Robust Optimal Dispatch of Power Systems with Wind Farm

Jinhua Zhang *, Bo Gu †, Hang Meng ‡, Chentao Fu §, Xueling Zhu ¶

Abstract

With the rapid development of new energy power generation, large-scale wind power generation has been integrated into power grids. However, the fluctuation and discontinuity of wind power pose challenges to the safe and reliable operation of power systems. Therefore, constructing a reasonable dispatching method to manage the uncertainty of wind power output has become an important topic and this study was structured with this precise aim in mind. An ellipsoidal robust set of wind power outputs was initially constructed in accordance with the predicted value and predicted error of wind power. Second, a power system optimization dispatch model of automatic generation control (AGC) was established on the basis of the robust set. This model aimed to minimize the cost of power generation and maximize the use of wind power according to the following constraint conditions: power system power balance, upper and lower limit of wind and thermal power unit outputs, climbing power, and spinning reserve. Finally, the internal point method was employed to solve the example. Results show that, on the premise of safe operation, the total operating cost of the robust optimization dispatch method is decreased by 8.64% compared with that of the traditional dispatch method, and economic efficiency is improved. Robust optimal dispatch factors in the uncertainty of wind power output meaning the load shedding scenario seldom occurs, thereby enhancing operational reliability. This study can be used to improve the reliability and economics of power system operation and provide a basis for optimizing dispatch in power systems.

Keywords: wind power, uncertainty, prediction error, robust optimization, economics

1 Introduction

Many countries have been vigorously developing wind energy as an alternative supply of energy. More than 100 countries and regions have developed wind power, which has become a considerable part of the global energy market. In the last decade, the installed capacity of wind power has steadily risen in China, reaching 11% of the total installed capacity in 2020 [1]. However, due to the complex distribution of wind resources, power load centers do not align with wind power generation centers. The discontinuity and fluctuation of wind resources [2]; [3]also pose considerable challenges to power systems [4]; [5]. First, wind power generation requires no fossil energy, and the power grids absorb as much wind power as possible; these conditions decrease the amount of abandoned wind and reduce the use of fossil energy in power grids. Second, other units are needed due to fluctuations in wind power. However, these additional units increase start-stop costs and seriously impact operational efficiency. Finally, prediction errors of wind power cause uncertainty of power system dispatch. Overall, these problems adversely affect the economics of dispatch power systems with wind farms. Scholars have intensively studied the optimal dispatch of power systems with wind farms [6]; [7]. Traditional optimal dispatching methods based on deterministic modeling do not consider the uncertainty of wind power generation, and these methods cannot guarantee the economics and reliability of dispatches. Therefore, there is a clear need to construct a reasonable and reliable set of wind power uncertainty and establish a power system optimization dispatching model that considers the uncertainty of wind power [8]; [9]. To this end, the current study established a robust optimization dispatch model for power systems with wind farms and used the interior point method to solve the model. The results were compared with those of traditional dispatch methods to verify the effectiveness of the proposed model in the economic operations of power systems. This study also provides a scientific basis for the power system optimization dispatch strategy.

*Corresponding author, North China University of Water Resources and Electric Power, Henan Province, 450046, China e-mail

†North China University of Water Resources and Electric Power, Henan Province, 450046, China e-mail

‡North China Electric Power University, Beijing, 102206, China e-mail

§North China University of Water Resources and Electric Power, Henan Province, 450046, China e-mail

¶North China University of Water Resources and Electric Power, Henan Province, 450046, China e-mail

2 State of art

Scholars have conducted numerous studies on the optimal dispatch of power systems with wind farms from the perspectives of uncertainty modeling of wind power prediction and optimal dispatch method for solving uncertainty. However, an accurate probability distribution function of wind power cannot be obtained. Thus, Xie Jun [10] constructed a wind power uncertainty set based on the uncertainty of wind power probability distribution and produced a power system dispatch scheme. Ye Yida [11] used a nonparametric conditional probability prediction method to describe the uncertainty of wind power. The conditional probability distribution of wind power was obtained in accordance with different confidence levels and influencing factors, and a dispatch model of wind power consumption was established. Based on the opportunity constraint programming method, Zhang Xinyi [12] established an economic dispatching model of power systems with wind farms. Factoring in the uncertainty of wind power output and load prediction, the fluctuation of load and wind power output was respectively satisfied by positive and negative spinning reserves. Alismail [13] used two distributed planning models to solve the distribution of wind farms in different regions.

Although these methods can achieve good results, the probability distribution of uncertain factors of wind power is difficult to determine in practice. Moreover, it is time consuming to establish a model through probability distribution and planning.

Robust optimization is widely used to solve the uncertainty of wind power parameters [14]. In a given parameter range, robust optimization obtains a set of poor solutions and ensures the reliable dispatch of power systems in the worst situations. Chen [15] established a multi-time-scale power system robust dispatch framework . This framework greatly improved the capability of power systems to handle wind power fluctuations, but failed to consider the uncertainty of wind power prediction. Within the context of network-constrained generation dispatch under wind-related uncertainty, Gonzalez Cobos [16] presented a new robust approach with precise operation characterization of slow- and fast-acting generating units in a day-ahead co-optimized energy and reserve market. Although the dispatch of fast- and slow- generating units was considered, the uncertainty of wind power output was neglected. Methaprayoon [17] split predicted wind farm output into two parts: reliable and uncertain outputs. Reliable output of wind power was consumed through unit commitment, whereas uncertain output was consumed through the reserve unit. These conditions enhanced the wind power consumption capacity, improved reserve capacity, and decreased the economic efficiency of power systems. Doherty [18] proposed a reliability criterion for setting the reserve capacity of a large-scale wind power grid-connected power system, but disregarded the coupling relationship between reserve capacities in each period. A unified reliability index was considered in all periods, but this index was conservative in terms of economics.

Attarha [19] proposed an adaptive robust self-dispatch model for a wind producer paired with a compressed air energy storage system to participate in the day-ahead energy market. The proposed model addressed the uncertainty regarding wind power production and price forecast errors. However, he disregarded the coordinated operation of traditional and new energy units. Holttinen and Black [20]; [21] proposed an $n\sigma$ criterion considering load–wind power prediction errors. Following linear programming theory, the unbalanced power of the system could be compensated when $n = 3$ (99.7%), but the prediction error of wind power could not fully conform to normal distribution. Ortega Vazquez [22] proposed a reserve capacity optimization method based on the prediction error probability distribution and determined the optimal reserve capacity for each dispatch period. The method was compared with the n-1 criterion proposed by Holttinen [20] and simulation results showed that the proposed method was the most economical.

For the transmission grid, Li Ran [23] used robust optimization technology to control the uncertainty influence of new energy output on the power system and effectively reduce the operating cost of the interconnected system. However, this method required frequent power adjustments on the connection line, thereby introducing security risks into the system. Shui Yue [24] established a two-stage distributed robust optimization dispatch model and integrated the 1- and ∞-norms to build an uncertain set of wind power output, but the efficiency of the robust model was low. Wang Beibei [25] established a hybrid optimization dispatch model that considered the general characteristics of wind power prediction and the advantages of robust optimization and stochastic programming. In the dispatch process, stochastic programming and robust optimizations were performed by switching the prediction accuracy. The dispatch model could obtain good optimization results, but high requirements were imposed for the switching timing of stochastic and robust optimizations. The forecast confidence interval of wind power could be used to quantify the uncertainty of wind power output. Thus, the dispatching center could respond to uncertain changes in wind power and risks based on the confidence interval.

Some of the above studies disregarded the errors and uncertainties of wind power prediction, whereas others used high-precision dispatch models that reduced the efficiency of the solution. The current study used a confidence interval with confidence probability of 95%. An uncertainty set of wind power output and an economic dispatch model of robust optimization were established in accordance with the predicted expected data and prediction errors. Finally, the simulation results of the optimal dispatch model were solved by the interior point method and compared with those of the traditional optimal dispatch method. The results verified the economics and robustness of the proposed model.

The remainder of this study is organized as follows. Section III describes the construction of uncertain sets, establishes the optimal dispatch model for power systems with wind farms, and provides the solution method. Section IV uses the interior point method to solve the robust optimal dispatch model and analyze the simulation results. Section V summarizes the present study and draws relevant conclusions.

3 Methodology

3.1 Construction of uncertainty set

The uncertainty set describes the uncertainty of wind power output. The construction of the wind power uncertainty set directly influences the operating characteristics of the power system and the reliability and safety of system dispatch. The traditional uncertainty set is constructed on the basis of a certain wind power output confidence interval considering the time smoothing and spatial clustering effects of wind power output. However, this method is conservative and the constructed set covers many invalid areas, thereby increasing calculation time and complexity. Convex uncertainty sets can substantially reduce the conservativeness while ensuring the accuracy of the set. Thus, the present study considered an uncertain set construction method based on prediction errors [26]; [27]; [28]; [29] and took error distribution as Gaussian distribution. The basic model is as follows:

$$\tilde{w} = \{w_e + \triangle w | \triangle w^T R^{-1} \triangle w \leq c\}$$

where $\tilde{w}$ is the uncertainty set of wind power output,w_e is the predicted value of wind power output, $\triangle w$ is the prediction error of wind power output, R^{-1} is the correlation matrix of wind power prediction errors, and c is a constant corresponding to certain confidence probability α.

The covariance matrix can be used to represent and characterize the probability density of multidimensional random variables. The covariance matrix of wind power output $\tilde{w}$ is Σ:

$$\tilde{w} = w_e + \triangle w$$

where the expected value of the predicted output error is expressed as $E(\triangle w) = 0$, and the covariance is $cov(\triangle w) = \Sigma$. The prediction error can be further expressed as follows:

$$\triangle w = \Sigma^{1/2} v$$

where the expected value of random vector v is 0, and the covariance is a unit matrix. Both ends of the above formula are multiplied with $\Sigma^{1/2}$:

$$v = \begin{Bmatrix} v_1 \\ . \\ . \\ . \\ v_n \end{Bmatrix} = \Sigma^{-1/2} \triangle w = \Sigma^{-1/2} \begin{Bmatrix} \triangle w_1 \\ . \\ . \\ . \\ \triangle w_n \end{Bmatrix}$$

where n is the number of wind farms, and $\triangle w_n$ is the prediction error corresponding to wind farm n.

Given a Gaussian distribution of v, owing to the independent random variables, the distribution of $\|v\|_2$ can be expressed as follows:

$$\|v\|_2 = v^T v = \triangle w^T \Sigma^{-1} \triangle w = v_1^2 + v_2^2 + \cdots + v_n^2$$

where $\|v\|_2$ obeys Chi-square distribution with a degree of freedom n . The uncertainty set of the wind farm can be further expressed as follows:

$$\tilde{w} = \{w_e + \triangle w | \triangle w_T \Sigma^{-1} \triangle w \leq K_\alpha\}$$

where K_α is the constant corresponding to the chi-square cumulative distribution function under the given confidence level α.

In this uncertain set, any two variables of $\triangle w$ can represent the prediction errors of a wind farm in different periods or those of different power plants in the same period. This uncertainty set is an ellipsoidal uncertainty set, which is a convex set. Different from the traditional uncertainty set, this convex set can guarantee the reliability and stability by reducing the conservativeness.

3.2 Robust dispatch model for wind power

Based on the wind power prediction interval $[\underline{P}^w, \overline{P}^w]$ uploaded to the dispatch center and other prediction information, the dispatch center calculates the planned output of each wind farm, the planned output value P^a of automatic generation control (AGC) units, and the planned output value P^s of non-AGC units in conventional power plants using the latest prediction data. These components are taken as basic power points of each power plant and issued to the corresponding power plants to complete the dispatching [30]; [31].

3.2.1 Variable definition

Wind turbines and conventional units are separately defined. Uncertainty parameter variables are expressed with superscript "~" The parameters of each unit are set as follows.

(1) Wind farm: The set of the dispatch period of wind power is T , the superscript set of wind farm is W, the planned output value of wind farm k in the t period is $p_{k,t}^{w}$, the actual output value is $\tilde{p}_{k,t}^{W}$, the predicted value is $\tilde{p}_{k,t}^{fW}$, and the prediction error is $\triangle w_{k,t}$. The total planned output value of k wind farms in the t period is w_t . The total actual output value of k wind farms in the $t$period is $\tilde{w}_t$, $k \in W$, and $t \in T$. These variables satisfy the following relationship:

$$\tilde{p}_{k,t}^{w} = \tilde{p}_{k,t}^{fW} + \triangle w_{k,t}$$

$$w_t = \sum_{k \in W} p_{k,t}^{w}$$

$$\tilde{w}_t = \sum_{k \in W} \tilde{p}_{k,t}^{w}$$

According to Equations (7) and (9),

$$\tilde{w}_t = \sum_{k \in W} \tilde{p}_{k,t}^{w} = \sum_{k \in W} (\tilde{p}_{k,t}^{fW} + \triangle w_{k,t})$$

The uncertainty set represented by Equation (6) can be rewritten as follows:

$$\tilde{w} = \{\tilde{w}_t | \triangle w_t^T \Sigma^{-1} \triangle w_t \leq K_\alpha\}$$

where $\triangle w_t$ is the matrix formed by the prediction errors of k wind farms in the t period, namely,

$$\triangle w_t = \begin{Bmatrix} \triangle w_{1,t} \\ . \\ . \\ . \\ \triangle w_{k,t} \end{Bmatrix}$$

(2) Conventional unit: The planned output value of non-AGC unit i in the t dispatch period is $p_{i,t}^{s}$, where s is the subscript collection for non-AGC units and $i \in s$.

The planned output value of AGC unit j in the t dispatch period is $p_{j,t}^{a}$, where a is the subscript collection for non-AGC units and $j \in a$. The actual output of the AGC unit is $\tilde{p}_{j,t}^{a} = p_{j,t}^{a} - \alpha_j(\tilde{w}_t - w_t)$, where α_j is set by the operating personnel as the deviation power bearing coefficient borne by the AGC unit in the case of actual wind power deviation, and α_j satisfies $\sum_{j \in s} \alpha_j = 1, \alpha_j \geq 0$.

3.2.2 Objective Function

Robust dispatch aims to maximize the use of wind power and minimize the cost of power generation [32]:

$$\min\left\{\sum_{t=1}^{T}\sum_{i \in G^s} C_{i,t}(p_{i,t}^{s}) + \sum_{t=1}^{T}\sum_{j \in G^a} C_{j,t}(p_{j,t}^{a}) + \sum_{t=1}^{T}\sum_{k \in w} \Phi_{k,t}\left(\tilde{p}_{k,t}^{w}\right)\right\}$$

where $C_{i,t}\left(p_{i,t}^{s}\right)$ is the power generation cost of non-AGC unit i in the t dispatch period, $C_{j,t}\left(p_{j,t}^{a}\right)$ is the power generation cost of AGC unit j in the t dispatch period, and $\Phi_{k,t}\left(\tilde{p}_{k,t}^{w}\right)$is the actual output deviation penalty cost of wind farm k in the t period.

The power generation cost of the conventional unit is expressed as follows:

$$C_{i,t}\left(p_{i,t}^{s}\right) = a_{i,t}\left(p_{i,t}^{s}\right)^2 + b_{i,t}p_{i,t}^{s} + c_{i,t}$$

$$C_{\mathrm{j},t}\left(p_{i,t}^{s}\right) = a_{j,t}\left(p_{j,t}^{s}\right)^2 + b_{j,t}p_{j,t}^{s} + c_{j,t}$$

where $a_{i,t}, b_{i,t}, c_{i,t}$ are the respective coefficients of quadratic, linear, and constant terms of the quadratic expression of the power generation cost of non-AGC units; $a_{j,t}, b_{j,t}, c_{j,t}$are the respective coefficients of the quadratic, linear, and constant terms of the quadratic expression of the power generation cost of non-AGC units.

The wind power generation cost is based on the penalty of the deviation between the upper limit of the wind power prediction interval and the actual output value.

$$\Phi_{\mathrm{k},t}\left(\tilde{p}_{k,t}^{W}\right) = M_k\left(\bar{p}_{k,t}^{W} - \tilde{p}_{k,t}^{W}\right)^2$$

where M_k is the output deviation penalty coefficient of wind farm k , and $\bar{p}_{k,t}^{W}$ is the upper limit of the prediction interval of wind farm k .

3.2.3 Constraints

(1) Power balance constraints

$$sum_{i\in G^{i}} p_{i,t}^{s}+\sum_{j\in G^{a}} p_{j,t}^{a}+\sum_{k\in W} p_{k,t}^{W}=D_{t}$$

where D_t is the load in the t dispatch period.

(2) Constraints on the output limitation of conventional units

$$\underline{P}_{i,t}^{S}\leq p_{i,t}^{s}\leq\bar{P}_{i,t}^{s}$$

$$\underline{P}_{j,t}^{a}\leq P_{j,t}^{a}-\alpha_{j,t}\left(\tilde{w}_{t}-w_{t}\right)\leq\bar{P}_{j,t}^{a}$$

where $\bar{P}_{i,t}^{s}$ and $\underline{P}_{i,t}^{S}$ are the upper and lower output limits of non-AGC unit i in the t period, respectively; $\bar{P}_{i,t}^{a}$and $\underline{P}_{i,t}^{a}$ are upper and lower output limits of AGC unit j in the t period, respectively.

(3) Climbing rate constraints of conventional units

$$-R_{Di,t}^{s}\Delta\mathrm{T}\leq p_{i,t}^{s}-p_{i,t-1}^{s}\leq R_{U,t}^{s}\Delta\mathrm{T}$$

$$-R_{Dj,t}^{a}\Delta\mathrm{T}\leq p_{\mathrm{j},t}^{a}-p_{\mathrm{j},t-1}^{a}-\alpha_{j,t}\left(\tilde{w}_{t}-\tilde{w}_{t-1}-w_{t}+w_{t-1}\right)\leq R_{Uj,t}^{a}\Delta T$$

where $R_{Di,t}^{s}$and $R_{U,t}^{s}$ are the downward and upward climbing rates of non-AGC unit i in the $t$period, respectively; $R_{Dj,t}^{a}$ and $R_{Uj,t}^{a}$ are the downward and upward climbing rates of AGC unit j in the t period, respectively.

(4) Spinning reserve constraint

$$0\leq r_{j,t}^{a+}\leq R_{Uj,t}^{a}$$

$$0\leq r_{j,t}^{a-}\leq R_{Dj,t}^{a}$$

$$r_{j,t}^{a+}\leq\bar{P}_{j,t}^{a}-p_{j,t}^{a}+\alpha_{j,t}\left(\tilde{w}_{t}-w_{t}\right)$$

$$r_{j,t}^{a-}\leq p_{j,t}^{t}-\underline{P}_{j,t}^{a}-\alpha_{j,t}\left(\tilde{w}_{t}-w_{t}\right)$$

$$\sum_{j\in G^{a}} r_{j,t}^{a+}\geq R_{t}^{+}$$

$$\sum_{j\in G^{a}} r_{j,t}^{a-}\geq R_{t}^{-}$$

where R_t^+ and R_t^- are the upward and downward spinning reserves in the t dispatch period, respectively.

(5) Wind power output constraints

$$\underline{P}_{k,t}^{W}\leq p_{k,t}^{W}\leq\bar{p}_{W,t}$$

$$\tilde{w}_{t}\in\tilde{w}$$

where $\bar{p}_{W,t}$ and $\underline{P}_{k,t}^{W}$ is the upper and lower limits of the predicted output interval, respectively.

(6) Wind power climbing constraints

$$\tilde{P}_{k,t}^{w}-\tilde{P}_{k,t-1}^{w}\leq R_{Uk,t}^{W}\Delta\mathrm{T}$$

$$\sum_{t\in s} R_{Dk,t}^{s}+\sum_{j\in a} R_{D,t}^{a}\geq R_{Uk,t}^{w}\Delta\mathrm{T}$$

$$\bar{P}_{k,t}^{w}-\tilde{P}_{k,t}^{w}\geq R_{k,t}^{w}\Delta\mathrm{T}'$$

$$-R_{Dx,t}^{W}-\tilde{P}_{k,t}^{w}\geq R_{k,t}^{w}-\tilde{P}_{k,t-1}^{w}$$

$$\sum_{i\in s} R_{ik,t}^{v}+\sum_{j\in a} R_{j,t}^{a}\geq R_{Dk,t}^{w}\Delta\mathrm{T}$$

$$\tilde{P}_{k,t}^{w}-\underline{\tilde{P}}_{k,t}^{w}\geq R_{Dk,t}^{w}\Delta\mathrm{T}$$

Equations (30)–(35) are the upward climbing constraints of wind power. The climbing constraints of wind power output not only meet their own climbing rate and capacity constraints, but also ensure that conventional units have sufficient downward or upward climbing rates and capacities to address the fluctuation of wind power. $\overline{\tilde{P}}_{k,t}^{w}$ and $\underline{\tilde{P}}_{k,t}^{w}$ are the maximum and minimum possible outputs of wind farm in the period, respectively.

3.3 Model Solving

3.3.1 Model Solving Method

The interior point method can be used to solve the robust optimization dispatch model of power system with wind farms. This method can also be used to solve inequality constraints. By constructing the interior point penalty function in the feasible region, the original problem with inequality constraints is transformed into the extreme value problem of the objective function in the feasible region. The basic principle of this approach is as follows.

When using the interior point method to solve the optimization of the objective function h

$$\begin{cases} \min \quad f(x) \\ \text{s.t.} \quad g_u(x) \leq 0 \quad (u = 1, 2, 3, \cdots, 4) \end{cases}$$

the expression of the constructed penalty function is as below:

$$\varphi\left(x, r^{(k)}\right) = f(x) - r^{(k)} \sum_{u=1}^{m} \ln |g_u(x)|$$

The second term in Equation (31) is the penalty term, and $r^{(k)}$ is a penalty factor, which is a set of decreasing positive sequences, that is:

$$r^{(0)} > r^{(1)} > r^{(2)} > \cdots > r^{(k)} > r^{(k+1)} > 0$$

$$\lim_{k \to \infty} r^k = 0$$

The basic iterative solution process is shown in Figure 1.

(1) Select the initial value of the penalty factor and allowable error to satisfy the penalty factor $r^{(0)} > 0$, allowable error $\epsilon > 0$, and decreasing coefficient c.

(2) Let $k = 1$, and select the initial point $x^{(0)}$ of the variable within the feasible region of the constructed penalty function.

(3) Construct and solve a penalty function $\varphi\left(x, r^{(k)}\right)$ from $x^{(k-1)}$ using the unconstrained method to obtain the extreme point $x'\left(r^{(k)}\right)$.

(4) Check whether the extreme point meets the termination condition. If the termination condition is satisfied, then iterative calculation is stopped, and the optimal solution of the original objective function is $x'\left(r^{(k)}\right)$; otherwise, proceed to the next step.

(5) Take $r^{(k+1)} = Cr^{(k)}$ and $k = k + 1$ and return to Step (3).

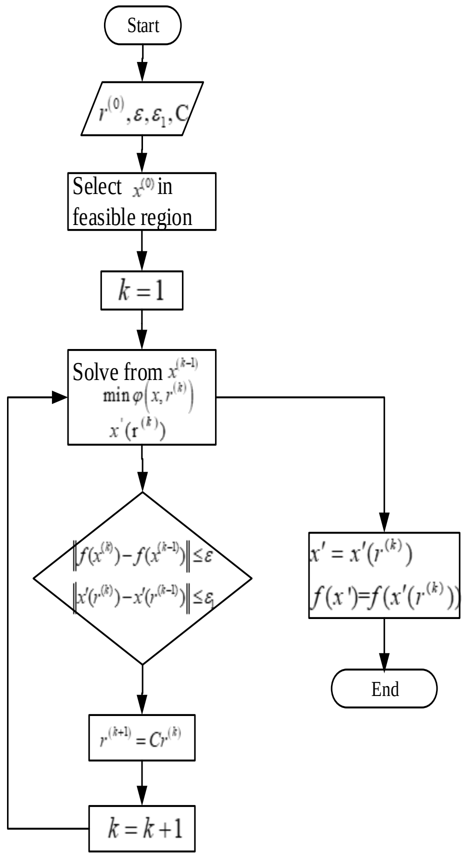

Figure 1: Calculation program diagram of the interior point method

3.3.2 Model Solving Process

With planned output value $P^s_{i,t}$ of non-AGC units, planned output value $P^a_{j,t}$ of AGC units, planned wind power output $P^W_{k,t}$, actual output value $\tilde{\mathbf{p}}^W_{k,t}$, predicted value $\tilde{\mathbf{p}}^W_{k,t}$, and predicted error Δw as decision variables, the constraints can be addressed for uncertainty set $\tilde{w}$. The solving process is shown in Figure 2.

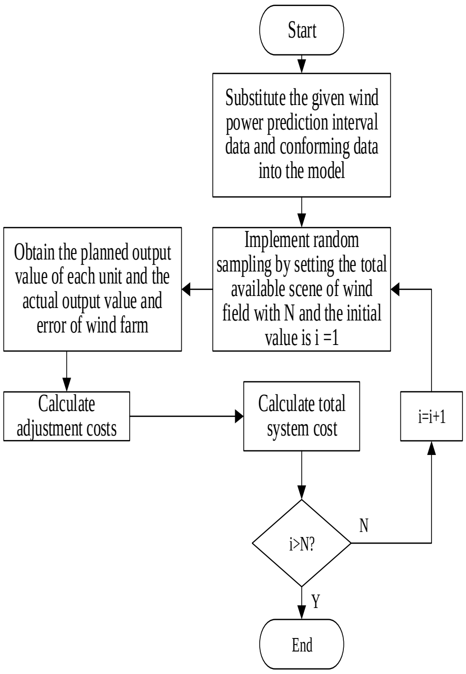

Figure 2: Calculation and algorithm flow chart

4 Result Analysis and Discussion

A power supply unit in a region was taken as an example to verify the robustness and economics of the proposed model. The results of the proposed model were compared with those of the traditional dispatch model to verify the robustness. The parameters of the conventional unit are shown in Table 1, where 4, 5, and 6 are AGC units, whereas the other units are non-AGC units. In this example, two wind turbines with capacities of 1500 (No. 1) and 2000 mw (No. 2) existed in the wind farm. The dispatch of each unit in 24 dispatch periods was studied. The standby release cost of the AGC units was also set to 80 USD/MW. The actual output deviation penalty coefficient of the wind farm was M_k=100. The prediction and load data were obtained from Reference [33] . The robust dispatch model was solved by the optimized interior point method and MATLAB 2013.

The uncertainty of wind power generation can be solved by establishing a suitable uncertainty set and applying this set to a robust economic dispatch model [34]. The above-mentioned construction methods for uncertainty sets are based on predicted values and prediction errors. These methods can construct the uncertainty set of similar wind farms in different periods and that of different wind farms in the same period. The uncertainty set was constructed in this study by different wind farms in the same period. Figure 3 shows the uncertainty sets of No. 1 wind farm and No. 2 wind power at t = 3. Figure 4 describes the uncertainty sets of No. 1 wind farm and No. 2 wind power at t=1. Figure 5 shows the uncertainty sets of Nos. 1 and 2 wind farms at t = 18. The ellipses in Figures 3, 4, and 5 assume that the power error of wind power obeys the Gaussian distribution. The uncertainty set was constructed when the probability distribution covers the prediction error with the confidence probability of 95%. The points in the figures represent the distribution of possible scene solutions. A total of 144 possible scene solutions were randomly taken. The established uncertainty set, which contains the scene solutions, has good convergence. In addition, the dispatch model has good convexity, which can enhance the applicability of the model. Most wind power can be consumed in practice. Thus, the phenomenon of extreme wind abandonment can be effectively reduced and the safe and reliable operation of the system can be guaranteed.

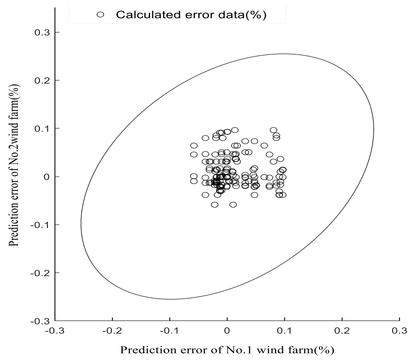

Figure 3: Uncertainty set of two wind farms constructed at t = 3

Figure 6 shows a comparison of the upward and downward spinning reserve capacities of the robust and the traditional economic dispatch models. Compared with traditional dispatch, robust dispatch requires the system to provide additional spinning reserve capacity to deal with the fluctuation of wind power generation. Consequently, the reserve release cost of robust dispatch is higher than that of traditional dispatch.

Table 2 shows a comparison of the simulation results of the two dispatches. The basic operating and reserve costs of robust dispatch are slightly higher than those of traditional dispatch. Thus, robust dispatch must reserve a certain spinning reserve capacity to handle the risks caused by the fluctuation of wind power generation. Through robust dispatch, the out-

Table 1: Setting of conventional unit parameters

Units	Upper limit of power /MW	Lower limit of power /MW	a/ (USD/MW2h)	b/ (USD/MWh)	c/) (USD/h)	Upward climbing rate /(MW/h)	Downward climbing rate /(MW/h)	Whether AGC or not
1	152	30.4	0	152	2165	120	120	0
2	152	30.4	0	152	2165	120	120	0
3	350	75	0	177	2250	420	420	0
4	591	200	0	165	2180	180	180	1
5	155	54.25	0	148	2080	180	180	1
6	155	54.25	0	148	2080	180	180	1

Table 2: Simulation result comparison between robust and traditional dispatch methods

Dispatch strategy	Basic operation cost / 10^6 USD	Reserve release cost / 10^5 USD	Wind curtailment penalty cost/ 10^7 USD	Load shedding cost /USD	Total cost / 10^7 USD
Robust dispatch	1.83	1.12	1.29	0	1.48
Traditional dispatch	1.78	0.89	1.54	25.6	1.62

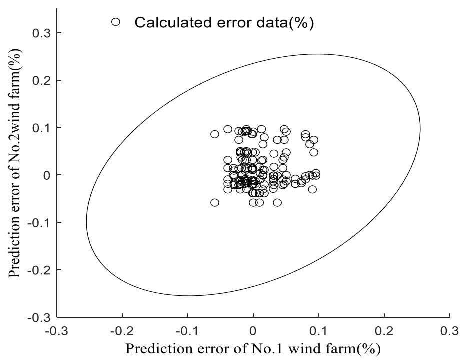

Figure 4: Uncertainty set of two wind farms constructed at t = 12

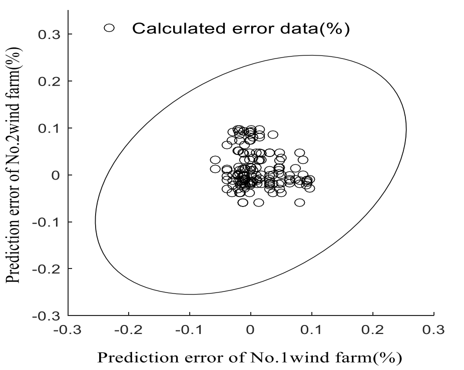

Figure 5: Uncertainty set of two wind farms constructed at t = 18

put of conventional units is reasonably arranged. Simultaneously, the AGC unit delivers robust dispatch in the permitted scene of wind power generation. When the uncertainty set contains most wind power outputs, the covered wind power output scenes need not be adjusted, and robust dispatch does not need a load shedding operation. The load shedding cost is low as well. The cost of robust dispatch is 1.48, which is lower than the traditional dispatch cost of 1.62. Hence, the cost is decreased by 8.64%. This finding indicates that robust dispatch is better in terms of economics than traditional dispatch. Compared with traditional dispatch, robust dispatch fully considers the uncertainty of wind power and rarely features load shedding. Therefore, robust dispatch enjoys good security and reliability.

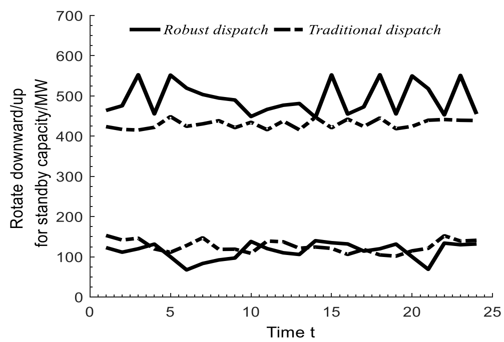

Figure 6: Reserve capacity comparison between traditional and robust dispatch methods

5 Conclusion

The large-scale integration of wind power into power grids poses considerable challenges to the safety, reliability, and economics of power system operations. In the prediction interval of wind power with certain confidence probability, this study established an uncertainty set with strong convexity on the basis of wind power prediction error to handle the uncertainty of wind power output. On this basis, this study constructed a robust scheduling model and verified the robustness and economics of the dispatch model by an example. The following conclusions may be drawn.

1. The convex uncertainty set constructed in accordance with the prediction error has low conservativeness while ensuring accuracy.
2. Compared with traditional dispatch, robust dispatch fully considers the uncertainty of wind power. Moreover, robust dispatch uses the AGC unit to adjust the output of the units and respond to the fluctuation of wind power output in the allowable scene of wind power generation. Wind curtailment is decreased substantially, thereby reflecting the strength of robust dispatch.
3. The basic operating cost of robust dispatch is similar to that of traditional dispatch. However, the standby cost of robust dispatch is higher than that of traditional dispatch, because it needs to reserve standby costs to handle changes in wind power. However, the cost of wind curtailment in robust dispatch is much lower than in traditional dispatch. Thus, robust dispatch enjoy the advantages of low total cost and high economic efficiency.

Combining the simulation model and the theoretical study of optimized dispatching of power systems with wind farms, this study proposed a robust optimization dispatch method to solve the uncertainty of wind power prediction. The proposed model is suitable for practical scenarios and provides a theoretical basis for optimized dispatch of power systems with wind farms. Therefore, multi-objective optimal dispatching of power systems with source load uncertainty will be considered in the future, based on the present study. Considering the coexistence of multiple types of power sources and multiple factors, such as environmental benefits, social benefits, reliability, and operating constraints, a multi-objective optimized dispatching model will be established to further improve the operational safety and economics of new energy power systems.

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