Environmental Science and Pollution Research (2023) 30:20980–20994
https://doi.org/10.1007/s11356-022-23591-8

RESEARCH ARTICLE

Distributed robust optimization for low-carbon dispatch of wind-thermal power under uncertainties

Jingliang Jin[1,2] · Qinglan Wen[1] · Yaru Qiu[1] · Siqi Cheng[1] · Xiaojun Guo[1,2]

Received: 25 November 2021 / Accepted: 8 October 2022 / Published online: 20 October 2022

Abstract
Faced with the requirement of carbon emission reduction in power industry, low-carbon power dispatch involving various low-carbon approaches has been recognized as one of effective ways. Concentrate on several important approaches: wind power integration and carbon reduction cooperation, it is necessary to deal with the uncertainties of wind power and carbon reduction modes for thermal power encountered in low-carbon power dispatch. For this purpose, this paper firstly presents a distributed robust optimization model synthetically considering robustness, economy, and environment. Next, wind power characterizations, scenario division and compression methods, and allocation algorithms of initial carbon emission rights are fully discussed for the convenience of model solution. Finally, empirical analysis shows that (1) the proposed model proves to be effective not only in coping with wind power uncertainties and reducing operating costs, (2) but also in dealing with the uncertainties of carbon reduction modes and reducing carbon emissions, and (3) low-carbon power dispatching strategies combining robustness, economy, and environment could be achieved through the proposed model and method, which are especially helpful to minimize interference from these two types of uncertainty more scientifically and reasonably.

Keywords Low-carbon power dispatch · Wind power integration · Carbon reduction cooperation · Robustness

Nomenclature

Variables:

T_f	the scheduled power output for the f th thermal power unit
W	the scheduled power output for wind power unit
W_s	the actual wind power output for scenario s
P_{load}	the total load demand of the power system
P_{loss}	the transmission line losses
$P(s)$	the normalized probability for each generated scenario s
c_f	the claim right of carbon emission for the f th thermal power unit
e_f	the initial carbon emission right for the f th thermal power unit

Parameters:

S'	the number of scenarios used for robustness comparison
M	the number of thermal power units
E	the total obligatory carbon emissions
r	the ratio of carbon emission reductions
a_f,b_f,d_f,g_f and h_f	cost coefficients for the f th thermal power unit
α_f,γ_f,λ_f,δ_f and τ_f	emission coefficients for the f th thermal power unit
$T_f^{\min}$	the minimum power generation limit of the f th thermal power unit
$T_f^{\max}$	the maximum power generation limit for the f th thermal power unit
B_{ij},B_{i0} and B_{00}	B-coefficients for the transmission network power loss

List of abbreviations:

CO_2	carbon oxides
ETS	emission trading system

Responsible Editor: Philippe Garrigues

✉ Jingliang Jin
chinajjl@ntu.edu.cn

1 College of Science, Nantong University, 9 Seyuan Road, Nantong, China

2 College of Economics and Management, Nanjing University of Aeronautics and Astronautics, 29 Jiangjun Avenue, Nanjing, China

PDF	probability distribution function
NSGA-II	nondominated sorting genetic algorithm-II

Introduction

Carbon emissions of electricity mainly come from large thermal power plants with fewer emission sources and more emissions, which is convenient to achieve large-scale and efficient carbon reduction through various low-carbon approaches (Wei et al. 2018). At the same time, with the increasing pressure of resources and environment, the deepening of market-oriented reform and the continuous improvement of users' requirements for electricity service quality, power industry is facing unprecedented challenges and opportunities (Zhang and Chen 2020). Building a more secure, economical, environment, and low-carbon power system has been increasingly set as target by the global power industry (Wang et al. 2019a, b, c). Undoubtedly, the development of low-carbon electricity has become a key strategy for promoting low-carbon economy, building smart power grid, and achieving sustainable development of power industry (Chen et al. 2021).

In the era of low-carbon electricity, the introduction of all kinds of low-carbon approaches will make the electric power industry appear obvious low-carbon characteristics and new operation modes, and bring extensive influence on power system operation (Menezes and Zheng 2018). As far as power dispatching is concerned, it refers to the decision-making and invocation of the operation mode and state of various electrical components on the basis of load forecasting, and the formation of certain dispatching plan on the corresponding time sequence (Hetzer and Yu 2008). In addition to the traditional security and economy, further attention should also be paid to carbon emissions from power system operation in the low-carbon environment; it is necessary to analyze the technical characteristics of various low-carbon power sources and impacts of their large-scale application on power system operation, and introduce a scientific and efficient "low-carbon power dispatching mode" (Li and Huang 2021; Xiang et al. 2021). Generally, the construction of low-carbon power dispatch is an interdisciplinary problem based on the theories of optimal power system dispatching, electricity price, and economic externalities, while the implementation of low-carbon power dispatch is a complex system engineering closely related to power dispatching technology, feed-in price mechanism, and carbon reduction policy (Shao et al. 2019; Jin et al. 2019).

Low carbonization of power dispatching could be realized in different ways, such as optimizing power sources structure and introducing incentive mechanism. Specifically, the global total installed capacity is significantly rising with the rapid development and application of renewable energy (Basu 2019). As a kind of zero-emission renewable energy, wind energy advanced rapidly and has progressively become an important option for developing clean energy. Governments around the world paid more and more attention to the rational use of wind energy, and wind power generation has gradually become a clean energy generation mode with great development potential (Zhao et al. 2017; Ren et al. 2020). Meanwhile, the introduction of carbon trading can promote the large-scale development of wind power and achieve energy saving and carbon reduction of power system. The main idea of carbon trading scheme is to control carbon emissions by creating legal carbon permits, or quotas, that allow them to be sold and bought like a commodity (Lin and Jia 2019). Since wind power generation has the advantage of no carbon emissions, the introduction of carbon trading is beneficial to reduce the costs of wind power generation, improve the competitiveness of wind power, and increase the outputs for energy-saving and environmentally friendly thermal power units, which is conducive to the promotion of low-carbon technologies (Tan et al. 2019). Above all, low-carbon power dispatch is facing multiple impacts of two low-carbon approaches: wind power integration and carbon reduction cooperation. Due to the uncertainties of wind power and carbon reduction modes for thermal power, low-carbon power dispatch becomes a more complex system with multiple uncertainties, which disturbs the safe operation of power system and poses new challenges to the current power dispatching process.

Nowadays, settling the low-carbon power dispatching problem under wind power uncertainties has gained widely concern from academia. To improve the reliability and flexibility of power system operation, Chen et al. (2016) propose a distributionally robust hydro-thermal-wind economic dispatch method which can not only depict wind power uncertainties through all possible probability distribution functions, but also optimize the expected operation cost in the worst distribution. By analyzing the power dispatching process as a dynamic sequential control problem, Meng et al. (2021) propose a Markov decision process model to formulate the optimal coordinated dispatching strategy which can deal with both load demand and wind power uncertainties. Integrating stochastic robust programming with interval two-stage programming, Ji et al. (2016) present a novel robust model for day-ahead dispatch and risk-aversion management involving wind power uncertainties, which can also retain the complete information based on low computation. In addition, the issues of low-carbon power dispatch under the influence of carbon reduction cooperation have also been investigated by many researchers. To supply a better view of the Belt & Road Initiative for coal power cooperation, Lin and Bega (2021) discuss the related evolutions, challenges, rationales, and prospects. Embedding the trading cost of carbon emission in the traditional economic dispatch model, Tsai and Yen (2011) simulate and analyze the impacts of the different strategies for generator's dispatch taking account of the carbon trading scheme. By proposing a novel characteristic function to describe possible minimal carbon emissions where power generation is prioritized by efficiency, Yang et al. (2020) formulate a graph restricted cooperative game model for the allocation of carbon reduction responsibilities among different areas. Generally speaking, low-carbon power dispatching problem is influenced by the joint action of many low-carbon approaches, and the uncertainties that come with them. In order to deal with the disturbances from various uncertainties, on the one hand, it is necessary to construct a more flexible dispatching decision frame from dispatching level and structure adjustment. On the other hand, it is equally important to treat low-carbon power dispatching problem under the new situation with an uncertain perspective, establish a new theory of low-carbon power dispatching strategies under the uncertain operation condition, and guide the formation and application of new dispatching methods.

Faced with the requirement of carbon emission reduction in power industry, low-carbon power dispatch involving various low-carbon approaches has been recognized as one of effective ways. Concentrate on several important approaches: wind power integration and carbon reduction cooperation, the influences of their uncertainties on low-carbon power dispatch cannot be ignored. Therefore, it is fairly meaningful to study robust optimization for low-carbon dispatch of wind-thermal power under uncertainties. Based on this, the purpose of our study is to solve the distributed robust optimization problem in the wind power integrated system imported with carbon reduction cooperation. Taking the effects of cost compression, carbon emission reduction, and uncertainty handling as evaluation criteria, by constructing the model and designing relevant solutions, this study tries to find the right balance separately between two types of contradictions in low-carbon power dispatch: robustness and economy, robustness and environment, and finally put forward low-carbon dispatching strategies taking into account robustness, economy, and environment comprehensively. With increasing focus on low-carbon power dispatch involving various low-carbon approaches, the method and result in this paper may be helpful to cope with the disturbances from the uncertainties of wind power and carbon reduction modes for thermal power more scientifically and reasonably.

This paper is organized as follows: "Preparation of methods" section discusses wind power characterizations, scenario division and compression methods, and the allocation algorithms of initial carbon emission rights. "Problem formulation" section develops a distributed robust optimization model synthetically considering robustness, economy, and environment. "Case study" section presents a discussion of numerical results achieved with comparative analysis. Finally, "Conclusion and recommendation" section concludes this paper with some policy suggestions.

Preparation of methods

Wind power characterizations

In face of the fluctuations in wind power output, it is obviously worth discussing the characterizations of wind power depending upon wind speed. To be specific, both wind power output and wind speed are regarded as random variables, and the former's statistical characteristics could be deduced from the probability distribution function (PDF) of wind speed. Generally, several kinds of wind speed PDF are frequently applied in wind speed forecasting: Weibull distribution, Gamma distribution, lognormal distribution, Burr distribution and Rayleigh distribution, etc. (Chang 2011).

Weibull distribution is relatively simple in form, which is explicit for wind speed, convenient for calculation, and has the widest application range. However, its fitting effect is only applicable in ordinary wind speed forecast, because it cannot fit some extreme values, and its PDF can be described as follows (Zhou et al. 2006):

$$f_V(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1}\exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{1}$$

where v represents the wind speed, k signifies the shape parameter (dimensionless), and c denotes the scale parameter (the same dimension of wind speed).

Besides, though lognormal distribution has a good overall fitting effect, the effect is not very good at too low or too high frequencies, and its PDF can be written as below (Jin et al. 2015):

$$f_V(v) = \frac{1}{\sqrt{2\pi\sigma v}}\exp\left[\frac{-(\ln v-\mu)^2}{2\sigma^2}\right] \tag{2}$$

where μ is the location parameter; σ is the scale parameter.

Due to the wide applications of above two distributions, integrate them and have complementary advantages. That is, the mixture of Weibull and lognormal PDF may be particularly relevant for normal wind speed forecast. Furthermore, the statistical characteristics of wind power output can be deduced from wind speed PDF, and the corresponding transformations are shown in the following form (Wang et al. 2019a, b, c):

$$w = \begin{cases} 0, & v < v_{in} \\ w_{rated}\frac{v-v_{in}}{v_r-v_{in}}, & v_{in} \le v < v_r \\ w_{rated}, & v_r \le v < v_{out} \\ 0, & v \le v_{out} \end{cases} \tag{3}$$

where w is the wind power output, w_{rated} represents the rated wind power output, v_{in} signifies the cut-in wind speed, v_r is the rated wind speed, and v_{out} stands for the cut-out wind speed.

Scenario division and compression

In order to ensure the robustness of wind power integrated system, a number of representative scenarios of wind power outputs should be determined before distributed robust optimization. Firstly, the interval of wind speed could be divided into multiple scenarios. Theoretically, the more wind speed scenarios are divided, the more accurate the description of wind power output will be (Aghaei et al. 2013). In particular, the selection of scenarios is to evenly divide the wind speed interval $\left[0, v_r\right]$ into S intervals respectively: $\left[0, \frac{1}{S}v_r\right], \left[\frac{1}{S}v_r, \frac{2}{S}v_r\right]$ $, \ldots, [\frac{S-1}{S}v_r, v_r]$, and the value of each wind power scenario ($w(s), s = 1, 2, ..., S$) based upon Eq.(3) together with its corresponding probability ($P(s), s = 1, 2, ..., S$) from Eqs.(1, 2) could be deduced.

So far, all scenarios of wind power have been obtained by dividing intervals, yet in fact a large amount of calculation is required if every scenario is involved, which obviously needs to be simplified. Next, synchronous back-generation subtractive method is adopted for scenario compression, and selected wind power scenarios are reduced to fewer scenarios for ensuring the minimum probability distance between the compression scenario set and the original scenario set. By using fewer wind power scenarios, the purpose of scenario compression technology is to maximize the randomness of wind power output and guarantee the calculation accuracy of model, and the steps are specially designed as follows (Biswas et al. 2019):

Step 1: Determining the scenario $w(s^*)$, $s^* \in (1, 2, ..., S)$, which not only takes into account the Euclidian distance $d(w(n), w(m))$ between different scenarios $w(m)$ and $w(n)$, but also concerns their probabilities $P(s^{(m)})$ and $P(s^{(n)})$, therefore the most unrepresentative scenario $w(s^*)$ is more likely to be eliminated:

$$P(s^*)\{\min_{s \ne s^*} P(s)d(w(s), w(s^*))\} = \min_{m \in \{1,2,...,S\}} P(s^{(m)})\{\min_{n \ne m, n \in \{1,2,...,S\}} P(s^{(n)})d(w(n), w(m))\} \tag{4}$$

Step 2: Selecting the scenario $w(s)$ that is closest to scenario $w(s^*)$, and $w(s)$ is paired with scenario $w(s^*)$ in step 1.

Step 3: Recounting the probability of scenario $w(s^*)$, which is closest to the probability of the deleted scenario, namely:

$$P(s^*) = P(s^*) + P(s) \tag{5}$$

Step 4: Updating the total number of scenarios:

$$S = S - 1 \tag{6}$$

Step 5: If the number of remaining scenarios is still greater than the number of required scenarios, then repeating step 1, otherwise terminating the operation.

As discussed above, the main flow chart of the synchronous back-generation subtractive method is plot in Fig. 1.

Initial carbon emission rights

Considering the importance of reasonable allocation of initial carbon emission right among each thermal power unit, it is necessary to explore the allocation algorithms of initial carbon emission rights balancing equality and rationality. To be specific, the carbon emission corresponding to unit approval hours is the carbon emission claim right promised by the government to the unit, while the total carbon control target of the power industry determined by the government is the gross amount of resources which can be allocated. Based on the theory of equitable allocation of claim right, there are several initial allocation algorithms of carbon emission right: proportional method, uniform gains method, uniform losses method, and Talmud rule (Herrero and Villa 2001; Moulin 2003).

1. Proportional method

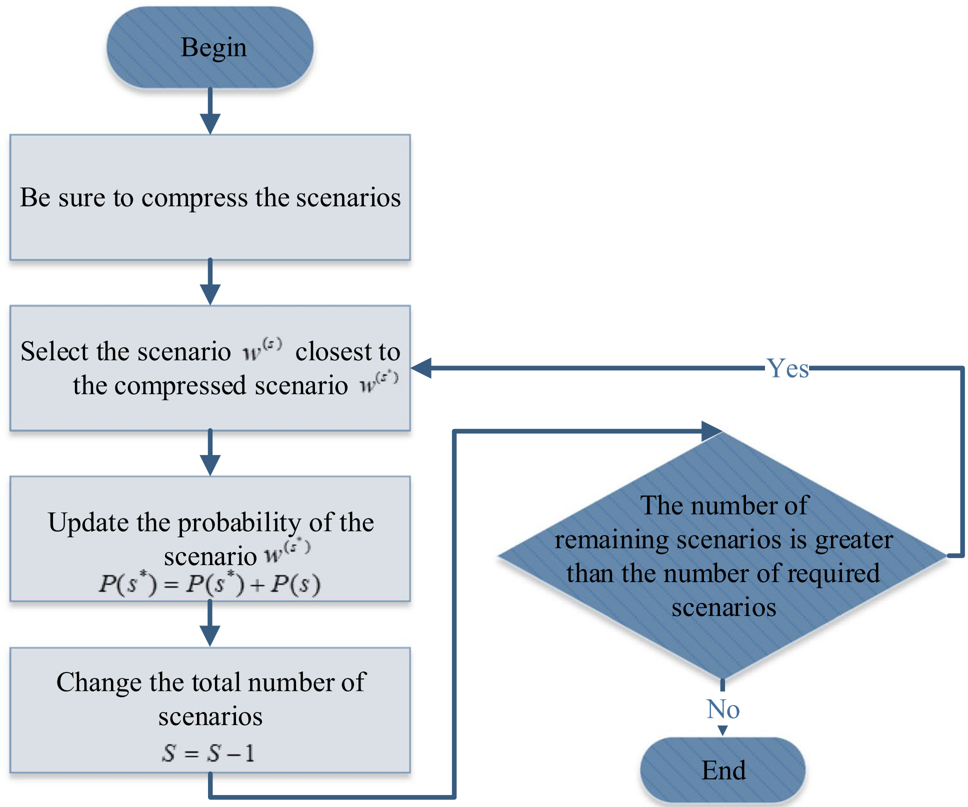
$$e_f = \frac{c_f}{\sum_{f=1}^{M} c_f}E, \quad 1 \le f \le M. \tag{7}$$

Where e_f is the initial carbon emission right of the f th thermal power generator, c_f is the claim right of carbon emission for the f th thermal power generator, and E is the overall obligatory carbon emissions.

Correspondingly, all claim rights will form a vector ($C = (c_1, c_2, ..., c_M)'$), and the whole carbon emission right for all thermal power units adopting proportional method ultimately constitute a vector ($W_{Pro}(M, E, C) = (e_1, e_2, ..., e_M)'$).

2. Uniform gains method

Fig. 1 Flow chart of scenario reduction method



$$e_f = \min\{\mu', c_f\}, \quad 1 \le f \le M. \tag{8}$$

Where μ' is the optimal solution of the following function:

$$\sum_{f=1}^{M} \min\{\mu', c_f\} = E. \tag{9}$$

Accordingly, all the carbon emission rights for the whole thermal power units using uniform gains method will form a vector $(W_{Ug}(M, E, C) = (e_1, e_2, \ldots, e_M)')$.

3. Uniform losses method

$$e_f = \max\{c_f - \mu, 0\}, \quad 1 \le f \le M. \tag{10}$$

Where μ is the optimal solution of the following function:

$$\sum_{f=1}^{M} \max\{c_f - \mu, 0\} = E. \tag{11}$$

Correspondingly, the whole carbon emission right for all thermal power units through uniform losses method will constitute a vector $(W_{Ul}(M, E, C) = (e_1, e_2, \ldots, e_M)')$.

4. Talmud rule

$$e_f = \begin{cases} W^f_{Ug}(M, E, \frac{1}{2}C), & E < \frac{1}{2}\sum_{f=1}^{M} e_f \\ \frac{1}{2}c_f + W^f_{Ul}(M, E - \frac{1}{2}\sum_{f=1}^{M} e_f, \frac{1}{2}C) & E \ge \frac{1}{2}\sum_{f=1}^{M} e_f \end{cases}, \quad 1 \le f \le M. \tag{12}$$

Where W_{Ugf} is the f th element of W_{Ug}; W_{Ulf} is the f th element of W_{Ul}.

Above four methods are important achievements of the theory of equitable distribution: proportional method expresses a neutral value orientation, similar to “work more and get more”; uniform gains method allocates the emission rights as equally as possible, and the allocation share should be biased toward the participants with lower claim rights; uniform losses method is the equal allocation from the angle of claim deficiency, which is beneficial to the participants with higher claim rights; Talmud rule is a method synthesizing uniform gains method with uniform losses method, it tends to be egalitarian and protect the weak when the total amount of resources is small, while its incentive is advanced and the overall efficiency is improved when the total amount of resources is large. Since different methods are the only allocation schemes satisfying their respective axioms, comprehensive strategies can be successfully achieved by weighted assignments. Specifically, the weights could be fixed as a simple average, or it can be set with the size of each claim right.

Problem formulation

Facing the disturbances from the uncertainties of wind power and carbon reduction modes for thermal power, it is necessary to ensure the robustness of the wind power integrated system imported with carbon reduction cooperation (Wei et al. 2016). Specifically, a maximization problem is required for finding some worse probability distributions in several generation output scenarios to minimize the negative externality costs deriving from wind power uncertainties, because those worse scenarios may cause remarkable rises of objective cost in the form of penalty. In addition, the uncertainties of carbon reduction modes for thermal power will complicate the measurement of carbon emissions and further influence system robustness, and therefore some worse carbon reduction scenarios should be singled out in the carbon emission rights constraint.

Based on these considerations, combined with the previous discussions of wind power characterizations and initial carbon emission rights, the present formulation treats low-carbon dispatch of wind-thermal power as a distributed robust optimization model which tries to minimize system operation costs while maximizing the disturbances from the uncertainties of wind power and carbon reduction modes for thermal power, and to meet carbon reduction requirements and some other general operation constraints. Comparing with the traditional robust optimization model only focusing on the worst scenario, the proposed model aims to find several worse scenarios of wind power and carbon reduction. Eventually, it will determine the production levels of scheduled units to satisfy generation constraints, which may coordinate robustness, economy, and environment of power system simultaneously.

Objective function

To deal with wind power uncertainties and further to ensure the economy and robustness of power system, a minimum-maximization form of distributed robust optimization is set up in the objective function described by Eq. (13), which consists of two parts, namely fuel costs of thermal power units and negative externality costs of insufficient or surplus wind power output.

$$\max_{s\in\Omega_W}\left\{\sum_{s=1}^{S'}P(s)\min\left[\sum_{f=1}^{M}C_f(T_f)+G_s(W)\right]\right\} \tag{13}$$

Where Ω_W is the feasible set of wind power output scenarios, $P(s)$ is the probability of scenario s, S' is the number of scenarios used for robustness comparison, C_f is the fuel cost function of the f th thermal power unit, T_f is the scheduled power output for the f th thermal power unit, M is the total number of thermal power units, G_s is the negative externality cost function when the wind power output is insufficient or surplus, and W is the scheduled power output for wind power unit.

As far as a single thermal power unit is concerned, its economic cost function is normally in the form of quadratic function. In fact, the consumption characteristic curve will have a superposition effect of impulse response named the valve point effect, when the steam turbine intake valve is suddenly opened. In order to ensure that the accuracy of model solution to be identified is not significantly affected, a sine function is usually added in the model, together with the economic cost function of the thermal power unit as follows (Zugno and Conejo 2015):

$$C_f(T_f)=a_fT_f^2+b_fT_f+d_f+|g_f\sin(h_f(T_f^{\min}-T_f))|,\quad 1\le f\le M\,. \tag{14}$$

where a_f, b_f, and d_f are the generation cost coefficients of the f th thermal power unit; g_f and h_f are the valve point cost coefficients for the f th thermal power unit; and $T_f^{\min}$ is the actual active power output lower limit of the f th thermal power unit.

In terms of wind power uncertainties, if the actual wind power output is greater than the scheduled output, it will result in a certain degree of wind power output waste. On the contrary, power shortages need to be purchased from thermal power, otherwise loads will be shed. Therefore, the negative externality cost function G_s related to wind power uncertainties ought to be added into the objective function as shown below:

$$G_s(W)=k_{penalty}\cdot|W-W_s|,\quad 1\le s\le S. \tag{15}$$

where k_{penalty} is the penalty coefficient; W_s is the actual wind power output for scenario s.

Constraint function

Real power output constraint

$$T_f^{\min}\le T_f\le T_f^{\max},\quad 1\le f\le M\,. \tag{16}$$

where $T_f^{\max}$ is the maximum power generation limit of the f th thermal power unit.

Real power balance constraint

The power balance constraint involving the system network loss which the power system must meet is indicated below (Wang et al. 2019a, b, c):

$$\sum_{f=1}^{M} T_f + W = P_{load} + P_{loss} \tag{17}$$

where P_{load} is the total load demand of the power system; P_{loss} is the transmission line losses.

Moreover, the DC power flow method including the line capacity constraints is utilized to compute the power flow on each line. Based on the Kron's loss formula (Wood and Wollenberg 1984), the format of transmission loss in Eq.(16) is expanded as follows:

$$P_{loss} = \sum_{i=1}^{M}\sum_{j=1}^{M} T_i B_{ij} T_j + \sum_{i=1}^{M} B_{i0} T_i + B_{00} \tag{18}$$

where B_{ij}, B_{i0}, and B_{00} are B-coefficients for the transmission network power loss.

Carbon emission rights constraint

Taking account of carbon reduction modes for thermal power, carbon emission rights constraints could be grouped under two headings: non-cooperative and cooperative mode. As for the cooperative mode, carbon emission rights constraint can be summarized as follows:

$$\sum_{f\in\varphi_i} E_f(T_f) \le \sum_{f\in\varphi_i} \mathrm{e}_f,\quad \forall\varphi_i \in 2^{\Omega_T}, 1 \le i \le (2^M - 1). \tag{19}$$

where E_f is the emissions function for the f th thermal power unit, e_f is the initial carbon emission right of the f th thermal power unit, and φ_i is a partition set of the universal set $\Omega_T = \{Unit_1, Unit_2, ..., Unit_M\}$ from all thermal power units. Besides, CO_2 emissions from the thermal power units can be measured as the superposition of a quadratic and an exponential function (Arula et al. 2015):

$$E_f(T_f) = \alpha_f T_f^2 + \gamma_f T_f + \lambda_f + \delta_f \exp(\tau_f T_f),\quad 1 \le f \le M\,. \tag{20}$$

where α_f, γ_f, λ_f, δ_f, and τ_f are emission coefficients for the f th thermal power unit.

Theoretically, it is supposed that wind power units have nearly no carbon emissions, thus the total carbon emissions of power system should satisfy the specific carbon emission reduction target, whatever the mode. This, to some extent, guarantees the environment of power system:

$$\sum_{f=1}^{M} E_f(T_f) \le (1-r)E,\quad 0 \le r \le 1\,. \tag{21}$$

where r is the ratio of carbon emission reductions; E is the total obligatory carbon emissions.

In particular, as for the non-cooperative mode, Eq.(19) could be specified as follows:

$$E_f(T_f) \le e_f,\quad 1 \le f \le M. \tag{22}$$

To be sure, considering the uncertainties of carbon reduction modes for thermal power, a M-units power system will totally contain up to $\left(2^M - M - 1\right)$ various scenarios for carbon reduction cooperation through the exhaustive method, which obviously increases the complexity of optimization. Different from the non-cooperative mode, some representative scenarios in the cooperative mode need to be selected for the convenience of calculation. In fact, to cope with the uncertainties of carbon reduction modes, $(M-1)$ representative scenarios for the sake of system robustness are composed of units with poorer performances in carbon emission reduction, and Eq. (19) can be simplified for cooperative mode as below:

$$\sum_{f\in\phi_i} E_f(T_f) \le \sum_{f\in\phi_i} \mathrm{e}_f,\quad \forall\phi_i \in \Omega_R \subset 2^{\Omega_T}, 1 \le i \le (M-1). \tag{23}$$

where Ω_R is the set of representative scenarios.

Case study

From the previous discussion, a distributed robust optimization model considering the uncertainties of wind power and carbon reduction modes for thermal power, together with the model solution are presented to solve the low-carbon power dispatching problem. Furthermore, this optimization model in a more general form is applicable to most cases, because different parameters for objectives, constraints, wind power characterizations, and initial carbon emission rights could be fixed upon actual situation. With the emergence of new low-carbon approaches for power dispatching, optimization for low-carbon dispatch of wind-thermal power under uncertainties needs to be investigated via the proposed model and solution. Specifically, taking the effects of cost compression, carbon emission reduction, and uncertainty handling as evaluation criteria, this study tries to find the right balance separately between two types of contradictions: robustness and economy, robustness and environment of the wind power integrated system imported with carbon reduction cooperation, and finally put forward low-carbon dispatching strategies taking into account robustness, economy, and environment comprehensively.

Scenario determinations for uncertainties

First of all, a 6-unit test system including non-smooth fuel cost and emission level functions along with one wind farm is used for ease of simulation. Some parameters are set as below: the operating parameters of thermal power units and the basic parameters of wind power units are respectively provided in Table 3 and Table 4 of Appendix, while the system load is 1731.5 MW and the total obligatory carbon emissions is 800 lb. Besides, losses should not be neglected, and the transmission loss matrix is also supplied in Appendix. To depict the characterizations of wind power output depending on wind speed, 1 month's wind speed data from Rudong, East China's Jiangsu Province, are collected to fit wind speed PDF (CMDN n.d.). To be specific, maximum likelihood method is applied to estimate the parameters of Weibull and lognormal distribution function discussed in "Objective function" section, and its parameter estimates are obtained: shape parameter $k = 3.071$, location parameter $\mu = 0.784$, scale parameter $c = 1.625$, $\sigma = 0.703$. Then the linear weighting method synthesizing lognormal distribution and Weibull distribution can be constructed as a mixture distribution, where its weight θ relies on the fitting effects of above two distributions:

$$f = \theta\left[\frac{k}{c}\left(\frac{v}{c}\right)^{k-1}\exp\left[-\left(\frac{v}{c}\right)^{k}\right]\right] + (1-\theta)\left[\frac{1}{\sqrt{2\pi}\sigma v}\exp\left[\frac{-(\ln v-\mu)^2}{2\sigma^2}\right]\right] \tag{24}$$

Next, to verify the fitting effects of wind speed PDFs, fitting curves of Weibull, lognormal, Weibull-lognormal distribution functions comparing to the wind speed histogram are plotted in Fig. 2, where wind speed interval is set as [0 m/s, 20 m/s] and the step size of equilateral points are defined as 0.05 m/s accordingly. Moreover, the Euclidean distances denoting the fitting effects between Weibull distribution, lognormal distribution, Weibull-lognormal distribution, and histogram are separately 0.127, 0.088, and 0.079, which reveals that mixture distribution of Weibull and lognormal distribution is more appropriate for actual wind speed data, and θ can be specially calculated as 0.591.

Table 1 Statistical characteristics for reduced scenarios

Scenario	Wind speed interval (m/s)	Wind power (MW)	$P(s)$
1	(0, 1.25)	0	0.21
2	(1.25, 2.5)	0	0.338
3	(2.5, 3.75)	17.857	0.218
4	(3.75, 6.25)	285.714	0.177
5	(6.25, 20)	1000	0.057

After obtaining the statistical characteristic of wind speed, wind power characterizations can be deduced from the relationship between wind power and wind speed, and the operating ranges of wind power outputs are subdivided into 16 different small intervals in Table 5 of Appendix. For the convenience of calculation, wind power scenarios are simplified as 5 scenarios via the method of synchronous back-substitution subduction, and their probabilities as well as different working situations are specially described in Table 1.

In terms of the uncertainties of carbon reduction modes, the 6-unit test system will have as much as 57 different scenarios for carbon reduction cooperation through the exhaustive method, which indeed increases the complexity of optimization. To simplify the calculation, it is necessary to choose some representative scenarios according to units' emission characteristics. As for the characteristic differences between 6 thermal power units, their carbon emissions per-unit generating capacity are shown in Fig. 3. Moreover, their emission intensities are sorted in ascending order: Unit6<Unit3<Unit5<Unit4<Unit2<Unit1.

Table 2 Operating costs and carbon emissions for cooperative and non-cooperative mode

Coop_1	r	0	0.1	0.2	0.3	0.4	0.5
	Costs ($)	83,231.04	86,120.05	89,606.63	93,538.35	98,244.81	104,911.35
	Emissions (lb)	791.36	720	640	560	480	400
Coop_2	r	0	0.1	0.2	0.3	0.4	0.5
	Costs ($)	82,992.05	86,120.05	89,606.63	93,538.35	98,244.81	104,911.35
	Emissions (lb)	797.49	720	640	560	480	400
Coop_3	r	0	0.1	0.2	0.3	0.4	0.5
	Costs ($)	81,130.32	84,370.75	88,018.4	92,284.49	97,712.52	104,902.58
	Emissions (lb)	797.49	720	640	560	480	400
Coop_4	r	0	0.1	0.2	0.3	0.4	0.5
	Costs ($)	78,963.3	82,675.67	87,087.62	91,978	97,704.48	104,902.58
	Emissions (lb)	797.49	720	640	560	480	400
Coop_5	r	0	0.1	0.2	0.3	0.4	0.5
	Costs ($)	78,849.09	82,675.67	87,087.62	91,978	97,704.48	104,902.58
	Emissions (lb)	800	720	640	560	480	400
Non-cooperative mode	r	0	0.1	0.2	0.3	0.4	0.5
	Costs ($)	85,435.27	87,586.01	90,492	93,905.78	98,244.81	104,911.35
	Emissions (lb)	791.36	720	640	560	480	400

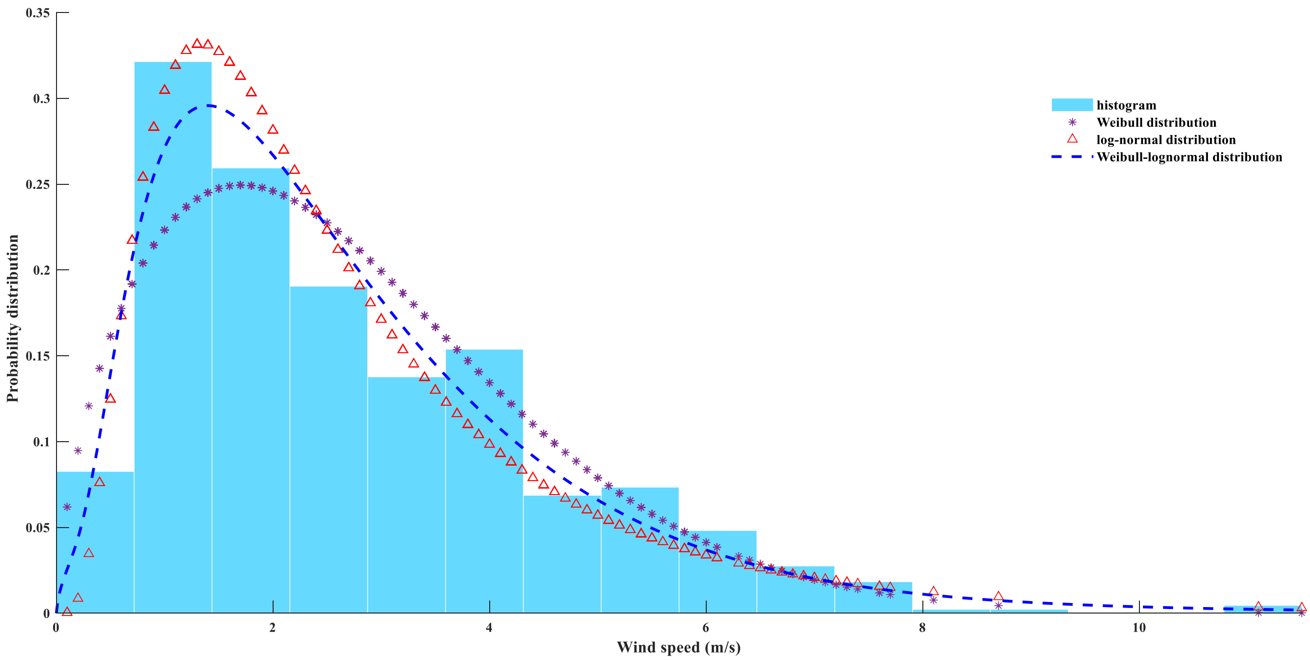


Fig. 2 Wind speed distribution

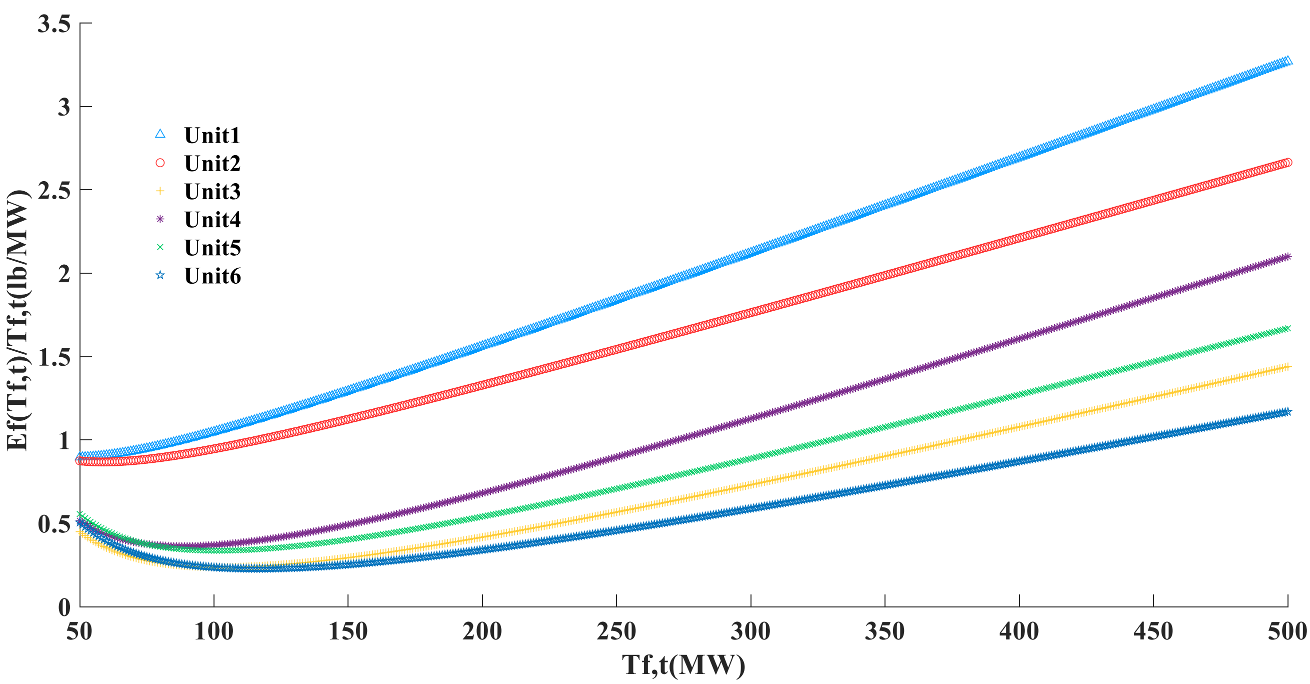


Fig. 3 Unit emission between different generators

Based on this, to meet the robustness of the power system affected by the uncertainties of carbon reduction modes, units with poorer performances in carbon emission reduction are selected into representative scenarios for carbon reduction cooperation: Unit1 only cooperate with Unit2 ($Coop_1$ scenario with 2 units), Unit1, Unit2, and Unit4 can cooperate with each other ($Coop_2$ scenario with 3 units); Unit1, Unit2, Unit4, and Unit5 can cooperate with each other ($Coop_3$ scenario with 4 units); Unit1, Unit2, Unit4, Unit5, and Unit3 can cooperate with each other ($Coop_4$ scenario with 5 units); and all units can cooperate with each other ($Coop_5$ scenario with 6 units).

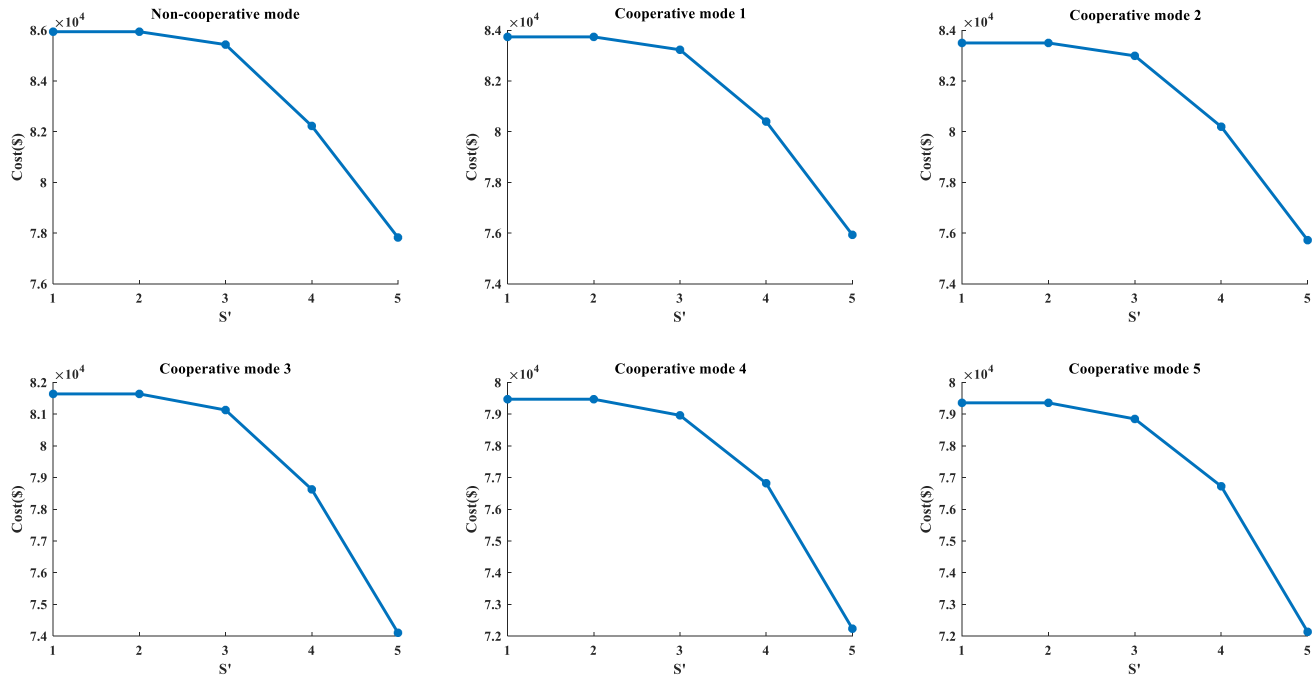


Fig. 4 Cost comparisons between different models

Robustness and economy of the model

Having finished the determinations of scenarios for wind power and carbon reduction cooperation, the distributed robust optimization model proposed could be optimized by NSGA-II through MATLAB programming (Li et al. 2015). In particular, the optimal front-end individual coefficient is set to 0.6, and the population size is fixed at 100 to guarantee the diversity and convergence of evolution population in optimization process. Besides, the maximum number of iterations is fixed at 200, the maximum evolutionary algebra is set to 2000, while the deviation of fitness function value is set as 0.01. Due to the research focus of this section, several general carbon reduction modes might as well be selected in the carbon emission rights constraint, where r is fixed at 0. In addition, the allocations of initial carbon emission rights through proportional method are offered in Table 6 of Appendix. To test the robustness and economy of the proposed model, comparisons of operating costs from the traditional robust optimization model, the stochastic programming model and the distributed robust optimization model are depicted in Fig. 4.

Whatever the carbon reduction mode selected, the operating cost of every distributed robust optimization model ($S^{'} = 2, 3, 4$) lies in the middle of the other two models: the traditional robust optimization model ($S^{'} = 1$) and the stochastic programming model ($S^{'} = 5$) in Fig. 4. The reasons for this phenomenon are as follows: the traditional robust method is to search the total cost under the worst wind power scenario, whose decision-making results focus more on robustness. While the stochastic programming method is used to calculate the expected cost with all various wind power scenarios, whose decision-making results concentrate more on economy. Combining the advantages of above two models, the distributed robust optimization model integrating several worse scenarios can achieve a good compromise between robustness and economy of the power system.

To verify the accuracy of the optimizations, Fig. 5 represents the scheduled power generation of all units including one wind farm for an optimal solution under various carbon reduction requirements. To be sure, without loss of generality, $S^{'}$ is set to 3 and non-cooperative mode is selected.

From Fig. 5, the optimal dispatching solutions for thermal and wind power units fluctuate with the parameter r increasing from 0 to 0.5, which puts added pressure on carbon emission reduction in the wind power integrated system. Concrete manifestations are thermal power units with lower generation costs undertake more scheduled power output, such as Unit1 and Unit3, while Unit4 and Unit6 undertake less. As the carbon reduction requirement is getting more and more rigorous, wind power unit takes on more and more scheduled power output (from 734 to 952 MW), namely higher and higher proportions of load demand (from 42.39 to 54.98%). So far, low-carbon power dispatching strategies with robustness and economy could be obtained by the distributed robust optimization model, which proves to be effective in coping with wind power uncertainties and reducing operating costs.

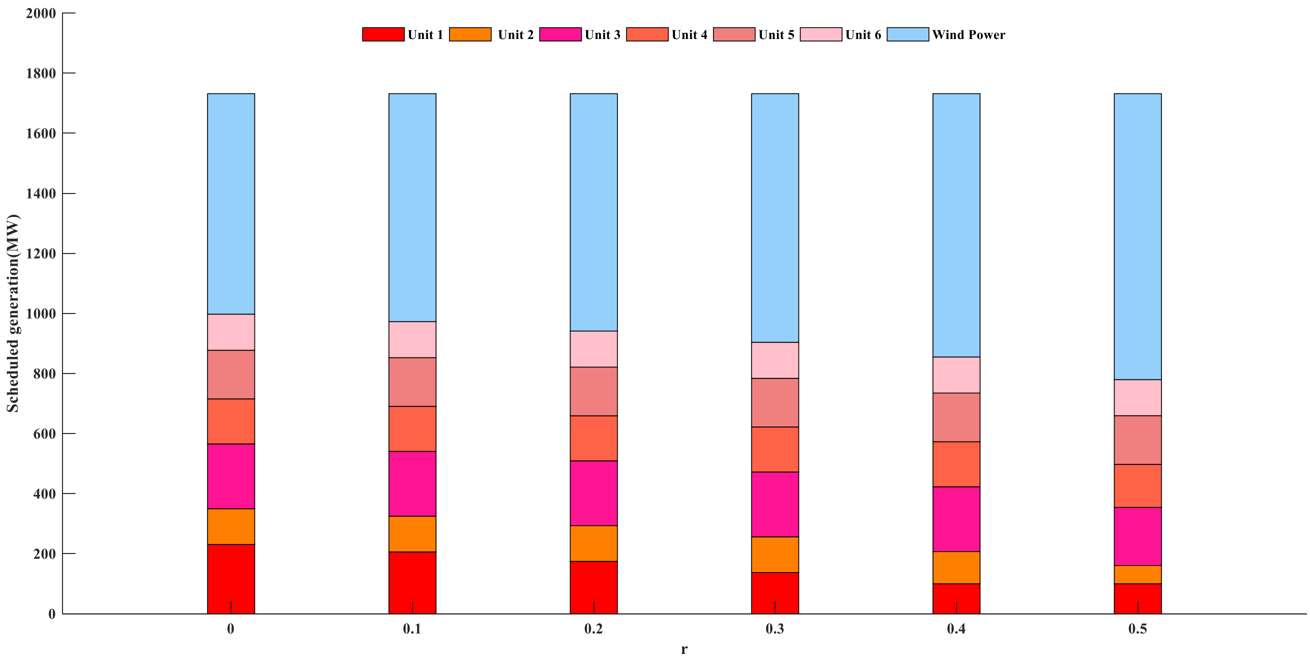


Fig. 5 Scheduled power generation for non-cooperative mode

Robustness and environment of the model

Although the robustness and economy of wind power integrated system have been guaranteed under the influence of wind power uncertainties, higher proportions of wind power will be unfavorable for the system reliability according to the present technical conditions, especially under stricter carbon reduction requirements. In this context, thermal power units also need to tap greater potential for carbon emission reduction through the cooperative way. Specifically, faced with the uncertainties of carbon reduction mode, 5 representative scenarios for the sake of system robustness have been determined in "Scenario determinations for uncertainties" section. To compare the effects of different carbon reduction mode, take $S^{'} = 3$ as an example, as the parameter r increases, fluctuations in operating costs and carbon emissions of cooperative and non-cooperative mode are presented in Table 2.

As illustrated in Table 2, the operating costs of cooperative mode are significantly less than that from non-cooperative mode through the vertical comparison, although there are some differences between scenarios for carbon reduction cooperation. And the rank of superior mode with lower operating costs has the following sequence: Coop_5 mode, Coop_4 mode, Coop_3 mode, Coop_2 mode, Coop_1 mode, and non-cooperative mode. Moreover, cooperative mode's carbon emissions are as much as that from non-cooperative mode, and they all satisfy the same carbon reduction requirements. The reason for this phenomenon is that more and more efficient thermal power units participate in the cooperative mode with the expansion of cooperation, which naturally reduces operating costs and relieves carbon reduction pressure. In the horizontal comparison, the negative externality costs gradually improve as r increases from 0 to 0.5, no matter what kind of carbon reduction mode, which is mainly due to the proportion rising of wind power with the increases of carbon reduction pressure. To further analyze the above conclusion, Fig. 6 quantitatively depicts all units' scheduled power generation for cooperation scenarios under various carbon reduction requirements.

As can be seen from Fig. 6, the proportion of wind power has been falling contrasted with the non-cooperative mode in Fig. 5, and these changes are more explicit under lower carbon reduction requirement. To vividly illustrate such differences, Fig. 7 describes the comparisons of scheduled power generation among several carbon reduction modes under various carbon reduction requirements.

From Fig. 7, carbon reduction modes based on representative scenarios are sorted by wind power proportion (largest to smallest): non-cooperative mode, *Coop* mode, $Coop_2$ mode, $Coop_3$ mode, $Coop_4$ mode, and $Coop_5$ mode. With the expansion of carbon reduction cooperation, more and more scheduled power generation could be undertaken by thermal power units under the same carbon reduction requirement, which can tap greater potential of thermal power units for carbon emission reduction and facilitate the achievement of carbon reduction targets. Furthermore, the decline in wind power proportion (as low as 37.88%) also ensures the robustness of wind power integrated system to a certain extent. In brief, low-carbon power dispatching strategies with

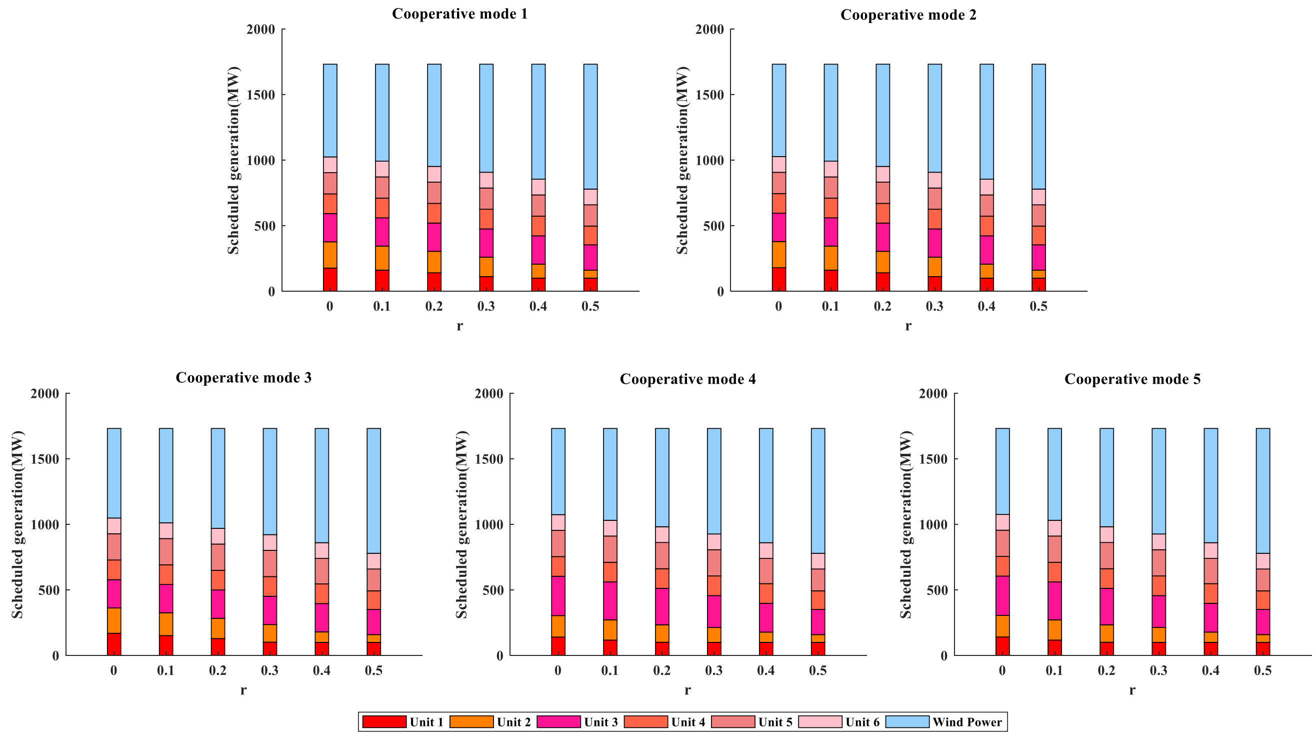


Fig. 6 Scheduled power generation for cooperative mode

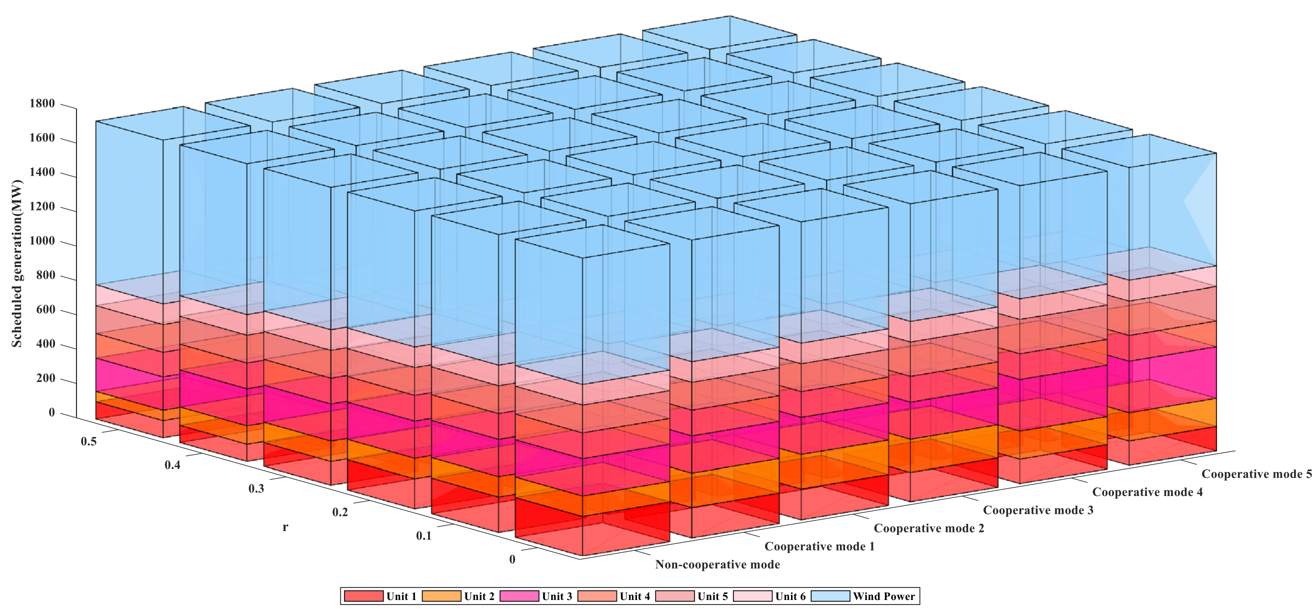


Fig. 7 Comparisons among several carbon reduction modes under various *r*

robustness and environment could be achieved through the distributed robust optimization model, which proves to be effective in dealing with the uncertainties of carbon reduction modes and reducing carbon emissions.

Conclusion and recommendation

To deal with the uncertainties of wind power and carbon reduction modes for thermal power encountered in low-carbon power dispatch, this paper firstly constructed a distributed robust optimization model and designed relevant solutions. Next, taking the effects of cost compression, carbon emission reduction, and uncertainty handling as evaluation criteria, this study has found the right balance separately between two types of contradictions: robustness and economy, robustness and environment of the wind power integrated system imported with carbon reduction cooperation, and finally put forward low-carbon power dispatching strategies taking into account robustness, economy and environment comprehensively.

The meaningful results obtained are mainly in the following two aspects: Firstly, combining the advantages of the traditional robust optimization model and the stochastic programming model, the distributed robust optimization model integrating several worse scenarios of wind power in the objective cost function can achieve a good compromise between robustness and economy of the power system, which proves to be effective in coping with wind power uncertainties and reducing operating costs. Secondly, to ensure both robustness and environment of the power system, some representative scenarios in the cooperative mode for thermal power are selected in the carbon emission rights constraint of the distributed robust optimization model, which proves to be valid in dealing with the uncertainties of carbon reduction modes and reducing carbon emissions. Specifically, carbon reduction cooperation in various forms is demonstrated to tap greater potential of thermal power units for carbon emission reduction, and further facilitate the achievement of carbon reduction targets. Based on this, low-carbon power dispatching strategies combining robustness, economy, and environment could be achieved through the proposed model and method, which will be helpful to cope with the disturbances from the uncertainties of wind power and carbon reduction modes for thermal power more scientifically and reasonably.

Aiming at two types of uncertainty mentioned above, this paper tries to solve the distributed robust optimization problem for low-carbon dispatch of wind-thermal power under uncertainties. However, the above problem may be influenced by some other uncertainties, and this will require that we carry on investigating their characterizations and then exploring reasonable coping style, which may coordinate low-carbon power dispatching strategies from more comprehensive perspectives.

Appendix

See Tables 3, 4, 5 and 6

Table 3 Parameters of thermal power units

Unit	1	2	3	4	5	6
$T_f^{\min}$(MW)	100	50	80	50	50	50
$T_f^{\max}$(MW)	500	200	300	150	200	120
a_f($/(MW)^2)	0.007	0.0095	0.009	0.009	0.008	0.0075
b_f($/MW)	7	10	8.5	11	10.5	12
d_f($)	240	200	220	200	220	190
g_f(**$**)	130	110	120	110	120	100
h_f(Rad/MW)	0.0315	0.03	0.045	0.03	0.04	0.0052
α_f(lb/(MW)^2)	0.00583	0.00461	0.00381	0.00513	0.00419	0.00319
γ_f(lb/MW)	0.32767	0.32767	− 0.54551	− 0.54551	− 0.51116	− 0.51116
λ_f(lb)	13.85932	15.85932	40.2669	40.2669	42.89553	42.89553

Table 4 Parameters of wind power units

v_{in}(m/s)	v_r(m/s)	v_{out}(m/s)	w_{rated}(MW)
3	10.8	25	100

Table 5 Statistical characteristics for all scenarios

Scenario	Wind speed interval (m/s)	Wind power (MW)	$P(s)$
1	(0, 1.25)	0	0.21
2	(1.25, 2.5)	0	0.338
3	(2.5, 3.75)	17.857	0.218
4	(3.75, 5)	196.429	0.118
5	(5, 6.25)	375	0.059
6	(6.25, 7.5)	553.571	0.028
7	(7.5, 8.75)	732.143	0.013
8	(8.75, 10)	910.714	0.007
9	(10, 11.25)	1000	0.004
10	(11.25, 12.5)	1000	0.002
11	(12.5, 13.75)	1000	0.001
12	(13.75, 15)	1000	0.001
13	(15, 16.25)	1000	0.001
14	(16.25, 17.5)	1000	0
15	(17.5, 18.75)	1000	0
16	(18.75, 20)	1000	0

Table 6 Allocations of initial carbon emission rights

Unit	1	2	3	4	5	6
e_f(lb)	400	120	100	80	70	30
E(lb)	800					

The transmission loss formula coefficients are:

$$B = \begin{pmatrix} 0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\ 0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\ 0.0007 & 0.0009 & 0.0031 & 0.0001 & -0.001 & -0.0006 \\ -0.0001 & 0.0001 & 0 & 0.0024 & -0.0006 & -0.0008 \\ -0.0005 & -0.0006 & -0.001 & -0.0006 & 0.0129 & -0.0002 \\ -0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.015 \end{pmatrix}$$

Author contribution Jingliang Jin: conceptualization, methodology, investigation, validation, writing—original draft; Qinglan Wen: resources, data analysis, investigation, software, writing—review and editing; Yaru Qiu: investigation, data analysis, software, formal analysis; Siqi Cheng: resources, software, formal analysis; Xiaojun Guo: supervision, validation, review and editing.

Funding The authors gratefully acknowledge the financial support provided by the National Natural Science Foundation of China (nos. 71603135, 71804190, 71834003, 71934007), National Social Science Foundation of China (no. 21BGL302), Jiangsu Social Science Foundation Project (no. 20GLD013), and the Nantong University Scholarship for Overseas Studies.

Data availability Wind speed data from Rudong, East China's Jiangsu Province, analyzed during the current study are available in the "China Meteorological Data Network": http://data.cma.cn.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

Aghaei J, Niknam T, Azizipanah-Abarghooee R, Arroyo JM (2013) Scenario-based dynamic economic emission dispatch considering load and wind power uncertainties. Int J Electr Power Energy Syst 47:351–367

Arula R, Velusamia S, Ravi G (2015) A new algorithm for combined dynamic economic emission dispatch with security constraints. Energy 79:496–511

Basu M (2019) Economic environmental dispatch of solar-wind-hydro-thermal power system. Renew Energy Focus 30:107–122

Biswas PP, Suganthan PN, Mallipeddi R, Amaratunga GAJ (2019) Optimal reactive power dispatch with uncertainties in load demand and renewable energy sources adopting scenario-based approach. Appl Soft Comp 75:616–632

Chang TP (2011) Estimation of wind energy potential using different probability density functions. Appl Energy 88:1848–1856

Chen Y, Wei W, Liu F, Mei SW (2016) Distributionally robust hydro-thermal-wind economic dispatch. Appl Energy 173:511–519

Chen ZL, Zhao WG, Zheng HY (2021) Potential output gap in China's regional coal-fired power sector under the constraint of carbon emission reduction. Energy Policy 148:111888

CMDN (n.d.) China Meteorological Data Network. Hourly observation data from surface weather stations in China. http://data.cma.cn
Herrero C, Villa A (2001) The three musketeers: from classical solutions to bankruptcy problems. Mat Soc Sci 42(3):307–328
Hetzer J, Yu DC (2008) An economic dispatch model incorporating wind power. IEEE Trans Energy Convers 23(2):603–611
Ji L, Huang GH, Huang LC, Xie YL, Niu DX (2016) Inexact stochastic risk-aversion optimal day-ahead dispatch model for electricity system management with wind power under uncertainty. Energy 109:920–932
Jin JL, Zhou DQ, Zhou P (2015) Modeling for dynamic economic emission dispatch under uncertainty. Electr Power Comp Syst 43(14):1630–1643
Jin JL, Zhou P, Li CY, Guo XJ (2019) Low-carbon power dispatch with wind power based on carbon trading mechanism. Energy 170:250–260
Li T, Huang QY (2021) Green thermal power dispatching based on environmental information during the energy transition period. J Clean Prod 320:128843
Li YQ, Liao SM, Liu G (2015) Thermo-economic multi-objective optimization for a solar-dish Brayton system using NSGA-II and decision making. Int J Electr Power Energy Syst 64:167–175
Lin BQ, Bega F (2021) China's Belt & Road Initiative coal power cooperation: transitioning toward low-carbon development. Energy Policy 156:112438
Lin BQ, Jia ZJ (2019) Impacts of carbon price level in carbon emission trading market. Appl Energy 239:157–170
Menezes FM, Zheng XM (2018) Regulatory incentives for a low-carbon electricity sector in China. J Clean Prod 195:919–931
Meng FY, Bai Y, Jin JL (2021) An advanced real-time dispatching strategy for a distributed energy system based on the reinforcement learning algorithm. Renew Energy 178:13–24
Moulin HJ (2003) Fair division and collective welfare. The MIT Press, Massachusetts, pp 21–51
Ren MJ, Jiang X, Yuan JH (2020) Wind power integration and emission reduction via coal power retrofits in China's quota-based dispatch system: a case study of Jilin Province. Environ Sci Pollut Res 27:11364–11374
Shao CZ, Ding Y, Wang JH (2019) A low-carbon economic dispatch model incorporated with consumption-side emission penalty scheme. Appl Energy 238:1084–1092
Tan QL, Mei SF, Ye Q, Ding YH, Zhang YM (2019) Optimization model of a combined wind-PV-thermal dispatching system under carbon emissions trading in China. J Clean Prod 225:391–404
Tsai MT, Yen CW (2011) The influence of carbon dioxide trading scheme on economic dispatch of generators. Appl Energy 88(12):4811–4816
Wang LH, Zhang BY, Li QQ, Song W, Li GG (2019) Robust distributed optimization for energy dispatch of multi-stakeholder multiple microgrids under uncertainty. Appl Energy 255:113845
Wang QW, Wang YZ, Hang Y, Zhou P (2019) An improved production-theoretical approach to decomposing carbon dioxide emissions. J Environ Manag 252:109577
Wang Y, Hu QH, Li LH, Foley AM, Srinivasan D (2019) Approaches to wind power curve modeling: a review and discussion. Renew Sustain Energy Rev 116:109422
Wei W, Liu F, Wang JH, Chen LJ, Mei SW, Yuan TJ (2016) Robust environmental-economic dispatch incorporating wind power generation and carbon capture plants. Appl Energy 183:674–684
Wei YM, Chen H, Chyong CK, Kang JN, Liao H, Tang BJ (2018) Economic dispatch savings in the coal-fired power sector: an empirical study of China. Energy Econ 74:330–342
Wood AJ, Wollenberg BF (1984) Power generation, operation and control. Wiley Inc, USA
Xiang Y, Wu G, Shen XD, Ma YH, Gou J, Xu WT, Liu JY (2021) Low-carbon economic dispatch of electricity-gas systems. Energy 226:120267
Yang L, Zhang Q, Ji JN (2020) A cooperative game analysis for the allocation of carbon emissions reduction responsibility in China's power industry. Energy Econ 92:104960
Zhang Q, Chen WY (2020) Modeling China's interprovincial electricity transmission under low carbon transition. Appl Energy 279:115571
Zhao XL, Liu SW, Yan FG, Yuan ZQ, Liu ZW (2017) Energy conservation, environmental and economic value of the wind power priority dispatch in China. Renew Energy 111:666–675
Zhou W, Yang HX, Fang ZH (2006) Wind power potential and characteristic analysis of the Pearl River Delta region China. Renew Energy 31:739–753
Zugno M, Conejo AJ (2015) A robust optimization approach to energy and reserve dispatch in electricity markets. European J Oper Research 247(2):659–671