) \\ &- \left|\tilde{v}_i\right|\left|\tilde{v}_j\right| g_{ij} \sin(\theta_i^0 - \theta_j^0) \end{aligned} \tag{11}$$

Since formula (10) and (11) are asymmetrical and the line admittance values are not modified, the elements in the admittance matrix are extended to achieve a simplification.

The formula can be extended to cover line charging and other components like transformers and busbar shunts.

To approximate the reactive power in the stable start LPAC model, we consider the phase difference φ between the target voltage and the actual voltage.

$$\left|\tilde{v}\right| = \left|\tilde{v}^t\right| + \varphi \tag{12}$$

Substituting into the equation, get

$$\begin{aligned} Q_{ij} &= -(\left|\tilde{v}_i^t\right|^2 + \left|\tilde{v}_i^t\right|\varphi_i + \varphi_i^2) b_{ij} - (\left|\tilde{v}_i^t\right|\left|\tilde{v}_j^t\right| + \left|\tilde{v}_i^t\right|\varphi_j + \\ &\left|\tilde{v}_j^t\right|\varphi_i + \varphi_i\varphi_j)(g_{ij}\sin(\theta_i^0 - \theta_j^0) - b_{ij}\cos(\theta_i^0 - \theta_j^0)) \end{aligned} \tag{13}$$

$$Q_{ij} = Q_{ij}^t + Q_{ij}^{\Delta} \tag{14}$$

$$\begin{aligned} Q_{ij}^{\Delta} &= -(2\left|\tilde{v}_i^t\right|\varphi_i + \varphi_i^2) b_{ij} - (\left|\tilde{v}_i^t\right|\varphi_j + \left|\tilde{v}_j^t\right|\varphi_i \\ &+ \varphi_i\varphi_j)(g_{ij}\sin(\theta_i^0 - \theta_j^0) - b_{ij}\cos(\theta_i^0 - \theta_j^0)) \end{aligned} \tag{15}$$

Q_{ij}^t has target voltages, so they may be similar to $\tilde{Q}_{ij}^t$. Q_{ij}^t contain nonlinearities and non-convex items, making them more challenging. If we approximate it with the linear term of the Taylor series, we can get the following:

$$\tilde{Q}_{ij}^{\Delta} = -\left|\tilde{v}_i^t\right| b_{ij}(\varphi_i - \varphi_j) - (\left|\tilde{v}_i^t\right| - \left|\tilde{v}_j^t\right|) b_{ij}\varphi_i \tag{16}$$

In summary, LPAC mainly replaces the sinusoidal function with the phase angle difference approximation, and approximates the rest of the string functions through a series of linear constraints with only the phase angle difference, and the following is the trend linearization model.

$$P_{ij} = \left|\tilde{v}_i^t\right|^2 g_{ij} - \left|\tilde{v}_i^t\right|\left|\tilde{v}_j^t\right|(g_{ij}\hat{c}_{ij} + b_{ij}\theta_{ij}) \tag{17}$$

$$\begin{aligned} Q_{ij} &= -\left|\tilde{v}_i^t\right|^2 (b_{ij} + b_{ij}^c) - \left|\tilde{v}_i^t\right|\left|\tilde{v}_j^t\right|(g_{ij}\theta_{ij} - b_{ij}\hat{c}_{ij}) \\ &-2\left|\tilde{v}_i^t\right|(b_{ij} + b_{ij}^c)\varphi_i + \left|\tilde{v}_i^t\right| b_{ij}\varphi_j + \left|\tilde{v}_j^t\right| b_{ij}\varphi_i \end{aligned} \tag{18}$$

$$\left|\tilde{v}_i\right| = \left|\tilde{v}_i^{\,t}\right| + \varphi_i \tag{19}$$

$$\begin{aligned} &\hat{c}_{ij} \ge -\sin(hq - \theta_0)(\theta_{ij} - hq + \theta_0) + \cos(hq - \theta_0), \\ &h \in \{1, 2, 3, ..., p\}, q = 2\theta_0 / (p+1) \end{aligned} \tag{20}$$

wherein, $\tilde{v}_i^t$ is the known target voltage value of node i, which is generally taken as the rated voltage. φ_i is the difference between the two variables. $\hat{C}_{ij}$ is an approximation of The approximation of $cos\theta_{ij}$. p is the $\pm\theta_0$ given the upper and lower limits, and the number of tangents involved in θ_0 is to simulate the equivalent cosine function, and q is defined as the tangent interval at equivalence.

III. An Optimization Model That Takes Into Account the Uncertainty of Wind Power Output To Improve the Absorption Capacity

A. Related Constraints

1) Grid transmission capacity constraints

Grid transmission capacity can directly affect the reduction rate of wind power. In regions with more favorable wind resources, larger wind turbines are necessary to enhance efficiency. However, when the power transmission capacity of the system is constrained and there is surplus power, moderate restrictions on wind power output are essential to ensure safe operation of the grid. Consequently, the subsequent model employs a DC power flow approach, ensuring all transmission lines remain within operational limits, accounting for the stochastic nature of wind power:

$$-\overline{f}_L \le f_L^s \le \overline{f}_L \tag{21}$$

$$\begin{aligned} f_L^s &= \sum\nolimits_{n \in I_B} S_{Ln}(P_{Gn}^s + \Delta P_{Gn}^s \\ &+ C_{Wn}P_{Gn}^{s,AVG} + C_{Wn}P_{Gn}^s - P_{Dn}^s) \end{aligned} \tag{22}$$

Where f_L^s The power flow of the branch L under the typical load mode S is a random parameter. f_L is the transmission capacity limit for branch L, which is a known parameter. I_B is a known parameter for the system nodes. S_{Ln} is the power sensitivity matrix linking the branch power flow L and the injected power at node n, a known parameter. P_{Dn}^s is the load power of typical mode S and is a known parameter.

2) Power Balance Constraints

Constraints on system power balancing require the system to meet power supply and balancing needs at each typical load. Since the DC power flow model that needs to be built does not take into account the loss of the network, the limitations can be as follows:

$$\sum_{i\in I_w} P_{Wi}^{s,AVG} C_{Wi} + \sum_{i\in I_G} P_{Gi}^{s} = \sum_{i\in I_B} P_{Dn}^{s} \tag{23}$$

where C_{wi} is the number of fans; $P_{wi}^{s,AVG}$ is the active output of the fan; P_{Gi}^{s} is the active output of thermal power units; P_{Dn}^{s} is the size of the load.

3) Unit peak shaving depth

For ordinary units, its function not only needs to adapt to various typical load patterns in real time, but also needs to reserve some power range to adapt to changes in wind power. The stochastic component of wind power can be described as the sum of fluctuating power and predicted power, while the power generation plan of a conventional unit can also be determined by wind fluctuation and wind power forecasted power. Therefore, thermal power unit output is divided into two components, one is the output base point in the case of wind power prediction, P_{Gj}^{s}, and the other is the output adjustment size reserved by the unit, ΔP_{Gj}^{s}, which is used to cope with wind power fluctuations. Therefore, when the wind fluctuates in a fixed and uncertain set, the robust operational range of conventional units offers ample peak shaving capacity to offset wind power fluctuations:

$$P_{Gj}^{\min} u_j^s \le P_{Gj}^{s} + \Delta P_{Gj}^{s} \le P_{Gj}^{\max} u_j^s, j = I_G \tag{24}$$

In the formula, P_{Gj}^{max} and P_{Gj}^{min} represent the upper and lower bounds of power for the conventional unit, serving as fixed parameters. u_j^s is the variable $[0,1]$, which denotes the start-stop states of the conventional unit under load mode S. I_G is a collection of nodes for a conventional unit.

4) Linear Redistribution Strategy

In general, it is not enough to determine the robust operating area of a conventional unit to balance the wind power fluctuations, but also to establish the relationship between the capacity that the unit can regulate and the wind energy fluctuations. Considering the current situation, we propose a linear redistribution strategy to absorb the wind energy fluctuating power of the system according to it:

$$\Delta P_{Gj}^{s} = -\sum T_{ij}^{S} \Delta P_{w}^{s} C_{wi} \tag{25}$$

$$\sum_{i\in I_w} \Delta P_{wi}^{s} C_{wi} + \sum_{i\in I_G} \Delta P_{Gi}^{s} = 0 \tag{26}$$

In the formula, T_{ij}^{s} is the linear adjustment coefficient of the wind power fluctuation of node j of the conventional unit connected to node i under the typical load mode S.

5) Unit ramp-up rate

In order to smooth out wind fluctuations, it is not enough to rely on conventional units to adjust to a depth sufficient to cope with wind changes, which requires thermal power or hydropower units to adjust the hourly power change in real time to track rapid changes in wind speed. Conversely, if the power variation constraints of ordinary units in the system are not taken into account, it is overly optimistic that these engines will be able to quickly adapt to their power, thereby smoothing out wind power output in the event of high wind fluctuations, which may lead to compromised safety of the grid. Therefore, it is important to take into account the limitations of the ramp speed of conventional units to deal with wind fluctuations.

The following formula will be established by establishing a link between the conventional unit ramp-up rate and the maximum fluctuation of wind power:

$$\left| C_{wi} \bullet \Delta P_{Wi}^{s} \right| \le R_{wi}, i \in I_w \tag{27}$$

$$\left| \Delta P_{Wi}^{s} \right| \le \min\left\{ R_{wUj}, R_{Dj} \right\}, i \in I_G \tag{28}$$

where R_{wi} represents the maximum rate of change of wind power per minute. R_{wUj} and R_{Dj} denote the upper and lower bounds of the ramp-up rate for the conventional unit, respectively.

B. Establishment of Consumption Model

Based on the previous analysis, the primary factors influencing wind power integration are grid connection technology, grid transmission capacity, and the peak regulation capability of units. This paper investigates the impact of grid transmission power limitations on the absorption rate of wind power, that is, by comparing the transmission power constraints of two different sets of grid transmission power, it is verified that increasing the grid transmission power can improve the wind power absorption rate. Specifically, firstly, determine a branch transmission power range with a small upper and lower bounds, that is, the limit is small, to obtain the P_{ij} wind power consumption rate (reduction rate) in 24 periods, and then modify the limit of branch transmission power (generally relax the limit a little) to obtain the wind power consumption rate (reduction rate) in 2 4 periods, and verify the feasibility of measures to increase the consumption rate by comparing the two sets of wind power reduction rates. The objective function for the wind power absorption rate model can be defined as follows:

$$D_{ct}^{i} = \sum_{t\in T} (\xi_{i,t} - P_{i,t}^{r}) / \sum_{t\in T} \xi_{i,t} \tag{29}$$

In the formula, D_{ct}^{i} denotes the wind power reduction rate, $\xi_{i,t}$ denotes the predicted output of wind power, and $P_{i,t}^{r}$ denotes the actual wind power output. Building on this model, the worst-case scenario of wind power output is also considered. This problem can be described by the double-layer optimization model, and the core of the model is the optimization problem focusing on the output of thermal power units and wind turbines, aiming to minimize wind power curtailment without considering wind power uncertainty. The outer model addresses the secondary optimization problem under the worst-case scenario of wind power output. Therefore, the objective of this study is to achieve the following objective function:

$$\min_{P_{wp}\in\Phi}^{\max} f = \min_{P_{wp}\in\Phi}^{\max} \sum_{i\in w} D_{ct}^{i} \tag{30}$$

where ϕ represents the set of wind power that meets the aforementioned requirements.

To sum up, under the framework of robust optimization, a robust optimization model for wind power consumption is developed to minimize wind power reduction rate considering the constraints of the normal operation of the system. It can be summarized as the following equation:

$$\begin{cases} \max\min f, P_{wp} \in \Phi \\ s \cdot t \cdot \\ A(x, y, \tilde{P}_{wP}) < 0 \\ B(x, y, \tilde{P}_{wP}) = 0 \end{cases} \tag{31}$$

where x denotes the output of the thermal power unit, and y denotes other decision variables excluding the thermal power unit output. Superscript "~" only indicates that the parameters referred to by the model are uncertain.

IV. Verification of Examples

A. Example Introduction

Make improvements based on the IEEE-39 node system, as shown in Fig. 1, yalmip and cplex are employed to assess the impact of various factors on wind power curtailment rates. The system under study includes 39 bus nodes, 46 transmission branches, 10 conventional units, and one wind turbine is installed at 14 nodes, 11 nodes, and 24 nodes. The load characteristics are expressed in a constant load mode, with a total load of 6254.23 MW.

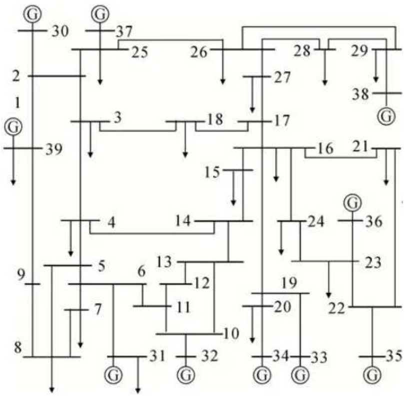

Fig. 1. IEEE-39 Node System Network Diagram

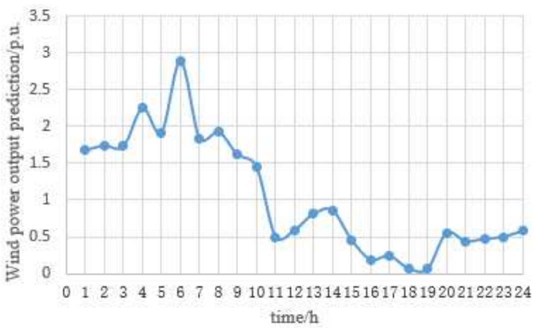

Fig. 2. Trends in wind power in one day

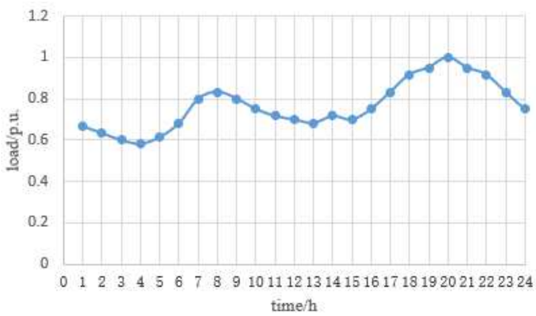

Fig. 3. Trends in load in one day

In this scenario, it is assumed that wind resources are uniform across all nodes, limiting the system's accessibility to just three wind farms. This considers constraints related to construction periods and investments in wind farm infrastructure. Furthermore, to depict the significant variability in wind power generation, each wind farm's output is modeled as a random variable. Specifically, its value fluctuates randomly between zero and its grid-connected capacity. Assuming that under normal weather conditions, the typical wind power output forecast in a day can be depicted in Fig. 2 below, since the wind strength varies at different times of the day.

Similarly, the typical load varies throughout the day, which can be described in Fig. 3 below.

B. Discussion of Robust Parameters

1) Robust optimized security

To assess the enhancement of power grid safety following robust optimization of wind power, we analyze the safety performance of wind power capacity planning and system operation under two models: deterministic output and robust optimization. The robust optimization method, which accounts for the stochastic nature of wind power output, can be viewed equivalently as a collection of random parameters. An uncertainty set can then be employed to encapsulate the range of possible wind power outputs. While the measurement method does not directly incorporate the randomness of wind power, it employs a defined parameter to represent wind power, effectively treating it akin to simulating a thermal power unit. To illustrate the benefits of robust planning in wind capacity optimization, we compare two planning methods.

Firstly, the wind power output is considered as a deterministic set, that is, the 11-node, 24-node and 14-node wind turbines in the example are changed to similar thermal power unit models, and the uncertainty of their output is no longer considered, the robust parameter (set at 0.5) serves as the coefficient for both the upper and lower bounds, and the wind power output is represented by a set defined by its upper and lower bounds, so that the output set is essentially analogous to that of thermal power units. As per the established optimization model, the objective function aims to minimize the reduction rate of wind power. When wind power output is treated as a deterministic parameter, the reduction rate for wind farm 1 is 0%, for wind farm 2 is 9.47%, and for wind farm 3 is 0%. This indicates that the predicted capacities of wind farms 1 and 3 are fully grid-connected, while the reduction rate for wind farm 2 remains relatively low. Thus, this planning scheme appears more optimistic in its outlook.

Secondly, the uncertain set derived from robust optimization serves as the output range for wind power. Specifically, wind farms at 11, 14, and 24 nodes are considered typical, with their output described using this uncertain set. Based on the established optimization model, the objective function aims to minimize the reduction in wind power output. With a robust parameter set at 0.5, it's found that wind farm 1 experiences a reduction rate of 53.31%, while wind farms 2 and 3 both see a reduction rate of 50%. Thus, it can be concluded that the wind power reduction rates at these three wind farms are generally high.

Comparing the two planning methods, when wind power uncertainty is taken into account versus treating it as deterministic, the optimization model predicts that all wind power outputs are connected to the grid. Despite achieving a low wind power reduction rate and adopting an optimistic wind power planning scheme, this approach poses a threat to power grid security. Similarly, when the wind power output is treated as an uncertain set, although its absorption rate is significantly reduced, connecting it to the grid reduces the threat to grid security. Given that grid operation prioritizes safety as the primary requirement, it is preferable to sacrifice some wind power absorption rate to ensure a safety margin for the grid. Therefore, adopting the robust optimization planning scheme for wind power is preferable.

2) Change in attribution rate with robust parameters

The following is an analysis of how robust parameters affect the absorption rate of wind power. The robust parameters are proposed to meet the needs of decision-makers to facilitate the construction of different wind power output sets. According to the derivation above, the smaller the robust parameter, the smaller the uncertain output set of the resulting wind power. In this section, an example is used to verify the change of wind power reduction rate when the robust parameters change. Let the robust parameters vary between 0.1 and 0.5, and the corresponding trend of wind power reduction rates is depicted in Fig. 4.

From Fig. 4, it is evident that as the robust parameter value increases, the uncertainty set constructed for wind power output becomes larger, leading to greater fluctuations in wind power changes. This situation is detrimental to wind power integration into the grid, resulting in higher wind power reduction rates. Therefore, to minimize the wind power reduction rate, we choose a robust parameter of 0.15 for the analysis in the following content.

C. *The Influence of Grid Capacity On the Reduction Rate*

We know that the factors that affect wind power consumption are: grid transmission capacity, wind farm grid-connected technology, and peak regulation capacity of non-wind

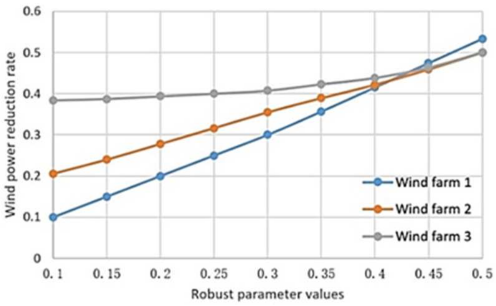

Fig. 4. The reduction rates of wind farm 1, wind farm 2, and wind farm 3 change with robust parameters

turbines. This subsection focuses solely on studying the impact of grid transmission capacity on the capacity of wind power that can be connected to the grid for consumption. Additionally, the ramp-up rate of non-wind turbines and the technical output range of these units also impose constraints on the integration of wind turbines into the grid.

1) Grade-up rate of thermal power units

Generally speaking, thermal power units have a relatively fast ramp-up rate, typically ranging from 50% to 100% per minute. In this example, the ramp-up rate of the thermal power unit is set as follows: starting from the second hour, the unit can ramp up to 80% of its maximum output within one hour. That means the regulation capacity of typical thermal power units is adequate to manage the fluctuations in wind power output from wind farms connected to nodes 11, 14, and 24.

2) The maximum and minimum technical output of thermal power units

Due to the high costs and complexity associated with starting and stopping thermal power units, and the numerous critical processes involved, the minimum technical output of these units is set to 30% of their maximum output. Similarly, to maintain spare capacity, there is a limit on the maximum output of thermal power units, allowing them to operate at up to 80% of their maximum output, with the remaining 20% reserved as spare capacity.

3) The influence of grid transmission capacity on the absorption rate of wind turbines

It is assumed that the output limits of thermal power units remain fixed throughout the day, while the output of wind turbines varies over the 24-hour period, subject to upper and lower bounds constraints specific to each time period. According to the law of node power balance, it is derived that the total inflow power at a node equals the total outflow power. Additionally, the power flowing through each branch is constrained within specified limits, which correspond to the transmission capacity limits of the grid. Firstly, the transmission capacity of the grid branches connected to nodes 11, 14, and 24, where wind farms are located, is constrained within -15 to 1.5 per unit (p.u.). That means the input of wind power into the grid is constrained by the grid's capacity, resulting in reduction rates of 28.15%, 50.51%, and 43.98% for wind farms located at nodes 11, 14, and 24, respectively, as indicated by the earlier wind power change trend. The daily trend of wind power consumption rates is depicted in Figure 5-(b), (d), and (f).

Secondly, the transmission power limits on the grid branches are adjusted, and here, the limits are directly cancelled. Subsequently, by substituting the data reflecting the wind power change trend over a day, reduction rates of wind power amount to 15%, 24.04%, and 38.75% respectively for wind farms at nodes 11, 14, and 24. The daily trend of wind power consumption rates is illustrated in Figure 5-(a), (c), and (e).

Comparing the wind power output diagrams under the two constraints, it is evident that after adjusting the transmission

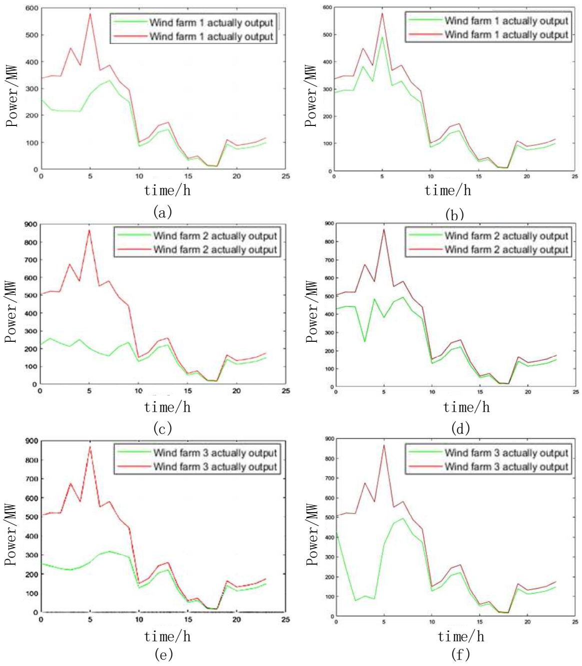

Fig. 5. The output of the wind farm before and after the power of the branch is restricted

power limits on the grid branches—specifically, relaxing these limits—the wind power output increases compared to before the relaxation. Consequently, the wind power reduction rates decrease by 46.71%, 52.41%, and 11.89% respectively for wind farms located at nodes 11, 14, and 24. It is evident that relaxing the transmission capacity limit of the grid within a certain range effectively enhances the absorption rate of wind power.

In summary, based on the IEEE39 node system, this section firstly verifies the beneficial impact of robust optimization on grid security when wind power is integrated into the power grid, and then verifies its relationship with the wind power reduction rate by changing the robust parameters, and determines other constraints other than the grid transmission capacity constraint. Then, by adjusting the grid transmission capacity limit within a certain range, it is confirmed that altering this constraint can enhance the rate at which wind power is consumed or absorbed into the grid. Indeed, this reasoning aligns logically: when the transmission capacity of grid branches is increased, wind power can more effectively supplement the output of thermal power units, compensating for reductions in wind power caused by its inherent uncertainty.

V. Conclusion

In this study, a strategy for improving the absorption capacity of power grid based on robust optimization is proposed, and the corresponding optimization model is constructed. This strategy uses robust optimization to deal with the uncertainty of wind power output, realizes the determination of the upper and lower bounds of wind power output, and discusses the main factors affecting wind power consumption. Finally, taking the IEEE-39 system as the basic example, the model is established by yalmip programming, and the influencing factor of wind power absorption rate is selected to limit the transmission capacity of the grid for analysis. The simulation results show that this strategy can effectively improve the wind power absorption rate.

Acknowledgment

This study is sponsored by State Grid Xinjiang Electric Power Co., Ltd. Considering the uncertainty in wind power output, employing robust optimization can effectively improve the reduction rate of wind power. Studying the reduction rate of wind power before and after imposing restrictions on wind power branches would be beneficial in assessing the impact of these constraints (5108-202218280A-2-343-XG).

References

[1] Ren Yan, Hou Shangchen, Zheng Yuan, et al. Hydropower & Pumped Storage,2024,10(02):18-23+26.

[2] Zhao Qian, Chen Fangfang. Times Agricultural Machinery, 2020, 47(04): 53-54.

[3] Zhao Liang. Research on robust optimization planning method and application of transmission network with new energy power system[D].Huazhong University of Science and Technology,2016.

[4] Shi Yunhui. Multi-stage robust dispatching method of power system considering the uncertainty of renewable energy[D].Zhejiang University, 2021.

[5] Yang Yao. Distributed coordination optimization of electricity-gas integrated distribution network considering uncertainty[D]. Xi'an University of Technology, 2021.

[6] Zhong Wuzhi, Huang Siyu, Cui Yang, Xu Jiakai, Zhao Yuting. Coordinated and optimal scheduling of wind-solar thermal-carbon capture virtual power plant considering source-load uncertainty[J].Power System Technology, 2020, 44(09):3424-3432.