Economic Emission Dispatch for Wind Power Integrated System with Carbon Trading Mechanism

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Abstract: Nowadays, the power system is faced with some new changes from low-carbon approaches, though these approaches have proved to be effective in developing low-carbon electricity. Specifically, wind power integration and carbon trading influence the traditional economic emission dispatch (EED) mode, allowing for the disturbance of wind power uncertainties and the fluctuation of carbon trading price. Aiming at the above problems, this study firstly builds a stochastic EED model in the form of chance-constrained programming associated with wind power reliability. Next, wind power features are deduced from the statistic characteristics of wind speed, and thus the established model is converted to a deterministic form. After that, an auxiliary decision-making method based on the technique for order preference by similarity to an ideal solution (TOPSIS) is designed to draw the optimal solution based upon the specific requirements of carbon emission control. The simulation results eventually indicate that the minimization of fuel costs and carbon emissions comes at the expense of wind power reliability. Meanwhile, carbon emission reduction can be effectively realized by carbon trading rather than a substantial increase in fuel costs, and carbon trading may help to improve power generation efficiency. Furthermore, carbon trading prices could be determined by the demands of carbon emission reduction and power generation efficiency improvement.

Keywords: low-carbon; wind power integration; EED; carbon trading; TOPSIS

1. Introduction

With the rapid development of the social economy and the continuous progress of science and technology, people’s demand for electric power resources is increasingly urgent [1]. However, electrical production not only needs to consume a large amount of traditional energy, but also releases carbon dioxide (CO₂), which causes the greenhouse effect [2]. Against this background, low-carbon electricity development naturally becomes one of the important measures to accelerate the sustainable development of the electric power industry [3]. In recent years, many low-carbon approaches have been carried out in power systems [4].

In the process of power generation, wind power as a kind of renewable energy has the advantages of being renewable, environmentally friendly and cheap, so a large amount of wind power integration into the power system has become an effective low-carbon approach [5,6]. China’s installed wind power capacity had already reached 281 million kilowatts by the end of 2020, of which offshore wind power generation occupied about 9 million kilowatts [7]. While in the process of power dispatching, based on guaranteeing the safe operation of the power grid, economic emission dispatch (EED), synthesizing fuel costs and CO₂ emissions simultaneously, has become a commonly used power dispatching technology [8]. It not only needs to meet the safety and economic requirements of traditional power dispatching, but also to reduce CO₂ emissions as much as possible [9]. Obviously, EED, with its many advantages, is identified as a more practical approach for
low-carbon electricity development [10]. Moreover, when adapting a clean development mechanism (CDM), carbon trading acting as a new trading mode prompts the power industry to regulate excessive CO$_2$ emissions and to further relieve the environmental pressure in the process of power trading, where the CO$_2$ emission trading system (ETS) is currently being set up all over the world [11,12]. Specifically, the transaction volume from China’s nine local pilots was higher: the total CO$_2$ emissions of transactions were nearly 2.15 billion yuan at the end of 2020, which was an increase of 3% compared with 2.08 billion yuan in 2019 [13]. Taken together, wind power integration, EED and carbon trading are three current approaches beneficial for low-carbon electricity development. Accordingly, more interactions between them are emerging as well. In particular, the appearances of wind power integration and carbon trading may bring new changes to power dispatching problem, while the traditional EED models are no longer totally adapt to these new changes.

As a kind of abundant and competitive renewable energy, wind power in the power system has become the focus of research by many scholars. To supply investors and researchers with a better understanding of China’s wind power development and to offer them reasonable investment references, Zhang et al. saw China as a member of the world and elaborated its status, role and impact on global wind power development from a global perspective [14]. Taking into account the wind power networking project, Li et al. carried out an overall analysis of the carbon emissions during its whole life cycle based on the life cycle assessment theory, where the results prove that the wind power project has great potential in carbon emissions control compared to thermal power stations [15]. Wang et al. provide an all-round review of curve modeling techniques for wind power, including wind data analyses, wind data preprocessing and different wind power curve models, while it was found that the universal model cannot always outperform other models in any circumstances [16].

Moreover, as a classic power dispatching model, many researchers continuously explore the EED problem and make new progress. By utilizing an advanced constraint handling technique as the superior feasible solution approach, Chen et al. proposed a constrained multi-objective population extremal optimization algorithm to improve the EED performance of renewable power generation [17]. To provide a more flexible and effective tool for carbon emission control compared with the traditional generation-side penalty scheme, Shao et al. proposed a consumption-side carbon emission penalty scheme, where consumers were penalized according to their individual carbon emission responsibilities and penalty rates [18]. For hedging random fuzzy wind power in response to the demand for integrated multi-period economic emission dispatch, Chen et al. presented a conditional value-at-credibility model, which proved to be feasible and effective in solving multi-period EED, considering wind power uncertainty [19].

Meanwhile, more and more scholars have also begun to study new problems with the emergence of the ETS in the power system. To correctly dispatch thermal power generation and renewable energy power generation, Tan et al. built an optimization model of the combined wind–photovoltaic–thermal dispatching system based on a carbon emissions trading mechanism [20]. Cao et al. examined an ETS which covered both the electricity and cement sectors, and the simulations indicated that carbon emissions control policies were progressive in that higher income households bore a bigger burden [21]. By using trading data from seven pilot carbon emission trading markets in China between 2013 and 2016, Lv et al. evaluated the validity of the carbon emission trading policy in the view of corporate innovation, which proved to be effective in driving corporate carbon-reduction innovation [22]. However, owing to alternative special emphasis, the above research paid little attention to wind power integration and simultaneous EED and carbon trading, and the relationships between them were also ignored, but are quite necessary in low-carbon electricity development.

Nowadays, the power system is faced with some new challenges from low-carbon approaches, though these approaches have proved to be effective in developing low-
carbon electricity [23]. Specifically, wind power integration and carbon trading influence traditional EED mode, allowing for the disturbance of wind power uncertainties and carbon trading price fluctuations. As one of the essential processes in low-carbon electricity development, exploring the effects of wind power integration and carbon trading on EED becomes especially significant. To achieve this, it is quite meaningful to investigate the EED problem in a wind power integrated system with a carbon trading mechanism. Based on the above considerations, this paper tries to establish how wind power reliability affects the optimal dispatching solution, how carbon emission reduction and power generation efficiency improvements are influenced by carbon trading price and how to set the rational price of carbon trading according to the specific requirements of carbon emission reduction and power generation efficiency improvement. Concentrating on wind power integration, EED and carbon trading simultaneously, together with the relationships between them, this paper may help the decision-makers to choose low-carbon power dispatching strategies more scientifically and rationally.

This paper is organized as follows: Section 2 builds a stochastic EED model considering wind power reliability; Section 3 studies the statistical characteristics of wind energy, and the effect of decision-making methods upon carbon trading price; Section 4 presents a case study to investigate the relationships between wind power integration, EED and carbon trading; and Section 5 summarizes the full text and provides some conclusions.

2. Problem Formulation

In consideration of the effect of wind power uncertainties on the optimal dispatch strategy for wind power integrated systems, the traditional EED model is required to be modified to describe this effect. To be specific, the probabilities of real power balance constraints related to wind power uncertainties are defined as confidence levels to reflect wind power reliability. In other words, the present formulation treats this EED problem as a chance-constrained programming model for minimizing both fuel costs and carbon emissions under uncertainty, and to satisfy both load demand and system operation constraints.

2.1. Objective Function
2.1.1. Cost Function

Assuming there is no cost once the wind power generators are up and running, the major consideration of generation cost is the thermal power generator’s cost in the wind power integrated system, and the cost function is constructed as follows [24]:

\[ \min F_1 = \min \sum_{i=1}^{N} C_i(P_i) \]  

(1)

where \( F_1 \) is the total costs of the power system; \( C_i \) is the thermal power generator’s cost function; \( P_i \) is the scheduling output for the thermal power generator; and \( N \) is the number of thermal power generators.

Generally, the cost function is a quadratic function for a single thermal power unit. In the actual operation of the system, the phenomenon of wire drawing superimposes a pulsating effect on the characteristic curve of unit consumption; that is, the valve point effect. In order to improve the accuracy of the EED model, a sine function is usually added to the cost function which is further developed as shown below [25]:

\[ C_i(P_i) = a_i P_i^2 + b_i P_i + c_i + |e_i \sin(f_i (P_i^{\text{min}} - P_i))|, \quad 1 \leq i \leq N \]  

(2)

where \( a_i, b_i, c_i, e_i \), and \( f_i \) are the cost function coefficients for \( i \), the thermal power generator; and \( P_i^{\text{min}} \) is the thermal power generator’s lower limit of power generation.
2.1.2. Emission Function

The wind power generators do not produce carbon emissions directly, as wind power is clean energy, while the thermal power units do produce some carbon emissions, thus the emission function is shown below [26]:

$$\min F_2 = \min \sum_{i=1}^{N} E_i(P_i)$$

where $F_2$ is the total carbon emissions of the power system; and $E_i$ is the emission function for the thermal power generator.

The total carbon emissions arising from thermal power generators could be depicted as a quadratic function in the following form [27]:

$$E_i(P_i) = \alpha_i P_i^2 + \gamma_i P_i + \lambda_i, \quad 1 \leq i \leq N$$

where $\alpha_i$, $\gamma_i$ and $\lambda_i$ are the thermal power generator's emission coefficients.

2.2. Constraint Function

2.2.1. Real Power Output Constraint

In order to ensure the normal operation of the thermal power generator, the requirements of the upper and lower limits of power generation ought to be satisfied [28]:

$$p_{i\text{min}} \leq P_i \leq p_{i\text{max}}$$

where $p_{i\text{max}}$ is the power generation upper limit for the thermal power generator.

2.2.2. Real Power Balance Constraint

Due to the wind power uncertainties, wind power output ought to be considered as a random variable, and the constraints of the power equilibrium which the wind power integrated system should satisfy under certain confidence levels can be formulated as the probability forms [28]:

$$\Pr\left\{ \sum_{i=1}^{N} P_i + P_w \leq P_{\text{load}} + P_{\text{loss}} \right\} \leq \alpha$$

where $P_w$ is the wind power output; $P_{\text{load}}$ is the total load demand; $P_{\text{loss}}$ is the transmission line losses; and $\alpha$ is the confidence level, thus the reliability of the wind power integrated system can be defined as $1 - \alpha$.

In particular, $P_{\text{loss}}$ in Equation (6) based on Kron’s loss equation can be described as follows [29]:

$$P_{\text{loss}} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_i P_j B_{ij} + \sum_{i=1}^{N} P_i B_{i0} + B_{00}$$

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

3. Model Implementation

3.1. Uncertainty Processing

With respect to the proposed EED model in the form of chance-constrained programming, a real power balance constraint appears as a random event on account of the wind power uncertainties, and this model should be switched to a deterministic form for the ease of the optimization process [30]. Specifically, the statistical characteristics of wind power output could be deduced from the probability distribution function (PDF) of wind speed.

There are mainly five kinds of wind speed PDF: Weibull distribution, gamma distribution, Rayleigh distribution, log-normal distribution and Burr distribution, which are widely applied in wind speed forecasting.
The Weibull PDF can be defined as shown below [31]:

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

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

The gamma PDF can be written as indicated below [31]:

\[
f_V(v) = \frac{v^{\zeta-1}}{\beta^\zeta \Gamma(\zeta)} \exp \left( -\frac{v}{\beta} \right)
\]

where \( \zeta \) is the shape parameter; \( \beta \) is the scale parameter; and \( \Gamma \) is the gamma function.

The Rayleigh PDF can be formulated as follows [32]:

\[
f_V(v) = \frac{v}{\tau} \exp \left( -\frac{v^2}{2\tau^2} \right)
\]

where \( \tau \) is the scale parameter.

The log-normal PDF can be defined as follows [32]:

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

where \( \mu \) is the location parameter; and \( \sigma \) is the scale parameter.

The Burr PDF can be written as follows [32]:

\[
f_V(v) = \frac{\epsilon \varphi \left(\frac{v}{\omega}\right)^{-1}}{\omega \left[1 + \left(\frac{v}{\omega}\right)^\epsilon\right]^{\varphi+1}}
\]

where \( \epsilon \) is the shape parameter; and \( \omega \) and \( \varphi \) are the scale parameters.

The Weibull distribution in a relatively simple form has the widest application range, which is explicitly for wind speed, and convenient to calculate. However, its fitting effect is only good for ordinary wind speed, for it cannot fit some wind speed characteristics at extreme values. The gamma distribution is the first distribution model used to depict wind speed. The Rayleigh distribution sets a high standard for data, which requires not only mass data but also for the dispersion degree of the data to be as small as possible, and the fitting error is usually around 10%. The fitting effect of the log-normal distribution is generally good, but its effect is poor when the wind speed frequency is too low or high. The Burr distribution also has excellent results, but this model is a little complex and its solution seems a bit complicated. In summary, every distribution has its own advantages and disadvantages, so it is necessary to further explore which one is more suitable for the statistical characteristics of wind speed in the actual application.

Based on the wind speed PDF, the statistical characteristics of wind power output may further be determined, and the corresponding transformation could be formulated as a linear relationship [33]:

\[
W = T(V) = aV + b, \quad v_i \leq V \leq v_r
\]

where \( W \) is wind power output; \( V \) is wind speed; \( v_r \) represents the rated wind speed; \( v_i \) denotes the cut-in wind speed; and \( T \) signifies a transformation, and

\[
a = \frac{w_{\text{rated}}}{v_r - v_i}, \quad b = -\frac{w_{\text{rated}}}{v_r - v_i} \left( v_r - v_i \right)
\]
where \( w_{\text{rated}} \) is rated wind power. Relying on Equation (13), the PDF of wind power output together with its cumulative distribution function (CDF) can be induced as below:

\[
f_{W}(w) = f_{V}(T^{-1}(w)) \left[ \frac{dT^{-1}(w)}{dw} \right] = f_{V}\left( \frac{w - b}{a} \right) \left| \frac{1}{a} \right|, \quad 0 < w < w_{\text{rated}} \tag{15}\]

\[
F_{W}(w) = \int_{0}^{w} f_{W}(x) dx, \quad 0 < w < w_{\text{rated}} \tag{16}\]

After discussing the statistical characteristics of wind power output, the constraint in Equation (6) can be converted into a deterministic form:

\[
\Pr\left\{ \sum_{i=1}^{N} P_{i} + P_{w} \leq P_{\text{load}} + P_{\text{loss}} \right\}
= \Pr\left\{ 0 \leq P_{w} < P_{\text{load}} + P_{\text{loss}} - \sum_{i=1}^{N} P_{i} \right\}
= F_{W}\left( P_{\text{load}} + P_{\text{loss}} - \sum_{i=1}^{N} P_{i} \right) - F_{W}(0) = \alpha \tag{17}\]

Taken together, uncertain constraints in the proposed EED model are quantitatively deduced, and finally, a deterministic model is established to obtain the optimal dispatch strategy for a wind power integrated system.

### 3.2. Decision-Making

With regards to the above deterministic EED model, such a multi-objective optimization problem has multiple objectives and each objective function is contradictory. That is, the increase in proximity of the cost function to the optimal value will cause the emission function to move away from its optimal value. The solutions of the proposed EED problem are a set of non-inferior solutions, since no solution is better than any of the others with respect to multi-objectives [26]. For obtaining the optimal dispatch strategy, a set of “best” solutions could be selected from these non-inferior solutions via specific evaluation methods, such as inferior solution distance method (TOPSIS), analytic hierarchy process, reordering method, superior and hierarchical sequence method, etc. [34,35]. By virtue of TOPSIS, this section manages to draw the optimal solution as the decision-making scheme, and therein the definitions of the weight of each objective function become a key problem. The critical decision steps which can provide convenience for the selection of an optimal dispatch strategy, and specifically the relationship between carbon trading prices and the optimal objectives’ weights are devised as follows [36]:

Step 1: Supposing that the obtained Pareto-efficient solution set is \( X = \{x_{1}, x_{2}, \cdots, x_{K}\} \), \( F_{m}(x_{i}) (i = 1, 2, \cdots, K; m = 1, 2) \), \( m \) is the number of the objective function corresponding to the solution. Calculating the normalized decision matrix \( (f_{im})_{K \times 2} \) for the purpose of simply calculation, where \( f_{im} \) is the normalization of \( F_{m}(x_{i}) \):

\[
f_{im} = \frac{F_{m}(x_{i})}{\sum_{i=1}^{K} F_{m}^{2}(x_{i})}, \quad i = 1, 2, \cdots, K; m = 1, 2. \tag{18}\]

Step 2: Assuming that the weight of the cost function \( F_{1} \) is \( \omega_{1} \), and the weight of the emission function \( F_{2} \) is \( \omega_{2} \), these two weights may fluctuate with the carbon trading price \( P_{\text{CDM}} \); the higher the \( P_{\text{CDM}} \), the more benefits (thermal power generators with lower emissions) or fees (thermal power generators with higher emissions) the power system has to afford. That is, \( P_{\text{CDM}} \) is positively correlated with \( \omega_{2} \), which is inclined to carbon emission control. \( \omega_{2} \) cannot be defined as \( P_{\text{CDM}} \) directly, for the latter has to be normalized:

\[
\omega_{2} = \frac{F_{2}^{\text{Unit}} \cdot (P_{\text{CDM}})}{F_{1}^{\text{Unit}} + F_{2}^{\text{Unit}} \cdot (P_{\text{CDM}})}, \quad \omega_{1} = 1 - \omega_{2} \tag{19}\]
where $\rho$ is a compensation coefficient relying on the current average $P_{CDM}$, and $F_{1\ Unit}^{Unit}$, $F_{2\ Unit}^{Unit}$ stand for per unit cost and per unit emission respectively.

$$F_{1\ Unit}^{Unit} = \sum_{i=1}^{N} C_i(P_i = 1\ MW), \quad F_{2\ Unit}^{Unit} = \sum_{i=1}^{N} E_i(P_i = 1\ MW) \tag{20}$$

Step 3: Defining the ideal solution $A^+$ and the non-ideal solution $A^-$:

$$A^+ = \{f_1^+, f_2^+\} = \left\{\min_i \{f_{i1}\}, \min_i \{f_{i2}\}\right\} \tag{21}$$

$$A^- = \{f_1^-, f_2^-\} = \left\{\max_i \{f_{i1}\}, \max_i \{f_{i2}\}\right\} \tag{22}$$

Step 4: Generating the separation measures $d^+_i$ and $d^-_i$ for each solution based on $A^+$ and $A^-$, together with $\omega_1$ and $\omega_2$:

$$d^+_i = \sqrt{\sum_{m=1}^{2} (\omega_m \cdot f_{im} - \omega_m \cdot f_{im}^+)^2}, \quad i = 1, 2, \cdots, K. \tag{23}$$

$$d^-_i = \sqrt{\sum_{m=1}^{2} (\omega_m \cdot f_{im} - \omega_m \cdot f_{im}^-)^2}, \quad i = 1, 2, \cdots, K. \tag{24}$$

Step 5: Figuring out each solution’s relative distance $R_i$, which reflects the distance from each solution to the non-ideal solution, and ultimately extracting the Pareto-efficient solution with the largest relative distance $R_j$:

$$R_j = \max_i \left\{R_i = \frac{d^-_i}{d^+_i + d^-_i}\right\} \tag{25}$$

4. Case Study

From the discussions in Sections 2 and 3, the modeling and implementation of power dispatching problems have been adequately presented, and the proposed model with general forms has been identified as suitable for current low-carbon development by setting various parameters of wind power output and carbon trading price. By virtue of the multi-objective optimization algorithm and multi-attribute decision-making method, this study tries to further study how wind power reliability affects the optimal dispatching solution, how carbon emission reduction and power generation efficiency improvement are influenced by carbon trading price, and how to set the rational price of carbon trading according to the specific requirements of carbon emission reduction and power generation efficiency improvement.

In this study, together with one wind power generator, a classic six-unit system with an emission level and non-smooth fuel cost was applied to test the performance of the proposed EED model [37]. The test system’s operating coefficients are offered in Table A1 of the Appendix A, and the parameters of the wind power unit are supplied in Table A2. Furthermore, the system’s demand was set as 900 MW, and the transmission loss matrix is also supplied in the Appendix A.

4.1. Description of Wind Power Output

In order to simulate the distribution function of wind power output relying on wind speed, one month’s wind speed data from Rudong, East China’s Jiangsu Province, was collected to describe the statistical characteristics of wind speed [38]. More specifically, the maximum likelihood method was used to estimate the parameters of different wind
speed PDFs as discussed in Section 3.1, and the estimated values of each distribution’s parameters are shown in Table 1:

Table 1. Parameter estimation of wind speed distribution.

|                | Shape Parameter | Scale Parameter | Location Parameter |
|----------------|-----------------|-----------------|-------------------|
| Weibull        | 3.071           | 1.625           | Null              |
| Gamma          | 2.404           | 1.138           | Null              |
| Rayleigh       | Null            | 2.308           | Null              |
| Log-normal     | Null            | 0.703           | 0.784             |
| Burr           | 6.557           | 1.829           | 4.733             |

Based on Table 1, fitted curves for these five kinds of wind speed PDFs are plotted in Figure 1, where the histograms of actual wind speed are regarded as a reference picture. Specifically, the step size was set as 0.05 m/s and a series of equilateral points were selected from the wind speed interval (0 and 10 m/s).

Figure 1. Wind speed distribution.

To compare the simulation effects from different wind speed PDFs, the Euclidean distance between the estimated probability density of each curve and the estimated probability density of the histogram was calculated, as shown in Table 2. Specifically, the probability density function values of various curves were calculated respectively at the same equal-point abscissa value derived from the estimated histogram probability density.

Table 2. Distances between the histogram and each probability distribution function (PDF).

| PDF              | Weibull | Gamma | Rayleigh | Log-Normal | Burr |
|------------------|---------|-------|----------|------------|------|
| Distance         | 2.2070  | 2.1869| 2.2767   | 2.1653     | 2.1988|

It can be seen from Table 2 that the Euclidean distance between the log-normal distribution and histogram was the smallest, therefore the fitting effect of the log-normal distribution is considered to be the best one for the current wind speed data. At the same time, since the classical distribution of the wind speed forecast is the Weibull distribu-
tion, the linear weighting method combining the log-normal distribution and the Weibull distribution is formulated as the final form of wind speed distribution:

\[
f = \Theta \left[ k \left( \frac{\nu}{c} \right)^{k-1} \exp \left( -\frac{\nu}{c} \right) \right] + (1 - \Theta) \left[ \frac{1}{\sqrt{2\pi} \sigma} \exp \left( -\frac{\left( \ln\nu - \mu \right)^2}{2\sigma^2} \right) \right]
\]  

(26)

where the weight is \( \Theta \), which can be defined as follows:

\[
\Theta = \frac{d_2}{d_1 + d_2}
\]

(27)

where \( d_1 \) is the distance between the Weibull distribution and histogram, and \( d_2 \) is the distance between the log-normal distribution and histogram, thus \( \Theta \) depending on \( d_1 \) and \( d_2 \) can be quantitatively fixed as 0.4952, based on Table 2.

Furthermore, the CDF of the wind power output in Equation (17), which can provide convenience when dispatching optimization, can be finally deduced in the following form:

\[
F_W(w) = \begin{cases} 
\Theta \cdot \left[ 1 - \exp \left( \frac{k}{\nu} - \frac{1}{\nu} w \right) ^k \right] + (1 - \Theta) \cdot \Phi \left( \frac{\ln(\frac{1}{\nu} + \frac{1}{\nu} w) - \mu}{\sigma} \right) & 0 < w < w_{\text{rated}} \\
1 & w \geq w_{\text{rated}}
\end{cases}
\]

(28)

With regards to the simplified restriction in Equation (17), it should be noted especially that the standard normal distribution function in Equation (28) could be approximated by an analytic expression of the scheduling output \( P_i \) [39], and then the upper and lower bounds related to the restriction can be achieved the traversal way.

### 4.2. Impact Analysis of Wind Power Reliability

After simulating the wind power output, the proposed EED model was converted into a deterministic form. Next, with reduction in the total fuel costs and carbon emissions of the power system as optimization goals, the proposed EED model was minimized by NSGA-II through MATLAB software. To guarantee the diversity and convergence of the evolution of the population in the process of optimization, the optimal front-end individual coefficient was set as 0.6, and the population size was set to 100. Moreover, both the maximum evolutionary algebra and maximum number of iterations were set as 200, and the deviation of the fitness function value was fixed at 0.01. In order to explore how wind power reliability affected the optimal dispatching solutions, according to various reliability levels indicated by different confidence levels, the distributions of 60 non-dominated solutions representing three different levels of reliability were calculated and are depicted in Figure 2.

![Figure 2. Pareto-optimal frontier under different reliability levels.](Image)
From the above three figures, the distributions of the Pareto frontier which tracks both fuel costs and carbon emission fluctuations are always extensive and uniform. With the enhancement of the confidence level for chance constraint, the reliability of the wind power integrated system defined in Equation (6) becomes lower and lower, and directly impacts the optimal dispatching solutions. To illustrate the differences between the three figures in Figure 2 as far as two types of single-objective, Table 3 indicates the extreme values of fuel costs and carbon emissions in terms of different reliability levels.

Table 3. Extreme values under different reliability levels.

|α = 0.01| α = 0.05| α = 0.1|
|---|---|---|
|Economic Optimum| Emission Optimum| Economic Optimum| Emission Optimum| Economic Optimum| Emission Optimum|
|Cost ($)| 57,337.63| 57,027.19| 56,927.77| 60,210.96| 61,028.93| 56,927.77| 58,927.26| 63,542.26| 4529.59|
|Emission (lb)| 8429.21| 8698.77| 9257.96| 5686.42| 5477.35| 4529.59| 4529.59|

As indicated in Table 3, with an increase in confidence level, which leads to a decrease in the reliability of the wind power integrated system, the minimum fuel cost decreases from 57,337.63 to 56,927.77 dollars accordingly, and the minimum carbon emission simultaneously decreases from 5686.42 to 4529.59 lb. This is obviously the result of the improvement in the wind power generators’ power output, and the reduction in the thermal power generators’ power output. It suggests that the improvement in wind power proportion is conducive to the control of fuel costs and carbon emissions; however, it can reduce wind power reliability depending on its uncertainties. In other words, the minimization of fuel costs and carbon emissions comes at the cost of wind power reliability. To verify the accuracy of optimization, Table 4 lists all scheduled power generations for the final solution by taking α = 0.05 as an example.

Table 4. Scheduled generation (MW), respective (total) cost ($) and carbon emissions (lb) (α = 0.05).

|Number| T1| T2| T3| T4| T5| T6| Costs| Emissions|
|---|---|---|---|---|---|---|---|---|
|1| 93.89| 215.69| 108.24| 208.65| 138.38| 135.25| 59,070.78| 6413.47|
|2| 62.19| 307.30| 110.07| 214.09| 118.20| 81.11| 57,138.45| 8468.86|
|3| 100.67| 188.19| 108.00| 211.16| 148.53| 144.15| 59,088.21| 6101.35|
|4| 86.02| 232.33| 108.54| 210.67| 136.95| 125.73| 58,638.17| 6760.84|
|5| 64.30| 303.26| 109.90| 212.92| 119.36| 90.22| 57,217.80| 8338.80|
|6| 78.65| 244.44| 108.67| 209.11| 133.80| 125.47| 58,350.30| 6954.80|
|7| 103.71| 173.49| 108.23| 215.20| 154.01| 146.02| 60,166.34| 6021.04|
|8| 64.95| 301.91| 109.85| 212.46| 119.67| 91.13| 57,244.96| 8293.42|
|9| 75.83| 268.51| 109.12| 209.52| 126.82| 110.27| 57,865.35| 7435.30|
|10| 60.84| 315.24| 110.26| 214.76| 116.87| 81.92| 57,027.19| 8698.77|
|11| 89.96| 226.82| 108.36| 208.86| 136.43| 129.73| 58,795.99| 6608.48|
|12| 105.17| 168.72| 108.22| 215.66| 155.37| 147.52| 60,302.52| 5978.63|
|13| 82.17| 248.97| 108.69| 209.14| 131.25| 119.81| 58,271.32| 7022.16|
|14| 96.65| 204.42| 108.25| 210.64| 142.61| 137.61| 59,314.27| 6294.66|
|15| 79.24| 256.54| 108.72| 208.91| 129.60| 117.06| 58,112.13| 7170.50|
|16| 81.77| 251.00| 108.77| 209.29| 130.67| 118.56| 58,228.15| 7064.19|
|17| 92.57| 219.79| 108.28| 208.52| 137.39| 133.52| 58,968.06| 6477.16|
|18| 68.01| 284.84| 109.50| 211.08| 123.66| 102.95| 57,527.91| 7847.08|
|19| 68.84| 289.51| 109.65| 211.19| 122.29| 98.60| 57,463.39| 7955.93|
|20| 75.22| 269.03| 109.23| 211.01| 127.10| 108.48| 57,838.17| 7482.81|
|21| 65.95| 298.85| 109.80| 212.31| 120.33| 92.72| 57,294.73| 8212.44|
|22| 62.05| 311.33| 110.14| 214.09| 117.69| 84.63| 57,088.44| 8577.74|
|23| 62.41| 310.56| 110.11| 214.25| 118.07| 84.63| 57,107.78| 8563.10|
|24| 98.54| 195.60| 108.25| 211.91| 145.91| 140.15| 59,569.25| 6206.22|
|25| 100.14| 186.95| 108.25| 213.52| 149.79| 141.99| 59,801.24| 6141.55|
### Table 4. Cont.

| Number | \(T_1\) | \(T_2\) | \(T_3\) | \(T_4\) | \(T_5\) | \(T_6\) | Costs  |
|--------|--------|--------|--------|--------|--------|--------|--------|
| 26     | 67.18  | 287.04 | 109.54 | 211.16 | 123.17 | 101.93 | 57,487.37     |
| 27     | 94.55  | 212.47 | 108.08 | 208.43 | 140.23 | 136.45 | 59,164.30     |
| 28     | 91.98  | 221.54 | 108.32 | 208.60 | 137.02 | 132.64 | 58,923.49     |
| 29     | 70.71  | 282.99 | 109.47 | 211.30 | 123.90 | 101.73 | 57,576.34     |
| 30     | 88.11  | 230.93 | 108.41 | 208.90 | 135.46 | 128.32 | 58,690.83     |
| 31     | 71.76  | 279.78 | 109.27 | 210.83 | 124.57 | 103.80 | 57,634.42     |
| 32     | 72.78  | 277.35 | 109.36 | 209.92 | 124.78 | 106.27 | 57,711.35     |
| 33     | 91.35  | 223.30 | 108.34 | 208.64 | 136.65 | 131.82 | 58,879.08     |
| 34     | 90.50  | 225.45 | 108.38 | 208.82 | 136.45 | 130.52 | 58,826.66     |
| 35     | 69.10  | 285.80 | 109.56 | 212.04 | 123.53 | 100.07 | 57,516.75     |
| 36     | 67.42  | 294.05 | 109.61 | 211.06 | 121.32 | 96.54  | 57,385.42     |
| 37     | 101.70 | 183.72 | 108.05 | 212.20 | 144.92 | 59,918.71 |       |
| 38     | 83.77  | 238.82 | 108.64 | 210.08 | 134.98 | 123.95 | 58,492.26     |
| 39     | 95.76  | 201.87 | 108.28 | 209.93 | 142.17 | 136.97 | 59,368.24     |
| 40     | 67.71  | 290.13 | 109.66 | 212.46 | 122.46 | 97.67  | 57,436.09     |
| 41     | 80.28  | 242.11 | 108.62 | 209.08 | 134.08 | 128.32 | 58,407.13     |
| 42     | 97.78  | 199.51 | 108.23 | 211.17 | 143.44 | 139.38 | 59,471.74     |
| 43     | 78.08  | 260.03 | 109.47 | 209.49 | 141.51 | 136.65 | 58,879.08     |
| 44     | 95.31  | 223.30 | 108.34 | 208.64 | 136.65 | 131.82 | 58,826.66     |
| 45     | 64.09  | 305.20 | 110.06 | 214.22 | 119.13 | 87.21  | 57,179.79     |
| 46     | 78.63  | 255.72 | 108.63 | 208.50 | 118.53 | 58,127.24 |       |
| 47     | 103.20 | 175.63 | 108.22 | 214.83 | 153.25 | 45.49  | 60,107.62     |
| 48     | 65.29  | 295.45 | 109.76 | 212.24 | 121.29 | 95.96  | 57,338.91     |
| 49     | 81.25  | 252.14 | 108.76 | 209.21 | 118.25 | 58,204.04 |       |
| 50     | 71.73  | 280.93 | 109.47 | 210.87 | 124.22 | 102.86 | 57,619.10     |
| 51     | 61.54  | 313.11 | 110.21 | 214.60 | 117.35 | 83.09  | 57,058.90     |
| 52     | 98.70  | 196.02 | 108.12 | 214.83 | 153.25 | 45.49  | 60,107.62     |
| 53     | 64.00  | 305.33 | 110.03 | 213.70 | 119.01 | 87.87  | 57,182.21     |
| 54     | 77.10  | 263.11 | 109.03 | 209.73 | 112.78 | 57,968.19 |       |
| 55     | 72.33  | 278.89 | 109.41 | 210.33 | 124.54 | 104.80 | 57,671.40     |
| 56     | 73.35  | 274.34 | 109.04 | 209.60 | 125.72 | 107.99 | 57,748.46     |
| 57     | 93.30  | 217.53 | 108.26 | 208.59 | 137.94 | 134.48 | 59,024.33     |
| 58     | 77.46  | 261.17 | 108.90 | 209.93 | 129.09 | 113.56 | 58,007.44     |
| 59     | 61.02  | 314.61 | 110.24 | 214.70 | 117.01 | 82.31  | 57,036.68     |
| 60     | 83.72  | 237.67 | 108.25 | 207.74 | 134.20 | 128.36 | 58,524.60     |

#### 4.3. Impact Analysis of Carbon Trading Price

Having obtained the Pareto-optimal solutions under different reliability levels, it is necessary to select an appropriate method of decision-making via the specific evaluation method designed in Section 3.2, since no solution is superior to all the others with respect to multi-objectives. Furthermore, this section focuses on the impact analysis of the carbon trading price; hence, the reliability level as another parameter is assumed to be 0.95 (\(\alpha = 0.05\)) in accordance with Table 4. With increasing carbon trading price \(P_{\text{CDM}}\), the satisfying solutions with the largest relative distance under different weights \(\omega_2\), combined with the corresponding fuel costs and carbon emissions are summarized in Table 5. To clarify, \(\omega_1\) and \(\omega_2\), as defined in Equation (19), are the normalizations of \(P_{\text{CDM}}\), and specifically, \(\omega_2\) is positively correlated with \(P_{\text{CDM}}\), thus the impact analysis of \(P_{\text{CDM}}\) is roughly equivalent to the impact analysis of \(\omega_2\).

As \(\omega_2\) increases, the fuel costs and carbon emissions of satisfying solutions vary monotonically in Table 5. For the purposes of normalized comparison, Figure 3 depicts the correlations between \(\omega_2\) and the rate of change of the fuel costs and carbon emissions.
Table 5. Satisfying solutions combined with corresponding costs and emissions (α = 0.05).

| \( \omega_2 \) | Number | Distance | Costs ($) | Emissions (lb) |
|---------------|--------|----------|-----------|----------------|
| 0             | 10     | 1        | 57,027.19 | 8698.77        |
| 0.1           | 9      | 0.64     | 57,865.35 | 7435.3         |
| 0.2           | 1      | 0.68     | 59,070.78 | 6413.47        |
| 0.3           | 42     | 0.77     | 59,471.74 | 6236.89        |
| 0.4           | 3      | 0.83     | 59,808.21 | 6101.35        |
| 0.5           | 37     | 0.88     | 59,918.71 | 6069.54        |
| 0.6           | 37     | 0.91     | 59,918.71 | 6069.54        |
| 0.7           | 12     | 0.94     | 60,302.52 | 5978.63        |
| 0.8           | 12     | 0.97     | 60,302.52 | 5978.63        |
| 0.9           | 12     | 0.98     | 60,302.52 | 5978.63        |
| 1             | 12     | 1        | 60,302.52 | 5978.63        |

![Figure 3](image-url). Correlations between \( \omega_2 \) and the rate of change of the costs and emissions.

From the line charts in Figure 3, it can be found that the growth rate of fuel costs and the decrement rate of carbon emissions simultaneously increase as \( \omega_2 \) increases, namely due to the improvement in carbon trading price, whereas these rates of change become almost stable as soon as \( \omega_2 \) reaches 0.7. In particular, the decrement rate of carbon emissions fully exceeds the growth rate of fuel costs for any value of \( \omega_2 \) between 0 and 1. For example, the fuel costs increased by 4.29 and 5.74%, while the carbon emissions separately reduced by 28.3 and 31.27%, respectively, when \( \omega_2 \) varied from 0 to 0.3 and 0.7. In other words, carbon emission reduction can be effectively realized by carbon trading without significantly increasing fuel costs, considering that the decrement rate of carbon emissions is superior to the growth rate of fuel costs when the carbon trading price increases.

In addition, to find out how power generation efficiency improvement is influenced by carbon trading price, Figure 4 shows the proportions of power generation shared by six thermal power generators corresponding to different values of \( \omega_2 \).

With an increase in \( \omega_2 \), it is shown in Figure 4 that the power generation proportions shared by units 1 and 6 show a significant rising tendency, while the proportion shared by unit 2 appears to be an obviously decreasing trend. The reasons for this phenomenon are that the carbon emissions per-unit generating capacity from units 1 and 6 that are beneficial to carbon trading are smaller. As a consequence, \( \omega_2 \) has an obvious impact on the power generation proportions of units 1 and 6: the higher the carbon trading price, the more output power they can afford. On the contrary, there is a negative correlation between \( \omega_2 \) and the output power for unit 2, with a larger carbon emissions per-unit generating capacity. Specifically, the carbon emissions per-unit generating capacity among the six
different generators is shown in Figure 5. Based on the above discussion and analysis, it shows that carbon trading may contribute to the improvement of power generation efficiency, as units with a lower carbon emissions per-unit generating capacity benefit far more than others from carbon trading.

From what has been discussed above, it is found that carbon trading is beneficial for carbon emission reduction and power generation efficiency improvement. On the contrary, since carbon trading is implemented by carbon trading price setting, it is necessary to set a rational \( P_{CDM} \) according to the specific requirements of carbon emission reduction and power generation efficiency improvement. Table 6 mainly illustrates the comparison between \( \omega_2 \) and \( P_{CDM} \) based on Equations (19) and (20), and Table A1, besides the relationships with \( P_{CDM} \), shows the decrement rate of carbon emissions and the proportions shared by units 1 and 6. The \( P_{CDM} \) for \( \omega_2 = 0.5 \), with a moderate view on environmental protection, is assumed to be 41.39 (¥/ton), which is an average price from the Beijing carbon trading market in 2019 [13], so that different \( P_{CDM} \) corresponding to various \( \omega_2 \) can be obtained after deriving the compensation coefficient \( \rho \) in Equation (19). In theory, \( P_{CDM} \) depending on specific requirements could be set once the decrement rate of carbon emissions and the proportions shared by more environmental units are fixed in advance.
Table 6. Relationships between $\omega_2$, $P_{CDM}$, carbon emission decrement rate and proportions of units 1 and 6.

| $\omega_2$ | $P_{CDM}$ (¥/ton) | Decrement Rate (%) | Proportions (%) |
|------------|-------------------|-------------------|-----------------|
| 0          | 0                 | 0                 | 15.86           |
| 0.25       | 13.78             | 27.29             | 25.66           |
| 0.5        | 41.39             | 30.23             | 27.38           |
| 0.75       | 124.17            | 31.27             | 28.06           |
| 0.9        | 372.55            | 31.27             | 28.06           |

5. Conclusions and Recommendation

In order to solve the EED problem in wind power integrated systems with carbon trading mechanisms, this paper firstly builds a stochastic EED model in the form of chance-constrained programming. Next, the established EED model is converted to a deterministic form for the ease of the optimization process. After that, facing a set of non-inferior solutions for model optimization, an auxiliary decision-making method based on TOPSIS is designed to draw the optimal solution upon the specific requirements of carbon emissions control.

To find out how wind power reliability affects the optimal dispatching solution, how carbon emission reduction and power generation efficiency improvement are influenced by carbon trading price, and how to set the rational price of carbon trading according to the specific requirements of carbon emission reduction and power generation efficiency improvement, a classic six-unit system together with one wind power generator is introduced to settle this optimization problem in the case study. To begin with, the mixture of the log-normal and Weibull distribution functions with good forecasting performance is used to simulate wind power output, relying on actual wind speed data. Then, empirical analysis indicates that the improvement of wind power proportion is conducive to the control of fuel costs and carbon emissions; however, it will reduce wind power reliability depending on its uncertainties. In other words, the minimization of fuel costs and carbon emissions comes at the cost of wind power reliability. Moreover, carbon emission reduction can be effectively realized by carbon trading rather than a substantial increase in fuel costs, considering that the decrement rate of carbon emissions is superior to the growth rate of fuel costs when the carbon trading price increases. Additionally, carbon trading may contribute to the improvement of power generation efficiency, as units with a lower carbon emissions per-unit generating capacity will benefit far more than others from carbon trading. Furthermore, once the decrement rate of carbon emissions and the proportions shared by more environmental units are fixed in advance, carbon trading prices according to the specific requirements of carbon emission reduction and power generation efficiency improvement could be determined. In brief, within the framework of EED, the impacts of carbon trading and wind power integration on power dispatching are proved to be significant. With a lot of attention drawn to wind power integration, EED and carbon trading, the proposed model and the obtained conclusions can help decision-makers to choose low-carbon power dispatching strategies more scientifically and rationally.

This paper focuses on the EED problem in wind power integrated systems with carbon trading mechanisms, and more attention is paid to the influences of wind power integration and carbon trading on EED. However, there might be some other low-carbon approaches to power systems which allow us to investigate its corresponding impacts. Additionally, it may further explore the present EED problem from various perspectives. Another potential direction is to pursue the other effective optimization algorithms to solve the EED problem in this paper.
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Abbreviations

Variables:
- $P_i$: the scheduling output for the thermal power generator
- $P_w$: the wind power output
- $P_{load}$: the total load demand for the power system
- $P_{loss}$: the transmission line losses

Parameters:
- $N$: the number of thermal power generators
- $\alpha$: the confidence level
- $\theta$: the weighting factor
- $k, \zeta$ and $\epsilon$: the shape parameter
- $\mu$: the location parameter
- $v_i$: the cut-in wind speed
- $v_r$: the rated wind speed
- $w_{rated}$: the rated wind power
- $a_i, b_i, c_i, e_i$ and $f_i$: cost coefficients of the thermal power generator
- $\alpha_i, \gamma_i$ and $\lambda_i$: emission coefficients of the thermal power generator
- $B_{ij}, B_{i0}$ and $B_{00}$: transmission network power loss $B$-coefficients
- $P_{min}$: the power generation lower limit for the thermal power generator
- $P_{max}$: the power generation upper limit for the thermal power generator

List of abbreviations:
- CO$_2$: carbon oxides
- CDM: clean development mechanism
- EED: economic emission dispatch
- ETS: emission trading system
- PDF: probability distribution function
- CDF: cumulative distribution function
- NSGA-II: nondominated sorting genetic algorithm-II

Appendix A

See Tables A1 and A2.

The transmission loss formula coefficients are:

$$B = \begin{bmatrix} 
0.0017 & 0.0012 & 0.0007 & -0.0001 & -0.0005 & -0.0002 \\
0.0012 & 0.0014 & 0.0009 & 0.0001 & -0.0006 & -0.0001 \\
0.0007 & 0.0009 & 0.0031 & 0.0001 & -0.001 & -0.0006 \\
-0.0001 & 0.0001 & 0 & 0.0024 & -0.0006 & -0.0008 \\
-0.0005 & -0.0006 & -0.001 & -0.0006 & 0.0129 & -0.0002 \\
-0.0002 & -0.0001 & -0.0006 & -0.0008 & -0.0002 & 0.015 
\end{bmatrix}$$
Table A1. Generator characteristics.

| Unit  | 1     | 2     | 3     | 4     | 5     | 6     |
|-------|-------|-------|-------|-------|-------|-------|
| $P_{\text{max}}$ (MW) | 50    | 100   | 50    | 80    | 50    | 50    |
| $P_{\text{min}}$ (MW) | 200   | 500   | 150   | 300   | 250   | 200   |
| $a_i$ ($/\text{MW}^2$) | 0.01  | 0.006 | 0.0095| 0.007 | 0.0065| 0.0085|
| $b_i$ ($/\text{MW}$)   | 13    | 7     | 11    | 8.5   | 9     | 12    |
| $c_i$ ($)            | 250   | 190   | 260   | 180   | 160   | 230   |
| $e_i$ ($)            | 130   | 100   | 150   | 120   | 100   | 130   |
| $f_i$ (Rad/MW)       | 0.0350| 0.0315| 0.0360| 0.0350| 0.0052| 0.0400|
| $\alpha_i$ ($\text{lb}/(\text{MW})^2$) | 0.00419| 0.00719| 0.00583| 0.00983| 0.00761| 0.00461|
| $\gamma_i$ (lb/MW)  | $-0.32767$ | $0.52767$ | $-0.54551$ | $-0.54551$ | $-0.51116$ | $-0.51116$ |
| $\lambda_i$ (lb)    | 13.85932 | 43.85932 | 10.2669 | 40.2669 | 43.85932 | 10.2669 |

Table A2. Parameters of the wind farm.

| $v_i$ (m/s) | $v_r$ (m/s) | $v_o$ (m/s) | $w_{\text{rated}}$ (MW) |
|-------------|-------------|-------------|--------------------------|
| 3           | 10.8        | 25          | 150                      |

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