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Low-carbon generation expansion planning considering uncertainty of renewable energy at multi-time scales

Yuanze Mi¹, Chunyang Liu¹, Jinye Yang¹, Hengxu Zhang¹, Qiuwei Wu¹,²
1. Key Laboratory of Power System Intelligent Dispatch and Control of Ministry of Education (Shandong University), Jinan 250061, Shandong, P.R.China
2. Center for Electric Power and Energy, Department of Electrical Engineering, Technical University of Denmark, Kgs.Lyngby, Denmark

Abstract: With the development of carbon electricity, achieving a low-carbon economy has become a prevailing and inevitable trend. Improving low-carbon expansion generation planning is critical for carbon emission mitigation and a low-carbon economy. In this paper, a two-layer low-carbon expansion generation planning approach considering the uncertainty of renewable energy at multiple time scales is proposed. First, renewable energy sequences considering the uncertainty in multiple time scales are generated based on the Copula function and the probability distribution of renewable energy. Second, a two-layer generation planning model considering carbon trading and carbon capture technology is established. Specifically, the upper layer model optimizes the investment decision considering the uncertainty at a monthly scale, and the lower layer one optimizes the scheduling considering the peak shaving at an hourly scale and the flexibility at a 15-minute scale. Finally, the results of different influence factors on low-carbon generation expansion planning are compared in a provincial power grid, which demonstrate the effectiveness of the proposed model.

Keywords: Renewable energy, Multi-time scales, Uncertainty, Low-carbon, Generation planning.

0 Introduction

For carbon emission reduction, the installed capacities of wind turbines (WTs) and photovoltaics (PVs) have grown rapidly in China in recent years [1-2]. As of the end of 2019, the cumulative installed capacity of renewable energy exceeded 400 million kW, accounting for 34% of the global installed capacity of renewable energy [3-4]. Although wind and PV power have low carbon emissions, they pose inherent uncertainty and fluctuation challenges for the low-carbon planning and operation of a power system [5-6]. Therefore, it is necessary to fully consider the uncertainty of wind and PV power in a low-carbon generation expansion planning model.

Considerable research has been conducted on the correlation and fluctuation of renewable energies to capture their characteristics. In [7], a synergy coefficient based on the Pearson linear correlation coefficient was proposed to analyze the correlation between wind and PV power. Based on the probability distributions of wind and PV power, the Copula function was used to describe the spatial correlation in [8] and [9]; however, the temporal correlation was not considered. In [10], a wind power sequence model was
presented based on wind speed, considering the probability, autocorrelation, and season characteristics. In [11], a hybrid forecasting method based on a neural network was proposed by analyzing the forecasting methods of wind power and wind speed. In [12], a probability density model of wind power fluctuation was presented considering the statistical laws of wind power fluctuation at multi-time scales. In [13], a stochastic differential equation was used to capture the multi-time dependence structure of wind speed to derive predictive distributions and time-path trajectories. Although the correlation and fluctuation of renewable energies have been studied at certain scales, their uncertainty at multi-time scales still needs further study.

An integrated low-carbon generation expansion planning model was proposed in [14], which integrates and formulates the impacts of various low-carbon factors. A comprehensive generation planning model with a suitably modified objective function and additional constraints was proposed in [15] considering carbon emission trade and carbon tax. In [16] and [17], a generation planning model with carbon capture equipment was proposed, and the model results demonstrated that 90% carbon emission reduction can be achieved at the cost of a small amount of energy consumption. In [18], a generation planning model based on the operating characteristics of carbon capture equipment was presented, which considered carbon emission and primary coal supply constraints. A low-carbon generation expansion planning model was proposed by introducing the green certificate trade mechanism and the carbon trade mechanism [19] with consideration of the maximum income and renewable energy quota, carbon trade, and number of green certificates. A model considering economic and environmental benefits [20] was proposed based on investment decision optimization and multi-time scale optimization operation, and was found to be suitable for large-scale renewable energy integration. Although the method of low-carbon generation expansion planning was studied in the aforementioned research, the integration of low-carbon elements and the characteristics of renewable energy at multi-time scales should be further considered. For large-scale renewable energy integration in a power system, effect of the uncertainty at multi-time scales on the generation expansion planning cannot be considered simply.

The contributions of this paper are as follows. Aiming to solve the aforementioned problem, a two-layer low-carbon generation expansion planning model considering the uncertainty of renewable energy at multi-time scales is proposed based on the concept of decomposition coordination. The uncertainty at multi-time scales which is match investment decisions and multi-time scale operation assessment is considered in detail. In the upper layer of the model, the investment decision is optimized considering the uncertainty of renewable energy at a monthly scale. In the lower layer, the optimal operation is simulated to verify the peak regulation ability and flexibilities of the investment decision optimized in the upper layer. The peak regulation ability is verified by daily operation simulation at an hourly scale, whereas the flexibility is verified at a 15-minute scale. The model promotes carbon emission reduction while maintaining flexibility.

The remainder of this paper is organized as follows: an uncertainty model of renewable energy, which considers the spatio-temporal correlation and fluctuation at multi-time scales, is described in section 2. The proposed low-carbon generation expansion planning model comprising investment decision optimization and the operation simulation models is presented in section 3. A case study and simulation results are discussed in section 4, including the results and model comparisons. Finally, section 5 concludes the paper.

1 Uncertainty model of renewable energy at multi-time scales

1.1 Spatio-temporal correlation model of renewable energy

1.1.1 Probability density function of renewable energy

The kernel density estimation model is used in this study to describe wind power. The kernel density estimation is expressed as

\[
f(x) = \frac{1}{Nh} \sum_{i=1}^{N} K\left(\frac{x - x_i}{h}\right)
\]

where \( h \) is the smoothing coefficient \( (h > 0) \), \( K(\cdot) \) is the kernel function, and \( x_i \) is the \( i \)th sample of the variable, and the cumulative distribution function (CDF) can be obtained by integrating \( f(x) \).

PV power presents an approximately linear correlation [21] with irradiance. The beta distribution can be used to describe the irradiance in certain periods. Subsequently, the probability density function of PV power can be obtained as follows:

\[
f(y) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha)\Gamma(\beta)} \left(\frac{y}{y_{\text{max}}}\right)^{\alpha-1} \left(1 - \frac{y}{y_{\text{max}}}\right)^{\beta-1}
\]

where \( \alpha \) and \( \beta \) are the shape parameters of the beta distribution and \( y_{\text{max}} \) is the maximum PV power output.  

1.1.2 Spatial correlation model of renewable energy

Based on the probability distribution functions of wind and PV power, the Copula function [22] is used to describe the spatial correlation. The modeling steps are as follows:
1) The parameters of the probability distributions expressed in (1) and (2) are obtained by the maximum likelihood estimation.

2) The probability distribution functions obtained in 1) are regarded as the marginal distribution functions of the Copula function. Subsequently, the Kendall correlation coefficient and the Euclidean distance are employed to fit the Copula function indices [23-24].

3) The optimal Copula function obtained in 2) is used to generate the sequences considering the spatial correlation of wind and PV power using the Monte Carlo method. These sequences considering spatial correlation can be expressed as $[u_1^w, u_2^w, \cdots, u_N^w]$ and $[u_1^v, u_2^v, \cdots, u_N^v]$, respectively, where $N$ is the sequence length.

1.1.3 Spatio-temporal correlation model based on spatial correlation model

The sequences considering spatio-temporal correlation can be generated based on the model of temporal correlation and the sequences considering spatial correlation, which are described in section 2.1.2.

The temporal correlation model is as follows:

Let $h_{-1}$ and $h_t$ be the outputs of wind or PV power at times $t-1$ and $t$, respectively. Thus, the probability distributions of wind and PV power at the corresponding times can be expressed as $F_{i-1}(h_{-1})$ and $F_i(h_t)$, respectively. Based on the Copula theory, the joint probability density function at these adjacent times can be expressed as follows:

$$f_{y}(h_{-1}, h_t) = \frac{F(h_{-1}, h_t)}{\partial x_{-1} \partial y} = c(f_{i-1}(h_{-1}), f_i(h_t)) f_{i-1}(h_{-1}) f_i(h_t)$$

(3)

where $c(\cdot)$ is the probability density function of the optimal copula function, $F(h_{-1}, h_t)$ is the joint probability distribution, and $f_{i-1}(h_{-1})$ and $f_i(h_t)$ are the probability density functions of renewable energy at times $t-1$ and $t$, respectively.

Based on the conditional probability distribution theory, the probability density of renewable energy at time $t$ can be obtained using $h_{-1}$:

$$f_{y}(h_t | h_{-1}) = f_{x|y}(h_{-1}, h_t) = f_{i-1}(h_{-1}) c(f_{i-1}(h_{-1}), f_i(h_t)) f_i(h_t)$$

(4)

where $f_{x|y}(h_t | h_{-1})$ is the conditional probability density function of renewable energy at time $t$.

Based on the temporal correlation model, the wind power sequence considering the spatio-temporal correlation can be generated by the following steps:

1) $u_1^w$ is substituted for $h$ in (4).

2) The wind power sequence at time $t+1$ is updated based on the joint probability density in (4).

3) $t = t + 1$ is set, and step 2) is repeated until $t = N$.

Finally, the wind power sequence considering the spatio-temporal correlation is expressed as $[h_1^w, h_2^w, \cdots, h_N^w]$, where $h_i^w$ is the wind power output at time $i$. Similarly, the PV power sequence, $[h_1^v, h_2^v, \cdots, h_N^v]$, is also updated.

1.2 Fluctuation model of renewable energy

The spatio-temporal correlation is considered in the aforementioned generated sequences, whereas the fluctuation is not. The sequences still need to be modified by considering the fluctuation. The fluctuation distributions of renewable energy at multi-time scales are different. The normal distribution [8] has been commonly used to describe the fluctuation of renewable energy. t-location-scale and logistic distributions are introduced in this study to describe the fluctuation of renewable energy, which are more flexible than the normal distribution.

The probability density function of t-location-scale is expressed as

$$f(\Delta P) = \frac{1}{\sqrt{\pi} \Gamma \left(\frac{v}{2}\right)} \left[1 + \frac{(\Delta P - \mu)^2}{\sigma^2} \right]^{-\frac{v+1}{2}}$$

(5)

where $v$, $\mu$, and $\sigma$ are the shape, position, and scale parameter, respectively.

The probability density function of the logistic can be expressed as

$$f(\Delta P) = \frac{e^{-\frac{\Delta P - \mu}{\sigma}}}{\sigma \left[1 + e^{-\frac{\Delta P - \mu}{\sigma}}\right]^2}$$

(6)

where $\mu_i$ is the position parameter and $\sigma_i$ is the scale parameter.

The statistic, $S$, in the K–S test [25] and fitting error $I$ are introduced as indices to test the performance of fitting.

$$I = \sum_{i=1}^{N} (y_i - \bar{y}_i)^2$$

(7)

$$y_i = f(a_i)$$

(8)

where $I$ is the fitting error, $f$ is the fitting probability density function, $\bar{y}_i$ is the height of the $i$th histogram, $y_i$ is the value of the fitting probability density function at position $a_i$, and $a_i$ is the center of the $i$th histogram.

1.3 Sequence considering uncertainty at multi-time scales

Based on the data demand of the low-carbon generation expansion planning model proposed in this paper,
fluctuation models at multi-time scales are combined with the models considering the spatio-temporal correlation of wind and PV power to generate sequences at multi-time scales. The procedure of generating sequences at multi-time scales is shown in Fig 1. The method of generating wind power sequence is similar to that of PV power sequence. Taking wind power as an example in this section, the method is as follows:

Step 1: Based on the historical data of wind power, the hourly sequence considering the spatio-temporal correlation is generated by the model presented in section 2.1 and denoted as $\{h_1^w, h_2^w, \ldots, h_N^w, t = 1, 2, \ldots, N\}$.

Step 2: Based on the hourly sequence in step 1 and the fluctuation model at a 15-minute level, the sequence of the 15-minute level is generated. The wind power at period $t$ is $h_t^w$ in an ideal condition when the fluctuation is not considered.

Based on the fluctuation model described in section 2.2, the value of the fluctuation at the 15-minute scale during period $t$ is $\Delta P_{t,a}$, where

$$h_t^w = h_t^w + \Delta P_{t,a}$$   \hspace{1cm} (9)

$\Delta P_{t,a}$ and $h_t^w$ are the output of the wind power and the value of the wind power fluctuation at the $a$th 15-minute interval at period $t$, where $a = 1, 2, 3, 4$. The wind power sequence generated here is used for a 15-minute operation simulation in the generation planning model.

Step 3: Similarly, the hourly sequence of wind power is generated using the hourly fluctuation model to update the hourly sequence considering the spatio-temporal correlation.

$$h_t^w = h_t^w + \Delta P_{t,a}$$   \hspace{1cm} (10)

where $h_t^w$ and $\Delta P_{t,a}$ are the output of the wind power and the value of the wind power fluctuation at time $t$. The generated sequence here is used for hourly operation simulation on typical days in the generation planning model.

Step 4: Based on the hourly sequence in step 1, the capacity credit [19] is used to describe the monthly sequence. The capacity credit is calculated using the dichotomy method. The monthly sequence is used for investment decision optimization in the generation planning model.

2 Low-carbon generation expansion planning model

2.1 Framework of low-carbon generation expansion planning model

The uncertainty of renewable energy at multi-time scales and low-carbon elements are introduced into the traditional generation expansion planning model. Subsequently, the two-layer low-carbon generation expansion planning model considering the uncertainty of renewable energy at multi-time scales is proposed. Based on the concept of decomposition coordination, the scale of the problem can be simplified and the uncertainty at multi-time scales can be considered more accurately using the two-layer model than that by the traditional model. The upper layer model, i.e., the investment decision optimization, mainly considers the planning scheme, load growth, and total cost of the generation planning after the introduction of a carbon trading model and carbon capture power plants. The lower layer one, i.e., the operation simulation, comprises the typical daily operations considering peak regulation verification and a 15-minute operation considering flexibility verification. In addition, typical days are selected by clustering the generated sequences. By coordinated iteration and rolling correction between investment decision optimization and multi-time scale operation simulation, the optimized planning scheme with comprehensive benefits of economy, low-carbon emission, and flexibility is obtained. The overall framework is shown in Fig. 2.

2.2 Model of investment decision optimization

The investment decision is made monthly to consider the fluctuation and uncertainty of renewable energy accurately.

2.2.1 Objective function of investment decision optimization

$$\min C = F_{tv} + F_{ep} + F_{co2}$$   \hspace{1cm} (11)
2.2.2 Investment decision optimization constraints

1) Power balance constraint

\[
F_{\text{inv}} = \sum_{y=1}^{N} \sum_{i \in \Omega_i} \left( 1 - d_y \right) p_i U_i P_{\text{i,max}}
\]

where \( N \) is the number of planning months; \( \Omega_i \) is the set of candidate power plants; \( d_y \) is the discount coefficient in month \( y \), and \( d_y = (1 + r / 12)^{-y} \), where \( r \) is the annual discount interest rate; \( p_i \) is the discount coefficient in month \( y \); \( U_i \) is the capital cost; and \( P_{\text{i,max}} \) is the capacity of power plant \( i \).

\( F_{\text{op}} \) is the operating cost of a power plant, comprising its fixed operating cost and the fuel cost.

\[
F_{\text{op}} = \sum_{y=1}^{N} \sum_{i \in \Omega_i} d_y \left( G_{\text{i,y}} P_{\text{i,max}} + E_{\text{i,y}} f_i \right)
\]

where \( \Omega_i \) is the set of existing power plants, \( G_{\text{i,y}} \) is the fixed cost of power plant \( i \) in month \( y \), \( E_{\text{i,y}} \) is the power generation in month \( y \), and \( f_i \) is the power generation cost of power plant \( i \).

During the planning stage, the carbon trading cost, \( F_{\text{co2}} \), is expressed as

\[
F_{\text{co2}} = \sum_{y=1}^{N} P_{\text{co2}}
\]

where \( P_{\text{co2}} \) is the carbon trading cost in month \( y \),

\[
P_{\text{co2}} = \begin{cases} W_{C_{\text{CO2}}} (E_{\text{r},y} - E_{\text{r},y}^d), & E_{\text{r},y} \leq E_{\text{d},y} \\ W_{C_{\text{CO2}}} (E_{\text{r},y} - E_{\text{r},y}^d) + W_{\text{PC}} (E_{\text{r},y} - E_{\text{r},y}^d - E_{\text{h},y}^d), & E_{\text{r},y} > E_{\text{d},y} \end{cases}
\]

where \( E_{\text{d},y} \) is the carbon emission quota, which is denoted as

\[
E_{\text{d},y} = \sum_{t=1}^{T_y} P_{\text{Gr}}
\]

\( P_{\text{Gr}} \) is the total power generation of all power plants at time \( t \), \( \eta \) is the coefficient of the carbon emission quota, \( W_{C_{\text{CO2}}} \) is the carbon trading price, \( E_{\text{h},y} \) is the upper limit purchase of carbon emissions, and \( W_{\text{PC}} \) is the penalty fee for the excess of carbon emission quota.

2.2.2.2 Investment decision optimization constraints

1) Power balance constraint

\[
\sum_{i \in \{\xi, \zeta, \eta, \lambda \}} P_{i,y} \geq L_{\text{max},y} (1 + R_{\text{y}})
\]

where \( P_i \) is the available capacity of power plant \( i \) in month \( y \), which consists of the installed capacity of coal-fired power plants, the expected output of hydropower power plants, and monthly capacity credit for renewable energy considering multi-time scales. \( L_{\text{max},y} \) is the maximum load in month \( y \) and \( R_{\text{y}} \) is the coefficient of the reserve.

2) Electricity balance constraint

\[
\sum_{i \in \{\xi, \eta \}} E_{i,y} \geq E_{\text{y}}^m + E_{\text{b}} - E_{\text{e}}
\]

where \( E_{\text{y}}^m \) is the demand of electricity in month \( y \) and \( E_{\text{b}} \) is the coefficient of electricity reserve in month \( y \).

3) Primary energy supply constraint

The introduction of carbon capture technology may exacerbate the primary energy shortage because of the additional energy consumption. Therefore, the upper limit of the primary energy supply is set as

\[
\sum_{i \in \{\xi, \eta \}} E_{i,y} q_{i,m} \leq Q_{m,y}
\]

where \( q_i \) is the fuel consumption characteristics of fuel \( m \) and \( Q_{m,y} \) is the total supply of fuel \( m \) in month \( y \). Primary coal resources are considered in this study because of the inclusion of a coal-based system.

4) Carbon trade constraint

\[
\sum_{i \in \{\xi, \eta \}} P_{i,y} \geq \lambda_y \sum_{i \in \{\xi, \eta \}} P_{i,y}^m, \ y = 1, 2, \ldots, N
\]

where \( P_{i,y}^m \) is the increased installed capacity of renewable energy power plant \( z \) in month \( y \) and \( \lambda_y \) is the penetration coefficient of renewable energy installed capacity in month \( y \).

5) Penetration of renewable energy constraint

\[
\sum_{i \in \{\xi, \eta \}} P_{i,y} \geq \lambda_y \sum_{i \in \{\xi, \eta \}} P_{i,y}^m, \ y = 1, 2, \ldots, N
\]

6) Negative reserve constraint

\[
\sum_{i \in \{\xi, \eta \}} \theta \cdot P_{i,y} \geq L_{\text{max},y} R_{\text{down}}
\]

where \( \theta \) is the negative reserve coefficient of power plant \( I \) and \( R_{\text{down}} \) is the coefficient of the negative reserve demand in month \( y \).

2.3 Model of operation simulation

The operation simulation is used to verify the peak regulation and ramping abilities at hourly and 15-minute scales on typical days.

2.3.1 Hourly operation simulation on typical days

The objective function comprises the operating costs, penalty fees for curtailment, penalty fees for the loss of load, and carbon trading costs.
\[
\min C_w = \sum_{t=1}^{T} \sum_{i \in \Omega} P_{i,t} f_i + \sum_{t=1}^{T} \sum_{i \in \Omega} \rho_u U_{i,t} + \rho_d D_{i,t} + \sum_{t=1}^{T} (\rho_{res} E_{res,t} + \rho_{loss} E_{loss,t} + P_{co,t,t})
\]  

(22)

where \( T \) is the total number of operating hours on typical days, \( \Omega \) is the set of all operable power plants, \( P_{i,t} \) is the power output of power plant \( i \) at time \( t \), \( \rho_{res} \) is the penalty fee of renewable energy curtailment, \( E_{res,t} \) is the renewable energy curtailment at time \( t \), \( \rho_{loss} \) is the penalty fee of the loss of load, \( E_{loss,t} \) is the loss of load of the system, and \( P_{co,t,t} \) is the carbon trading cost of the system.

The constraints on typical daily hourly operation simulation are as follows:

1) Coal-fired power plants constraints

\[
\begin{align*}
\sum_{t=a+T_i}^{a+T_i+1} I_{i,t} & \geq T_{on,i}, \forall i \in \Omega_{the}, \forall t \\
\sum_{t=a}^{a+T_i-1} I_{i,t} & \leq T_{down,i}, \forall i, \forall t \\
I_{i,t} - I_{i,t+1} & \leq U_{i,t}, \forall i, \forall t \\
I_{i,t} - I_{i,t-1} & \leq D_{i,t}, \forall i, \forall t
\end{align*}
\]

(23)

where \( P_{i,min} \) is the minimum output of coal-fired power plant \( i \), \( P_{i,max} \) is the maximum output, \( I_{i,t} \) is the binary state status (1 for running status and 0 otherwise) at time \( t \), \( \Omega_{the} \) is the set of coal-fired power plants, \( T_{on,i} \) is the minimum uptime, \( T_{down,i} \) is the minimum downtime; \( U_{i,t} \) is the start-up binary variable, and \( D_{i,t} \) is the binary shutdown variable. The gas-fired and nuclear power plants are similar to the coal-fired power plants. The aforementioned constraints comprise the upper and lower output limits of the coal-fired power plants, minimum up-down time constraints, and logic constraints of the statuses.

2) Renewable energy constraint

\[
0 \leq P_{i,t} \leq \bar{s}_{i,t}, \forall i \in \Omega_{res}, \forall t
\]

(24)

where \( \bar{s}_{i,t} \) is the available output of a renewable energy power plant and \( \Omega_{res} \) is the set of renewable energy power plants.

3) Positive and negative reserve constraints

\[
\begin{align*}
\sum_{i \in \Omega_k} P_{i,t} & \geq (1 + R^+ t) L_t \\
\sum_{i \in \Omega_k} P_{i,t} & \leq (1 - R^- t) L_t
\end{align*}
\]

(25)

(26)

where \( R^+ t \) and \( R^- t \) are the positive and negative reserves of the system at time \( t \) respectively, and \( L_t \) is the load at time \( t \).

4) Power balance constraint

\[
\sum_{i \in \Omega_k} P_{i,t} + \sum_{i \in \Omega_{nuc}} P_{i,t} + E_{loss,t} = L_t
\]

(27)

2.3.2 Fifteen-minute operation simulation on typical days

The schedule of each power plant is obtained from the hourly operation simulation on typical days, as described in section 2.3.1.

The objective function of the 15-minute operation simulation comprises the operating costs, penalty fees for renewable energy curtailment, and penalty fees for insufficient ramping capacity.

\[
\min C_w = \sum_{t=1}^{T} \sum_{i \in \Omega} P_{i,t,f} f_i + \sum_{t=1}^{T} \sum_{i \in \Omega} \rho_{ramp} (P_{U,t} + P_{D,t}) + \sum_{t=1}^{T} (\rho_{res} E_{res,t} + \rho_{loss} E_{loss,t})
\]

(28)

where \( T_n \) is the total number of operating periods, \( \rho_{ramp} \) is the penalty fee for insufficient ramping capacity, and \( P_{U,t} \) and \( P_{D,t} \) are the relaxation of the upward and downward ramping capacities at time \( t \), respectively.

Note that the constraints are similar to those of the hourly operation simulation presented in section 1.3.1. The added 15-minute ramping constraints of the system are as follows:

\[
L_{t,a} - L_{t,a-1} \leq \sum_{i \in \Omega_k} v_{i,a} \Delta T + P_{U,t}
\]

(29)

\[
L_{t,a} - L_{t,a-1} \leq \sum_{i \in \Omega_k} v_{i,a} \Delta T + P_{D,t}
\]

(30)

where \( v_{i,a} \) and \( v_{i,a} \) are the upward and downward ramping rates, respectively.

2.4 Solving procedure

The proposed generation expansion planning model proposed in this paper is a mixed-integer linear programming model. Solver Cplex or Gurobi can be used to solve the model. The solving procedure is shown in Fig. 3.

![Fig. 3 Flowchart of solving procedure](image-url)
3 Case study

The generation expansion models are implemented in MATLAB using solver CPLEX 12.5 on a PC with an Intel Core(TM) i7-8750H CPU and 8 GB RAM, and the model is established using YALMIP.

3.1 Test system and data

The proposed low-carbon generation expansion planning model is applied to a provincial power grid covering 2020 to 2026. The installed capacity in 2020, in this case, is shown in Fig. 4.

![Fig. 4 Installed capacity in 2020](image)

The full life cycle carbon emissions of wind and PV power are considered in this study. The carbon emissions of wind and PV power are 0.252 and 0.246 kg/kWh [26-28], respectively. The overall carbon emission of coal-fired power is 0.89 kg/kWh.

The main operating parameters of the different types of power plants are listed in Table 1.

<table>
<thead>
<tr>
<th>Types</th>
<th>Generation cost (yuan/MWh)</th>
<th>Carbon emission (t/MWh)</th>
<th>Coal cost (t/1000MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal-fired</td>
<td>350</td>
<td>0.89</td>
<td>0.34</td>
</tr>
<tr>
<td>Carbon Capture</td>
<td>410</td>
<td>0.09</td>
<td>0.40</td>
</tr>
<tr>
<td>Gas-fired</td>
<td>610</td>
<td>0.4</td>
<td>0</td>
</tr>
<tr>
<td>Nuclear</td>
<td>84</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Pump</td>
<td>105</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hydro</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>WT</td>
<td>0</td>
<td>0.252</td>
<td>0</td>
</tr>
<tr>
<td>PV</td>
<td>0</td>
<td>0.246</td>
<td>0</td>
</tr>
</tbody>
</table>

The data of the candidate plants are summarized in Table 2.

<table>
<thead>
<tr>
<th>Types</th>
<th>Investment (million yuan/MW)</th>
<th>Fixed cost (million yuan/year)</th>
<th>Total capacity (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coal-fired</td>
<td>375</td>
<td>100</td>
<td>6400</td>
</tr>
<tr>
<td>Carbon Capture</td>
<td>393</td>
<td>115</td>
<td>12600</td>
</tr>
<tr>
<td>Gas-fired</td>
<td>315</td>
<td>113</td>
<td>7650</td>
</tr>
<tr>
<td>Nuclear</td>
<td>1150</td>
<td>450</td>
<td>8150</td>
</tr>
<tr>
<td>Pump</td>
<td>440</td>
<td>205</td>
<td>1800</td>
</tr>
<tr>
<td>Hydro</td>
<td>1136</td>
<td>295</td>
<td>480</td>
</tr>
<tr>
<td>WT</td>
<td>710</td>
<td>220</td>
<td>11220</td>
</tr>
<tr>
<td>PV</td>
<td>782</td>
<td>240</td>
<td>12100</td>
</tr>
</tbody>
</table>

The carbon trading price is set as 150 yuan/ton. The carbon emission quota is set as 0.75 ton/MWh. \( R^p_C \) is set as 10%. \( E_p \) is set as 0.4 times the carbon emission quota. The discount rate is set as 10%. \( W_p \) is set as 600 yuan/ton. \( \lambda_p \) is set as 30%. The threshold of peak regulation is set as 0.01 times the value of load in the corresponding period. The maintenance of the plants is arranged based on the maintenance schedule of the province.

3.2 Scenarios generation at different scales

The hourly fluctuation fitting indices of wind power and photovoltaic are shown in Table 3.

<table>
<thead>
<tr>
<th>Types</th>
<th>index</th>
<th>normal</th>
<th>t-location-scale</th>
<th>logistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>WT</td>
<td>( S )</td>
<td>0.0832</td>
<td>0.0197</td>
<td>0.0461</td>
</tr>
<tr>
<td>( I )</td>
<td>0.0051</td>
<td>0.0016</td>
<td>0.0031</td>
<td></td>
</tr>
<tr>
<td>PV</td>
<td>( S )</td>
<td>0.1733</td>
<td>0.1467</td>
<td>0.1550</td>
</tr>
<tr>
<td>( I )</td>
<td>0.1060</td>
<td>0.079</td>
<td>0.1024</td>
<td></td>
</tr>
</tbody>
</table>

Based on Table 3 the t-location-scale distribution is more accurate than the normal and logistic distributions to fit the hourly fluctuation.

Furthermore, the renewable energy fluctuations at other time scales are analyzed. The results demonstrate that the t-location-scale distribution is more suitable to fit the hourly fluctuation, whereas the logistic distribution is more accurate to fit the fluctuation at the 15-minute scale.

Using the historical data of 2019, the fitting results of different Copula functions are provided in Table 4.
Table 4 Parameters of candidate Copula functions

<table>
<thead>
<tr>
<th>Types</th>
<th>Model coefficient</th>
<th>Kendall coefficient</th>
<th>Euclidean distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gaussian</td>
<td>0.9796</td>
<td>0.8713</td>
<td>0.0057</td>
</tr>
<tr>
<td>t</td>
<td>0.9868</td>
<td>0.8964</td>
<td>0.0042</td>
</tr>
<tr>
<td>Gumbel</td>
<td>0.9074</td>
<td>0.8988</td>
<td>0.0041</td>
</tr>
<tr>
<td>Clayton</td>
<td>11.5878</td>
<td>0.8528</td>
<td>0.0099</td>
</tr>
<tr>
<td>Frank</td>
<td>35.7888</td>
<td>0.9134</td>
<td>0.0026</td>
</tr>
</tbody>
</table>

From Table 4 the optimal Copula function is Frank–Copula because of the maximum Kendall coefficient and the minimum Euclidean distance.

Using the proposed simulation method considering the uncertainty of renewable energy at multi-time scales and the provincial historical data, wind and PV power sequences are generated at the 15-minute and hourly scales.

The generated sequences are validated by the verification of the spatial correlation, autocorrelation, and fluctuation. Taking the generated sequences in a week at an hourly time scale as an example, the spatial correlation coefficients for the original and generated sequences are −0.3962 and −0.3621, respectively. Using the coefficients, the proposed method can capture the spatial correlation accurately. The verification of autocorrelation and fluctuation are shown in Fig. 5 and 6, respectively. The figures show that the autocorrelation function (ACF) and CDF for the generated sequence are similar to those for the original sequence. The proposed method can also capture the autocorrelation and fluctuation accurately.

3.3 Simulation results and analysis

The investment decision results of the proposed model and their costs are shown in Fig. 7 and listed in Table 5 respectively.

The added installed capacities of the coal-fired, carbon capture, gas-fired, hydro, pump, nuclear, wind power, and PV power are 3670 MW, 8400 MW, 5390 MW, 480 MW, 1800 MW, 8150 MW, and 15900 MW respectively. The power plants with low generation cost and low carbon emissions, i.e., pump, hydro, renewable energy, and nuclear, are placed into production in the early stages. Owing to the
limitation of the primary coal supply, carbon capture power plants with low carbon emissions are placed into production in large quantities until 2024 to deal with the increase in the load and system carbon emissions. At the end of the planning period, the installed capacity of the gas-fired plant gradually increases to alleviate the burden of the primary coal supply and the carbon emissions.

In addition, the effects of the introduction of carbon capture power plants and large-scale renewable energy integration on peak regulation are considered by hourly operation simulation of typical days. Taking the day of maximum load in 2026 as an example, the results of the simulation are shown in Fig. 8.

Based on Fig. 8 the nuclear power plants, coal-fired power plants with low generation costs, and carbon capture power plants with better peak regulation performance have priority for power generation. The proposed generation planning scheme has sufficient capacity for peak regulation and non-curtailment, which fully accommodates wind and PV power and promotes carbon emission reduction.

3.4 Comparison with traditional model

The proposed model in this paper is compared with the traditional model without considering the uncertainty of renewable energy at multi-time scales and the carbon capture power plants. The comparison results of the installed capacity in 2026 are shown in Fig. 9.

The key indices of the two low-carbon generation expansion planning schemes are listed in Table 6.

The proposed model performs better than the traditional model. The installed capacity of the coal-fired power plants is significantly reduced and the carbon capture power plants with low carbon emissions are placed into production on priority. Based on Table 6 compared to the traditional model, the proposed scheme reduces the total cost by 13.24 billion yuan and the carbon emissions by 82 million ton, which ensures the economic benefits of the system while achieving carbon emission reduction.

3.5 Sensitivity analysis of proposed model

1) Effects of carbon emission quota on planning results

Based on the proposed scheme, the carbon emissions quota is increased by 10% and decreased by 10% as comparison cases. The low-carbon generation expansion planning schemes in 2026 under different carbon emission quotas are shown in Fig. 10.

From Fig 10, the carbon emission quota has a significant impact on the installed capacities of the coal- and gas-fired plants in the planning period. The carbon-free power plants, such as nuclear, pump, and hydro plants, are placed into production on priority to alleviate the burden of carbon emissions under the condition of a low-carbon emission quota. Large-scale coal-fired power plants with low generation costs are placed into production to ensure economic benefits when the carbon emission quota is high.

2) Effects of carbon trading price on planning results

Based on the proposed scheme, the carbon trading price is increased by 20% and decreased by 20% as comparison cases. The low-carbon generation expansion planning
schemes under the different carbon emission quotas are shown in Fig. 11.

Carbon trading price has a significant effect on coal-fired and carbon capture plants. The coal-fired power plants are placed into production on priority with low-carbon trading prices, whereas the carbon capture and gas-fired power plants with higher generation costs have lower installed capacities. With the increase in the carbon trading price, the carbon capture, gas-fired, and nuclear power plants are placed into production on priority to alleviate the carbon emission burden.

3) Effects of penetration of renewable energy on planning results

Based on the proposed scheme, the penetration of renewable energy is increased by 10% and decreased by 10% as comparison cases. The low-carbon generation expansion planning schemes under the different proportions of renewable energy are shown in Fig. 12.

With the increase in the renewable energy penetration, system tends toward low carbonization. The carbon capture, gas-fired, and nuclear power plants with low carbon emissions are placed into production, whereas the proportion of coal-fired power plants with high carbon emissions is increasingly reduced.

4 Conclusion

In this paper, a two-layer low-carbon generation expansion planning approach considering the uncertainty of renewable energy at multi-time scales is proposed. Based on the comparison and sensitivity analysis, the following conclusions are obtained:

1) A low-carbonization power structure is achieved by considering the life cycle carbon emissions of renewable energy and introducing low-carbon technology and market.

2) Compared with the traditional model, the uncertainty of renewable energy at multi-time scales and carbon capture power plants are introduced into the model proposed in this paper. The renewable energy outputs are simulated more accurately, and the operation costs and carbon emissions are reduced correspondingly.

3) The installed capacity of the coal-fired power plants with high carbon emissions is decreased when the carbon quota is low and the carbon trading price is high. In comparison, the power plants with low-carbon emissions, such as carbon capture, nuclear, and renewable energy plant, are placed into production on priority.

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Declaration of Competing Interest

We declare that we have no conflict of interest.

References


Biographies

Yuanze Mi received his bachelor degree from the University of Jinan, Jinan, China in 2018. He is now pursuing his Master’s degree in electrical engineering from Shandong University, Jinan, China. His research interests include power system planning and operation.
Chunyang Liu received his B.S. and Ph.D. degrees in electrical engineering from Xi’an Jiaotong University, Xi’an, China in 2012 and 2018, respectively. He is now an assistant researcher with the Key Laboratory of Power System Intelligent Dispatch and Control of the Ministry of Education (Shandong University), P. R. China. His major research interests include energy management of microgrids and integrated energy systems.

Jinye Yang received her bachelor degree from Nanjing Normal University, Nanjing, China, in 2019. She is now pursuing his Master’s degree of Electrical Engineering in Shandong University, Jinan, China. Her research interests include power system planning and operation.

Hengxu Zhang received his bachelor degree from Shandong University of Technology in 1998 and his Master and Ph.D. degrees in electrical engineering from Shandong University in 2000 and 2003, respectively. He is now working as a professor with the Key Laboratory of Power System Intelligent Dispatch and Control of the Ministry of Education (Shandong University), P. R. China. His research interests include power system security and stability assessment, power system monitoring, and numerical simulation.

Qiuwei Wu obtained the B.Eng. and M.Eng. in Power System and Its Automation from Nanjing University of Science and Technology, Nanjing, China, in 2000 and 2003, respectively. He obtained the PhD degree in Power System Engineering from Nanyang Technological University, Singapore, in 2009. He was a senior R&D engineer with Vestas Technology R&D Singapore Pte Ltd from Mar. 2008 to Oct.2009. He has been working at Department of Electrical Engineering, Technical University of Denmark (DTU) since Nov. 2009 (PostDoc Nov.2009-Oct.2010, Assistant Professor Nov. 2010-Aug. 2013, Associate Professor since Sept.2013). He was a visiting scholar at Department of Industrial Engineering &Operations Research (IEOR), University of California, Berkeley, from Feb. 2012 to May 2012 funded by the Danish Agency for Science, Technology and Innovation (DASTI), Denmark. He has been a visiting professor named by Y.Xue, an Academician of Chinese Academy of Engineering, at Shandong University, China, since Nov. 2015. His research interests are modeling and control of wind power, electric vehicle, active distribution networks, energy management, and electricity market.

(Editor Dawei Wang)