Hindawi
Wireless Communications and Mobile Computing
Volume 2022, Article ID 5213270, 11 pages
https://doi.org/10.1155/2022/5213270

WILEY | Hindawi

Research Article

Power Grid Low Carbon Collaborative Planning Method Using Improved Cat Swarm Optimization Algorithm in Edge Cloud Computing Environment

Xiang Li[1], **Chong Guo**[2], **Chengjun Li**[1], **Tianyuan Xu**[1], **and Songyu Wu**[1]

[1]*Electric Power Research Institute, State Grid Liaoning Electric Power Co. Ltd., Shenyang, Liaoning 110006, China*
[2]*School of Information Science and Engineering, Shenyang Ligong University, Shenyang, Liaoning 110159, China*

Correspondence should be addressed to Chong Guo; guochong5189@sylu.edu.cn

Received 5 January 2022; Revised 26 January 2022; Accepted 15 February 2022; Published 7 March 2022

Academic Editor: Shalli Rani

The current power grid planning mostly realizes the calculation and analysis based on the factors of operation reliability or operation economy, but low-carbon green operation has become the main melody of power system development. Aiming to support the green and reliable operation of the power grid, this paper proposes a power grid low-carbon collaborative planning method based on improved cat swarm optimization algorithm. First, the carbon emission characteristics of the whole cycle of power grid construction are analyzed on the edge side, and a power grid planning model including environmental, economic, and reliability is constructed; on the cloud side, the cat swarm optimization algorithm is improved based on quantum mechanics and chaotic algorithm to achieve efficient solution to the power grid low-carbon planning model, which can support the stable and sustainable operation. Finally, the simulation experiment is realized based on IEEE 39 bus system. In this experiment, the construction cost and carbon emission of the proposed collaborative planning method are 23 million yuan and 2.28 t/MWh, respectively, which can reduce carbon emission while optimizing the construction cost and maintaining the low-carbon and stable operation.

1. Introduction

Traditional power grid planning is to formulate the planning scheme of the area where the power system is located on the basis of meeting the constraints of power balance, taking the load demand as the goal, taking safety, reliability, economy, and rationality as the basic conditions, and taking the location and capacity of power supply and power grid structure as the main contents [1, 2]. Reasonable power grid planning scheme plays a vital role in power grid construction and system operation.

In recent years, in order to improve global warming and maintain stable energy storage, green and sustainable energy supply strategy has become an important research object in power-related industries [3–5]. Power industry has significant carbon locking effect, which requires that the economy of the system and the benefits of carbon emission reduction should be included in power grid planning.

At the same time, vigorously developing renewable energy is an important demand for low-carbon transformation of social energy system. Large scale clean energy grid connection is an important feature of new energy power system. The proportion of renewable energy in the energy consumption structure in 2050 is expected to exceed 60%. Furthermore, as the main carbon emission source in the power industry, the low-carbon development planning of the power generation side has attracted extensive attention of scholars at home and abroad [6, 7].

In the traditional planning method, the goal of power grid planning is to achieve stable and reliable power supply. In addition to considering the reliability and economy, the new power system planning under the carbon trading environment should also include the carbon level into the evaluation system [8]. The essence of the evaluation decision-making of the model is the tripartite game of economic indicators, reliability indicators, and environmental indicators

[9]. How to combine carbon level assessment with power system planning decision-making [10], the establishment of low-carbon assessment system is the primary problem to ensure the optimal planning of new power system.

In view of the existing problems, in order to realize the low-carbon and efficient steady-state operation of power system, this paper proposes a collaborative planning method to realize the low-carbon sustainable development of power grid based on the efficient computing mode of cloud edge collaboration, which can effectively control the carbon emission content of power grid and ensure the green sustainable state of power grid. The main contributions of this paper are as follows:

(1) Fully analyze the carbon emission characteristics of power transmission and transformation equipment in the power grid in the whole life cycle on the edge side, then establish the carbon emission evaluation model of equipment in the whole life cycle, model the network loss based on DC power flow, and embed it into the power grid planning model to provide reliable and comprehensive low-carbon power grid model support for cloud side planning solution

(2) On the cloud side, the parameter update of cat swarm optimization (CSO) algorithm is improved based on quantum mechanics and chaos algorithm to solve the problem of local optimization of traditional algorithm. In the later stage of algorithm iteration, it can save population resources, improve the search ability of local optimization and the accuracy of global search, and then improve the efficiency of planning problem solving

The main contents of the rest of the paper are arranged as follows. The second section introduces the corresponding research on power grid low-carbon planning; the third section combs the overall framework of the paper; the fourth section realizes the simulation verification based on the improved standard example; the fifth section is the conclusion of this paper.

2. Related Work

Reasonable and effective planning methods for power grid to realize low-carbon economy will help to understand the actual low-carbon development level of power grid, feedback the implementation effect of low-carbon measures, and find the potential of power grid construction and improvement [11, 12]. And the research on power grid planning method and evaluation under the low-carbon development goal has very important practical significance for guiding the planning, construction, operation, and management of low-carbon power system.

The traditional linear programming model is essentially a nonlinear multiobjective optimization problem. At present, the existing power grid planning research only analyzes and discusses the reliability index or economic index, including the operation safety, power supply reliability, investment scale, and economic return after the power grid is put into operation.

At present, China's carbon dioxide emissions from electricity account for 38.73% of China's total carbon emissions from fossil energy [13]. Therefore, on the premise of adapting to the national economic development, it is an urgent problem to realize the adjustment of power energy structure and strategic planning and the road of sustainable development of power under the low-carbon mode [14].

Therefore, it is particularly important to introduce environmental indicators into the construction of planning model [15, 16]. In the power grid planning, the key issue for the energy system is to promote the clean energy transformation of the energy strategy of building a "national network" by introducing the analysis of carbon emission characteristics.

In fact, the contribution of power grid links to the realization of low-carbon power cannot be ignored [17, 18]. A reasonable power grid structure can not only reduce the power grid operation energy consumption but also reduce the comprehensive carbon emission intensity at the power generation side.

The research on low-carbon power grid planning is mainly divided into the following three aspects [19, 20]: (1) establish a low-carbon benefit evaluation model to compare and analyze the low-carbon benefits of different power grid planning schemes; (2) introduce low-carbon power technology, analyze its influence mechanism on the change of optimization planning scheme; (3) internalize the carbon emission cost, embed the objective function of the traditional model, or increase the carbon emission constraints to establish a low-carbon power grid planning model.

At present, there is still a relative lack of research on low-carbon grid planning, taking into account the new energy grid connection for power grid reliability or construction economy analysis. Reference [21] proposed a multiobjective transmission network planning model based on flexibility and economy to realize the dual optimization of minimum construction cost and optimal renewable energy treatment; reference [22] takes the adaptability index of supply-demand balance as the objective function of unit planning stage and the adaptability index of operation state and network structure as the objective function of network planning stage to realize the dual planning of network source; a mixed integer linear stochastic model is proposed in reference [23], which is used for the optimal expansion planning of distribution network and green energy devices to support the reliable and stable state; reference [24] is oriented to the analysis of effective deployment of green energy in urban microgrid with reliable power supply and optimal operation as the objective function.

However, the above literature lacks the characteristic analysis of carbon emission in the planning model. Considering only from the perspective of power grid reliability or operation economy, the planning model is not complete, which is difficult to meet the development needs of green sustainability of current power grid.

Aiming to these problems, this paper analyzes the carbon emission characteristics of the whole cycle based on the efficient treatment mode of cloud edge cooperation and constructs a power grid planning model including environmental, economic, and reliability; the improved CSO algorithm is introduced into the cloud to maintain the green and sustainable system.

3. Methodology Framework

3.1. Overall Framework. The processing and analysis mode of the integration of cloud computing and edge computing has strong data decision-making and analysis ability and can realize more accurate and fast model solving and calculation. Therefore, a power grid low-carbon planning method based on cloud side collaborative architecture to support the low-carbon sustainable operation of power grid is proposed. As shown in Figure 1, the low-carbon planning scheme under the cloud side collaborative architecture proposed in this paper includes two modules:

(1) *Cloud Network Source Collaborative Planning Analysis*. With the help of cloud server cluster, the traditional CSO algorithm based on quantum mechanics and chaos algorithm is improved to form the hierarchical multi-objective model and power supply collaborative planning, solve the problem of local optimization in the traditional algorithm, and realize the low-carbon sustainability planning analysis of the current power grid

(2) *Operation Characteristics and Model Analysis of Edge Network Source*. Aiming to better achieving the goal of power sustainability and green, taking into account the carbon emission characteristics of the whole life cycle of power grid planning, this paper establishes a green energy operation simulation model at the edge of the collaborative planning architecture to support the cloud to achieve efficient and accurate power grid low-carbon planning analysis

3.2. Low Carbon Factor Analysis and Modeling of Power Grid at the Edge. Aiming to better achieving the goal of sustainability and green, taking into account the carbon emission characteristics of the whole life cycle, this paper establishes a green energy operation simulation model at the edge of the collaborative planning architecture.

Taking wind power as an example, based on the historical output data, this paper simulates and generates the hourly sequential output sequence in line with the random output characteristics of new energy.

The wind speed model is

$$ds_{it} = -v_i(s_{it} - \bar{s}_i)dt + \sqrt{o(s_{it})}d\kappa_{it}, \tag{1}$$

$$o(s_{it}) = \frac{2v}{f(s)}\int_1^s (\bar{s} - x)f(x)dx, \tag{2}$$

where s_{it} is the simulated wind speed at time t of wind farm i; v_i is the exponential attenuation coefficient of autocorrelation function of wind speed corresponding to wind farm i; $\bar{s}_i$ is the average wind speed of wind farm i; $f(s)$ is the Weibull function of wind speed; $d\kappa_{it}$ is a random number sequence with normal distribution.

The wind speed can be accumulated hourly according to ds_t:

$$s_{it} = s_{it-1} + ds_t. \tag{3}$$

The output of the wind farm is

$$P_{it} = m_{it}(1 - \xi_i)u_i(s_{it}j_{id}j_{\text{is}}), \tag{4}$$

where P_{it} is the output of wind farm i at time t; m_{it} is the number of units available at time t of wind farm i; ξ_i is the wake effect coefficient of wind farm; u_i is the output characteristic curve of wind turbine; j_{id} and j_{is} are the correction coefficients of daily and seasonal characteristics of wind speed, respectively.

3.2.1. Life Cycle Carbon Emission Characteristics of Power Grid Planning. The construction, operation, maintenance, and scrapping of a large number of power transmission and transformation equipment in the power grid will consume a lot of energy and produce carbon emissions. In this paper, the whole life cycle evaluation method is used to analyze each link of the power grid, which can more comprehensively and scientifically analyze the low-carbon planning and investment decision-making of the power grid.

The life cycle analysis of transmission equipment is shown in Figure 2.

Based on the analysis of the whole life cycle of transmission equipment, the carbon emission assessment model of the whole life cycle of transmission equipment can be established.

The whole life cycle carbon emission of transmission equipment can be decomposed into

$$\varepsilon_{\text{ALL}} = \varepsilon_C + \varepsilon_O + \varepsilon_M + \varepsilon_F + \varepsilon_D, \tag{5}$$

where ε_{ALL} is the carbon emission in the whole life cycle; ε_C is the carbon emission during construction; ε_O is the carbon emission in operation; ε_M is the carbon emission in maintenance; ε_F is the fault carbon emission; ε_D is the carbon emission from decommissioning.

Based on the above analysis, the investment cost model of new lines can be established by introducing carbon emission cost:

$$C = \sum_{n}^{N_{\text{line}}} \left(c_n^{\text{line}} + \sigma_n \varepsilon_n^{\text{line}}\right), \tag{6}$$

where N_{line} is the investment payback period of the line; c_n^{line} is the equivalent annual value of the line investment; σ_n is the carbon emission price in the n year; $\varepsilon_n^{\text{line}}$ is the annual equivalent carbon emission of the line in year n. The line operation carbon emission caused by network loss is considered separately. $\varepsilon_n^{\text{line}}$ and c_n^{line} can be calculated by the

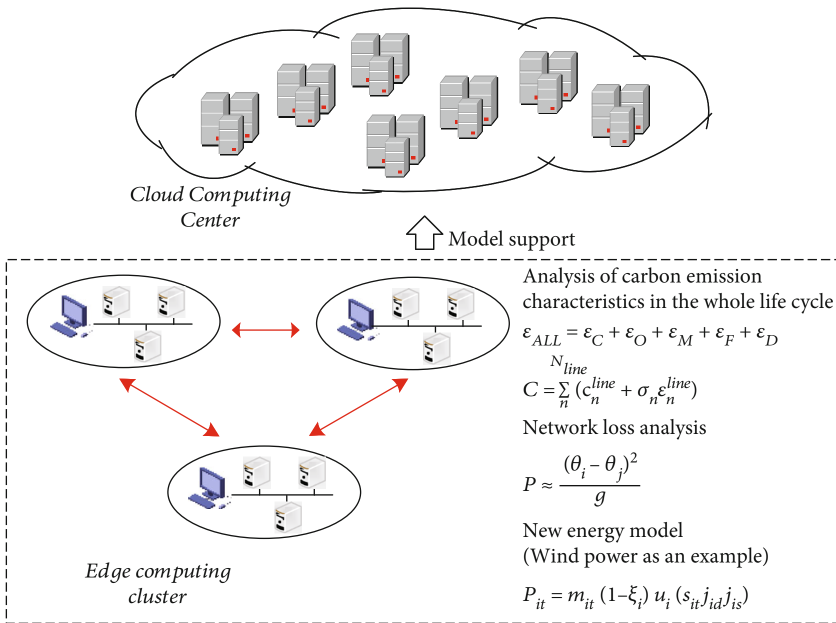


Figure 1: Overall architecture of the proposed method.

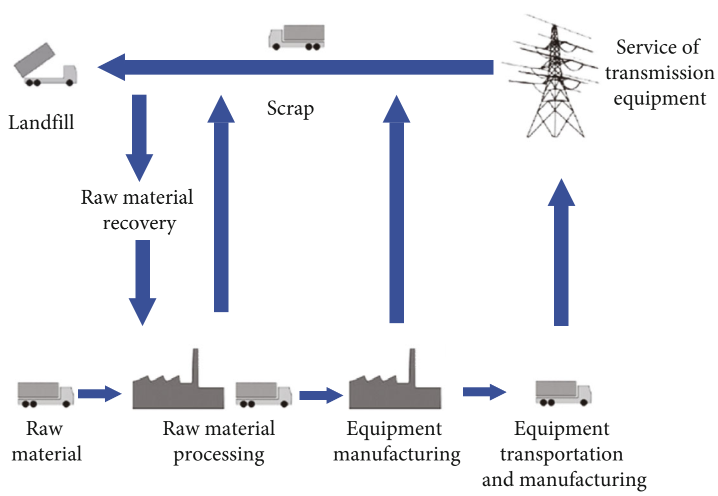


Figure 2: Life cycle of transmission equipment.

following formula:

$$\varepsilon_n^{\text{line}} = \frac{(\varepsilon_{\text{ALL}} - \varepsilon_O)}{N_{\text{line}}}, \tag{7}$$

$$c_n^{\text{line}} = \frac{(1+\alpha)^{N_{\text{line}}-n}\alpha}{(1+\alpha)^{N_{\text{line}}} - 1} C', \tag{8}$$

where C' is the investment amount of the line; α is the capital discount rate.

3.2.2. Reduce Power Grid Loss. Power grid loss will increase additional carbon emissions on the power generation side. Reducing loss is the most direct low-carbon measure in power grid links. In this paper, the network loss is modeled based on DC power flow and embedded into the power grid planning model to realize the collaborative optimization of network loss management and power grid planning [25].

Under the normal operation of high-voltage transmission network, the node voltage amplitude is close to 1.0 pu. Therefore, combined with the traditional AC power flow equation, the expression of active power loss P is

$$P \approx \frac{(\theta_i - \theta_j)^2}{g}, \tag{9}$$

where $\theta_i - \theta_j$ is the voltage phase angle difference; g is the conductivity of the line.

Equation (7) shows that the line network loss can be approximately expressed as the product of line conductance

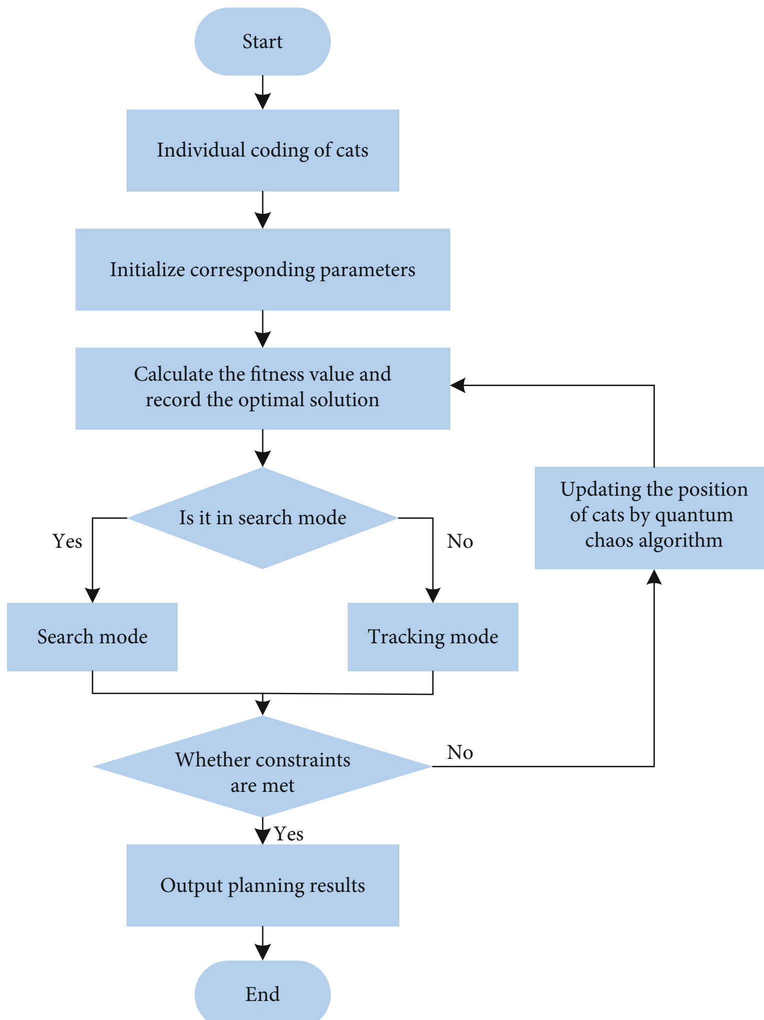


FIGURE 3: Power grid planning flow chart based on improved cat swarm algorithm.

and the square of node voltage phase angle difference, that is, the active power mainly depends on the node voltage phase angle difference.

3.3. Cloud Side Network Source Collaborative Planning Model Optimization. In this paper, the economy, reliability, and environmental benefits are comprehensively considered in order to build a hierarchical multiobjective collaborative planning model; based on the server cluster, the improved CSO algorithm is adopted to realize efficient multiobjective optimization and ensure the green sustainability of power grid planning and analysis.

3.3.1. Network Source Collaborative Planning Model. The low-carbon power grid planning model proposed in this paper is a bilevel planning model. The planning objectives and contents of each layer model are as follows:

(1) The upper model is mainly the construction cost model. The planning economy considers the construction cost and the operation cost after putting into operation, mainly including power grid investment cost. The upper model is as follows:

$$C_1 = C_{NCG} + C_{NL} + C_{LS} + C_{NC} + C_{NE}, \tag{10}$$

where C_{NCG} is the construction cost of power grid peak shaving power plant; C_{NL} is the construction cost of power grid line; C_{LS} is the cost of grid loss; C_{NC} is carbon emission cost; C_{NE} is the power purchase cost.

The C_{NCG} calculation model of construction cost of power grid peak shaving power plant is

$$C_{NCG} = \sum_{i=1}^{I} \mu_{NCG,i} x_i = \sum_{i=1}^{I} B_{NCG,i} \cdot \frac{r(r+1)^{NI}}{(r+1)^{NI}} \cdot x_i, \tag{11}$$

where x_i is a 0-1 decision variable, indicating the operation status for peak shaving generator unit, where 0 represents shutdown and 1 represents operation; $\mu_{NCG,i}$ refers to the annual value such as the investment cost of the generating unit i; I refers to the number of generator units to be added; $B_{NCG,i}$ refers to the initial investment cost of the generating unit i; r refers to the annual discount rate of the investment; NI refers to the planned service life.

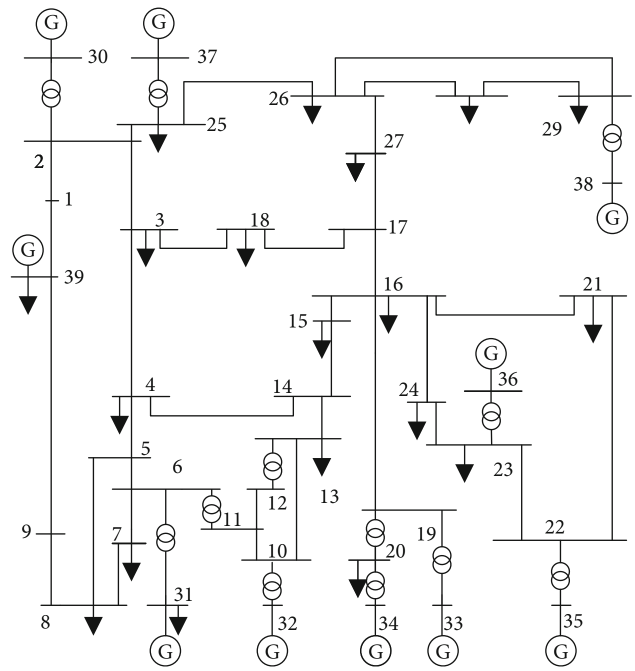


Figure 4: IEEE-39 bus power system.

Table 1: Characteristic parameters.

Generation type	Investment cost (¥/kW)	Operation cost (¥/MWh)	Fuel cost (¥/MWh)	Carbon emissions (t/MWh)
Wind power	8750	55	0	0
Solar energy	7850	75	0	0
Hydropower	25920	15	0	0
Nuclear power	17450	10	4	0
Gas	2990	35	100	0.75

The C_{NL} calculation model of power grid line construction cost is

$$\begin{aligned} C_{NL} &= \sum_{j=1}^{J} \mu_{NWT,j} y_j + \sum_{k=1}^{K} \mu_{NPV,k} z_k \\ &= \sum_{j=1}^{J} B_{NWT,j} \cdot \frac{r(r+1)^{NJ}}{(r+1)^{NJ}-1} \cdot y_j \\ &\quad + \sum_{k=1}^{K} B_{NPV,k} \cdot \frac{r(r+1)^{NK}}{(r+1)^{NK}-1} \cdot Z_k, \end{aligned} \tag{12}$$

where y_j and y_j are 0-1 decision variables, indicating the operation status of grid connected lines of wind farm and photovoltaic power station; J and K refer to the number of grid connected lines of the wind farm and the number of parallel lines of the photovoltaic power station to be added; $\mu_{NWT,j}$ and $\mu_{NPV,k}$ are the equivalent annual values of the investment cost of the corresponding grid connected lines, respectively; $B_{NWT,j}$ and $B_{NPV,k}$ are the corresponding initial investment costs, respectively; NJ and NK are the planned service life of corresponding lines, respectively.

The calculation model of power grid loss cost C_{LS} is

$$C_{LS} = \tau \sum_{d=1}^{D} \sum_{t=1}^{T} I_{d,t}^2 R_i t, \tag{13}$$

where τ represents the unit network loss electricity price, 10000 yuan/(kW·h); D is the total number of transmission lines used by the system; $I_{d,t}$ is the current on line d in the corresponding period t; R_i is the resistance of the corresponding line; T refers to the total number of time periods.

C_{NC} calculation model of carbon emission cost

$$C_{NC} = \omega \sum_{i=1}^{I} \sum_{t=1}^{T} e_{NCG,i} P_{NCG,i} \Delta t, \tag{14}$$

where ω represents the market carbon emission price; $e_{NCG,i}$ is the carbon emission intensity per unit power of unit i; $P_{NCG,i}$ is the corresponding active output of the unit i.

The power purchase cost C_{NE} can be set to a constant.

(2) The lower level model is mainly the new energy power generation cost model. The cost mainly includes the generation maintenance cost and power abandonment loss of new energy generator units. The loss caused by grid connection and power abandonment is taken as the reference objective function of power grid planning

$$C_2 = C_{NG} + C_{NQ}. \tag{15}$$

The C_{NG} calculation model of new energy power generation maintenance cost is

$$C_{NG} = \sum_{t=1}^{T} \left[c_{NG} \sum_{h=1}^{H} P_{h,t} \right] \Delta t, \tag{16}$$

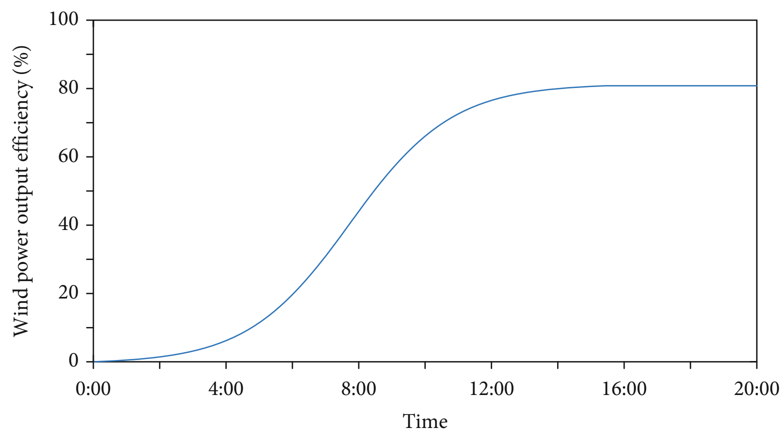
where c_{NG} is the unit power generation maintenance cost, respectively; $P_{h,t}$ is the actual active output of the new energy power generator set h for period t; T is the total number of time periods in the whole year.

The C_{NQ} calculation model of power loss cost is

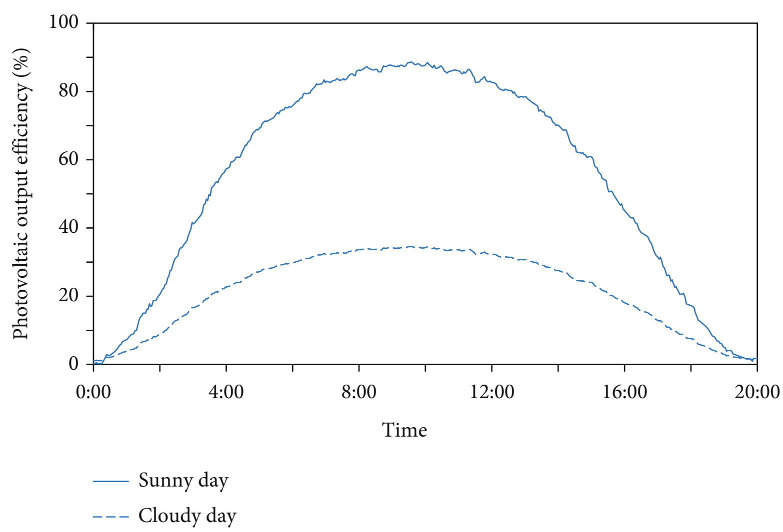
$$C_{NQ} = \sum_{t=1}^{T} \left[c_{NQ} \sum_{h=1}^{H} (P_{h,t} - P_{h0,t}) \right] \Delta t, \tag{17}$$

where c_{NQ} is the unit loss cost; $P_{h0,t}$ is the planned active output of unit h for period t; T is the total number of time periods in the whole year.

(3) For the above two-layer model, the following constraints are proposed in this paper



(a) Wind power



(b) Photovoltaic

Figure 5: Output curve of new energy unit.

Table 2: Optimal planning schemes under different methods.

Method	New line ($i \longrightarrow j$)	New green energy node and its unit capacity (MW)
The proposed method	21 → 27, 22 → 19, 17 → 26, 14 → 3, 5 → 8, 4 → 8, 2 → 8	22 (30), 21 (55), 17 (25), 14 (35), 5 (25), 4 (25)
Reference [21]	24 → 15, 24 → 14, 23 → 19, 14 → 2	24 (35), 23 (15), 18 (35), 14 (40), 5 (20)
Reference [22]	21 → 27, 16 → 3, 14 → 2, 11 → 3	21 (35), 16 (45), 14 (25), 11 (20)
Reference [24]	26 → 18, 17 → 4, 14 → 19	26 (20), 17 (35), 14 (25)

The power balance constraint formula is

$$P_t = A_t \theta_t, \tag{18}$$

where P_t refers to the injected power vector of the node in period t; A_t refers to the admittance matrix of nodes in period t; θ_t refers to the phase angle vector of node voltage in period t.

The branch power flow constraint formula is

$$|P_{d,t}| \leq P_{d,\max}, \tag{19}$$

where $P_{d,t}$ refers to the active power flow of branch d in period t; $P_{d,\max}$ is the upper limit value of branch d in period t.

The output constraint of generator set is

$$P_{NCG,\min} \leq P_{NCG,i} \leq P_{NCG,\max}, \tag{20}$$

where $P_{NCG,i}$ refers to the corresponding active output of the unit i; $P_{NCG,\min}$ refers to the lower limit of active output corresponding to the unit i; $P_{NCG,\max}$ is the upper limit of active output corresponding to the unit i.

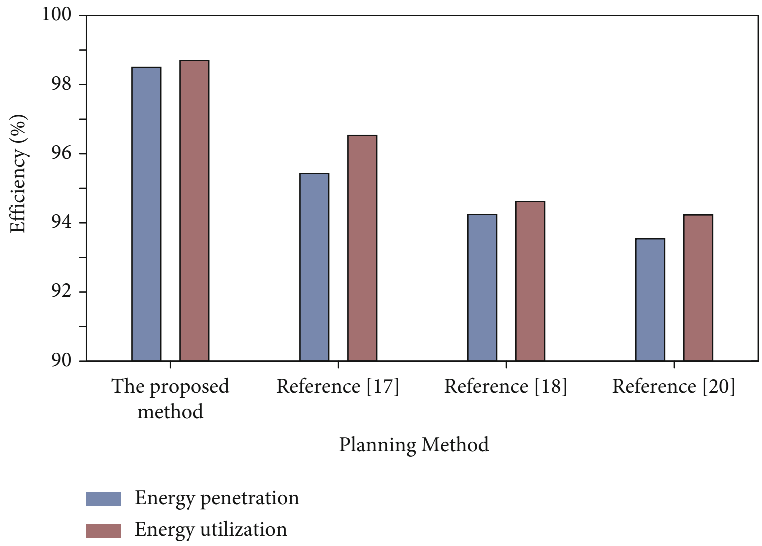


Figure 6: Grid connection of new energy under different methods.

Table 3: Analysis of economic and environmental indicators of different planning methods.

Method	Carbon emissions (t/MWh)	Total construction cost (100 million ¥)
The proposed method	2.28	0.23
Reference [21]	3.12	0.73
Reference [22]	4.85	1.23
Reference [24]	5.81	0.43

(4) Multiobjective programming model

The hierarchical multiobjective planning model is as follows:

$$\begin{cases} \min C_1 = C_{NCG} + C_{NL} + C_{LS} + C_{NC} + C_{NE}, \\ \min C_2 = C_{NG} + C_{NQ}. \end{cases} \tag{21}$$

Further, rewrite as

$$L - \min_{s \in S} \left[F_v C_v(s)\right]_{s=1}^{L}, \tag{22}$$

where $C_v(s)(v = 1, \cdots, L)$ is the objective function; $F_v(v = 1, \cdots, L)$ is used to mark that the objective function is at the v priority level; meanwhile, $F_v \geq F_{v+1}(v = 1, \cdots, L)$ indicates that level 5 takes precedence over level $v + 1$; $s \in S$ represents a set of constraints; $L - \min_{s \in S}$ represents the minimization condition, that is, the minimization analysis and calculation are carried out in the order of $F_1, F_2, \cdots, F_L$.

The characteristic of hierarchical multiobjective optimization model is that each goal in the model does not have the same priority in the whole model and has targeted priority levels, and only one goal is considered in each level.

3.3.2. Construction of Mathematical Model Based on Improved Cat Swarm Optimization Algorithm. The essence of power grid multiobjective optimization algorithm is to obtain the equilibrium solution of double-layer function at the same time. The optimization of the model can be realized by means of intelligent algorithms such as genetic algorithm and CSO algorithm [26–28]. The CSO algorithm can be updated by cats in different modes according to the corresponding speed and position formulas. Through the continuous updating of the global optimal value and local optimal value, the optimal solution of the problem to be solved is finally obtained [29].

The speed and position update formula of the cat in the iterative process is

$$V_{j,k}^{i+1} = V_{j,k}^{i} + \alpha \times \beta \times \left(G_{\text{best}}^{i} - V_{j,k}^{i}\right), \tag{23}$$

$$G_{j,k}^{i+1} = G_{j,k}^{i} + V_{j,k}^{i+1}, \tag{24}$$

where $V_{j,k}^{i+1}$ represents the updated velocity component of the j-th cat in the k dimensional space; α is a constant; G_{best}^{i} represents the global optimal solution after the i-th iteration; β is the random number between $[0, 1]$; $G_{j,k}^{i+1}$ represents the updated position component of the j-th cat in the k dimensional space; i is the number of iterations.

However, it should be noted that when solving the problem based on CSO algorithm, the cats in tracking mode can be randomly distributed at any position in the search space, which has the problem of local optimization.

Aiming at solving this problem, the quantum mechanical model is combined with the CSO algorithm to optimize the individual position in the cat population by using the characteristics of quantum. In the quantization process, the cat in the tracking mode takes the individual optimal position and the global optimal position as the goal and updates the cat's position by constantly moving in the delta potential well.

Quantum mechanics is an important branch of physics in the field of micro matter. It is not only an important part of the four mechanics of physics but also widely used in other disciplines [30]. The quantum in the algorithm has the characteristics that individuals in other algorithms do not have: noncloning, superposition, entanglement, and collapse. Due to the randomness of the speed and position of cats in the delta potential well, cats in the tracking mode can be randomly distributed at any position in the search space in the iterative process of cat group optimization, which improves the ability to get rid of local optimal points. The update expression of individual position in quantum space is

$$G_{j,k}^{i+1} = D_{j,k}^{i} + dc^{i}\left|M_k^i - G_{j,k}^i\right| \ln\left(y_1^{-1}\right), \quad (25)$$

$$D_{j,k}^{i+1} = y_2 H_{j,k}^i + (1 - y_2) W_k^t, \quad (26)$$

$$q^i = q_1 - (q_1 - q_2)\frac{i}{i_m}, \quad (27)$$

$$b = \begin{cases} -1 & y_3 \le 0.5, \\ 1 & y_3 > 0.5, \end{cases} \quad (28)$$

$$\left(O_1^i, O_2^i, \cdots, O_k^i\right) = \frac{1}{n}\left(\sum_{j=1}^{n} H_{j,1}^i, \sum_{j=1}^{n} H_{j,2}^i, \cdots, \sum_{j=1}^{n} H_{j,k}^i\right), \quad (29)$$

where $G_{j,k}^{i+1}$ represents the updated position component of the j-th cat in k dimensional space; i is the number of iterations; q^i is the expansion compression factor of the i-th iteration; O_k^i is the optimal location center of the population in the k dimensional space of the i-th iteration; y_1, y_2, and y_3 are random numbers of $[0, 1]$; $H_{j,k}^i$ is the historical optimal position component of individual j in i-th iteration k dimensional space; q_1 and q_2 are the initial and end values of expansion compression factors, respectively. In this paper, $q_1 = 1.25$ and $q_2 = 0.62$; n is the population number; i_m is the maximum number of traces.

Aiming to ensuring the optimal performance of full cycle optimization, through the research and analysis of chaos, it is used to improve the update steps of the algorithm based on this. Therefore, on the basis of quantum optimization cat swarm algorithm, by introducing tent mapping and using its randomness and ergodicity, CSO algorithm can avoid premature. The individual position update expression for each cat is

$$g_{j,k}^{i+1} = \begin{cases} 2g_{j,k}^i & 0 \le g_{j,k}^i \le 0.5, \\ 2\left(1 - g_{j,k}^i\right) & 0.5 \le g_{j,k}^i \le 1, \end{cases} \quad (30)$$

where $g_{j,k}^i \in [0, 1]$, and the mutual mapping transformation of chaotic vector $Og_{j,k}^i \in [a, b]$ can be realized based on the following formula.

$$g_{j,k}^i = \frac{Og_{j,k}^i - 1}{b - a} == \frac{a + g_{j,k}^i(\mathrm{b} - \mathrm{a}) - 1}{b - a}. \quad (31)$$

Although the combination of quantum mechanics and chaotic mapping theory and algorithm can balance the global and local search ability. However, the fixed mixing rate will weaken its balance effect in the early or late stage of the algorithm, so that the local and global search ability cannot achieve satisfactory results.

According to equation (30), this paper improves the value method of the mixing rate. The value of the mixing rate gradually decreases with the increase of the number of iterations, so that the number of individuals in the search mode can gradually increase with the increase of the number of iterations.

$$\eta^i = \eta_{\max}(\alpha)^{1+i/i_m - \cos\,(i/i_m)}, \quad (32)$$

where $\eta_{\max}$ is the maximum value of mixing rate; α is a fixed constant; i is the number of iterations; i_m is the maximum number of traces.

In the search mode of quantum chaotic cat swarm algorithm, the individuals with different fitness values have the same amount of variation, which makes the algorithm cannot make full use of the individuals with optimal fitness values in the search of local optimal values, thus, reducing the accuracy of local optimal solutions. As the number of individuals in the mutation pattern changes, the more the algorithm can adapt to the global variation, and the better the algorithm can adapt to the change of the number of individuals in the mutation pattern. The formula for copying an individual is

$$\zeta_j = \left[1 - \left|\frac{\mathrm{fitness}_j}{\sum_{j=1}\mathrm{fitness}_j}\right|\right] \times \zeta_{\mathrm{sum}}, \quad (33)$$

where ζ_j is the number of replicates of cat j; ζ_{sum} is the total number of replicates in the memory pool; $\mathrm{fitness}_j$ is the fitness value of cat j.

Figure 3 is the flow chart of low-carbon power grid collaborative planning method using quantum chaotic cat swarm algorithm proposed in this paper.

4. Experiment and Analysis

The simulation experiments all run in the same environment. The CPU processor is Intel (R) core (TM) i5-5200u and the fuselage memory is 12.0 GB. The simulation experiment and verification analysis are completed by MATLAB software.

4.1. Experimental Background and Parameters. IEEE 39 node is used as an example to realize the optimization experimental analysis. The simulation experimental system diagram is shown in Figure 4. There are 39 independent nodes in the system, of which 17 nodes have the installation conditions of renewable energy power supply. The IEEE 39 node standard example includes 39 terminal nodes (10 generator nodes, 21 load nodes, and 12 transformer nodes) and 46 power lines, of which 17 nodes have the installation conditions of renewable energy power supply.

The purpose of model optimization is to ensure the coordination and consistency between power supply and power grid planning and finally realize the low-carbon sustainable operation of power grid.

The unit operation characteristic parameters of various power generation modes are shown in Table 1. There is no difference in the parameters of the same type of unit set by each generator. The maximum capacity of reallowed to be connected to each node is 85 MW, and the allowable fluctuation range of node voltage is ±5%. Where the transmission price is 0.43 yuan/kWh and the carbon trading price is 50 yuan/ton.

For more intuitive expression, the fan output curve and photovoltaic power generation output curve are given, as shown in Figure 5.

4.2. Comparison of Different Optimization Objectives in Low Carbon Environment. Aiming to comprehensively evaluate the clean and low-carbon characteristics, this paper further introduces two evaluation indexes such as green energy penetration γ and utilization efficiency η [31, 32]. Penetration efficiency γ refers to the proportion of the total power generation of green energy in the total power consumption of system load in the planning period, which represents the comprehensive utilization capacity of the system for renewable energy; utilization efficiency η refers to the ratio of the actual power generation of green energy to the maximum available power supply under natural conditions.

In this paper, reference [21], reference [22], and reference [24] are used as comparative methods to verify the optimality of the proposed method.

Table 2 shows the optimal planning schemes for IEEE 39 bus system under different analysis methods and describes the planned lines and deployment of new energy units accordingly.

Figure 6 shows the grid connection of new energy under different planning methods.

It can be seen from Table 2 and Figure 6 that the grid planning algorithm proposed can achieve efficient calculation and analysis of new energy grid connection. After planning, the green energy penetration γ and utilization efficiency η are 98.56% and 98.72%, respectively; the planning effect of the comparison method is obviously poor. The green energy permeability and utilization efficiency after planning in reference [24] are 93.54% and 94.23%, which are 5.02% and 4.49% lower than the results of the proposed algorithm.

The reason is that the algorithm proposed adopts the way of cloud edge cooperation to model and analyze the whole cycle of power grid construction carbon emission on the edge side, which makes the solution model more reliable and complete; in the cloud, CSO algorithm is improved based on quantum chaos algorithm to improve the processing and analysis efficiency of the planning model.

Furthermore, this paper also makes a quantitative analysis on the carbon emissions and construction costs of the results of different planning methods. Table 3 shows the comparison of the two indicators.

As shown in Table 3, the proposed planning method can achieve better carbon emission at lower construction cost, and the construction cost and carbon emission are 23 million yuan and 2.28 t/MWh, respectively; Compared with reference [21], the construction cost and carbon emission are optimized by about 50 million yuan and 0.84 t/MWh, respectively.

5. Conclusion

In order to support the power grid to realize low-carbon and stable operation, a power grid low-carbon planning method using improved CSO algorithm is proposed. Relying on the cloud side collaborative computing mode, this method integrates the carbon emission characteristics into the grid planning model on the edge side and effectively solves the low-carbon scale of power grid based on the improved CSO algorithm based on quantum chaos algorithm in the cloud, so as to avoid the model solution falling into a suboptimal solution. The simulation results show that the proposed collaborative planning method can achieve a more reliable and green power grid operation state under the condition of low construction cost.

The exploration and construction of carbon trading market have gradually become the focus of power market. The future research direction is to further consider the elements of low-carbon power market in the traditional planning model, and then establish a relatively complete new power system planning model.

Data Availability

The data included in this paper are available without any restriction.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments

This work was supported by Science and Technology Project of State Grid Corporation of China (Contract no: SGLNDKOOKJJS2100068).

References

[1] A. B. Birchfield, T. Xu, and T. J. Overbye, “Power flow convergence and reactive power planning in the creation of large synthetic grids,” *IEEE Transactions on Power Systems*, vol. 33, no. 6, pp. 6667–6674, 2018.

[2] Y. Luo, Y. Zhang, M. Tang et al., “A novel receiving end grid planning method with mutually exclusive constraints in alternating current/direct current lines,” *Sustainability*, vol. 13, no. 13, article 7141, 2021.

[3] J. Nieto-Martin, T. Kipouros, M. Savill, J. Woodruff, and J. Butans, “Technoeconomic distribution network planning using smart grid techniques with evolutionary self-healing network states,” *Complexity*, vol. 2018, no. 1, Article ID 1543179, 18 pages, 2018.

[4] Y. Yang, J. Qiu, J. Ma, and C. Zhang, "Integrated grid, coal-fired power generation retirement and GESS planning towards a low-carbon economy – science direct," *International Journal of Electrical Power & Energy Systems*, vol. 124, no. 1, pp. 1–12, 2021.

[5] A. Bilich, E. Spiller, and J. Fine, "Proactively planning and operating energy storage for decarbonization: recommendations for policymakers," *Energy Policy*, vol. 132, no. 12, pp. 876–880, 2019.

[6] L. Olmos Camacho, M. L. Rivier Abbad, and J. I. Pérez Arriaga, "Transmission expansion benefits: the key to redesigning the regulation of electricity transmission in a regional context," *Economics of Energy & Environmental Policy*, vol. 7, no. 1, pp. 47–62, 2018.

[7] B. Ee and Z. Li, "Renewable energy based self-healing scheme in smart grid," *Energy Reports*, vol. 6, no. 1, pp. 166–172, 2020.

[8] S. Karimi-Arpanahi, M. Jooshaki, M. Moein-Aghtaie, M. Fotuhi-Firuzabad, and M. Lehtonen, "Considering forecasting errors in flexibility-oriented distribution network expansion planning using the spherical simplex unscented transformation," *IET Generation, Transmission and Distribution*, vol. 14, no. 24, pp. 5970–5983, 2020.

[9] S. Maximov, G. Harrison, and D. Friedrich, "Long term impact of grid level energy storage on renewable energy penetration and emissions in the Chilean electric system," *Energies*, vol. 12, no. 6, article 1070, 2019.

[10] Z. K. Pecenak, M. Stadler, and K. Fahy, "Efficient multi-year economic energy planning in microgrids," *Applied Energy*, vol. 255, no. 1, pp. 113771–113779, 2019.

[11] Z. G. Lu, J. T. Qi, B. Wen, and X. Li, "A dynamic model for generation expansion planning based on conditional value-at-risk theory under low-carbon economy," *Electric Power Systems Research*, vol. 141, no. 1, pp. 363–371, 2016.

[12] A. A. Majd, E. Farjah, and M. Rastegar, "Composite generation and transmission expansion planning toward high renewable energy penetration in Iran power grid," *IET Renewable Power Generation*, vol. 14, no. 9, pp. 1520–1528, 2020.

[13] Z. X. Yu, M. S. Li, Y. P. Xu, S. Aslam, and Y. K. Li, "Techno-economic planning and operation of the microgrid considering real-time pricing demand response program," *Energies*, vol. 14, no. 15, pp. 1–28, 2021.

[14] X. H. Yang, Z. X. Chen, X. Huang, R. Li, S. Xu, and C. Yang, "Robust capacity optimization methods for integrated energy systems considering demand response and thermal comfort," *Energy*, vol. 221, no. 1, article 119727, 2021.

[15] A. Jain, P. Das, S. Yamujala, R. Bhakar, and J. Mathur, "Resource potential and variability assessment of solar and wind energy in India," *Energy*, vol. 211, no. 1, article 118993, 2020.

[16] A. Thomas and P. Racherla, "Constructing statutory energy goal compliant wind and solar PV infrastructure pathways," *Renewable Energy*, vol. 161, no. 1, pp. 1–19, 2020.

[17] M. Kristiansen, M. Korpås, and H. G. Svendsen, "A generic framework for power system flexibility analysis using cooperative game theory," *Applied Energy*, vol. 212, no. 1, pp. 223–232, 2018.

[18] K. Imran, "Importance of GHG emissions assessment in the electricity grid expansion towards a low-carbon future: a time-varying carbon intensity approach," *Journal of Cleaner Production*, vol. 196, no. 1, pp. 1587–1599, 2018.

[19] H. Aimie, R. Thomas, and W. Ian, "Consumer engagement in low-carbon home energy in the United Kingdom: implications for future energy system decentralization," *Energy Research & Social Science*, vol. 44, no. 1, pp. 362–370, 2018.

[20] X. Chen, J. Lv, M. B. McElroy, X. Han, C. P. Nielsen, and J. Wen, "Power system capacity expansion under higher penetration of renewables considering flexibility constraints and low carbon policies," *IEEE Transactions on Power Systems*, vol. 33, no. 6, pp. 6240–6253, 2018.

[21] Z. Chen, Y. Hu, N. Tai, X. Tang, and G. You, "Transmission grid expansion planning of a high proportion renewable energy power system based on flexibility and economy," *Electronics*, vol. 9, no. 6, p. 966, 2020.

[22] M. Tang, J. Wang, and X. Wang, "Adaptable source-grid planning for high penetration of renewable energy integrated system," *Energies*, vol. 13, no. 13, pp. 3304–3326, 2020.

[23] M. Jooshaki, H. Farzin, A. Abbaspour, M. Fotuhi-Firuzabad, and M. Lehtonen, "A model for stochastic planning of distribution network and autonomous DG units," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 6, pp. 3685–3696, 2020.

[24] C. N. Kang and S. H. Cho, "Thermal and electrical energy mix optimization (EMO) method for real large-scaled residential town plan," *Journal of Electrical Engineering and Technology*, vol. 13, no. 1, pp. 513–520, 2018.

[25] D. Li, S. Yang, W. Huang, J. He, Z. Yuan, and J. Yu, "Optimal planning method for power system line impedance based on a comprehensive stability margin," *IEEE Access*, vol. 9, no. 1, pp. 56264–56276, 2021.

[26] X. J. Ran, X. B. Zhou, M. Lei, W. Tepsan, and W. Deng, "A novel K-means clustering algorithm with a noise algorithm for capturing urban hotspots," *Applied Sciences*, vol. 11, no. 23, pp. 11202–11221, 2021.

[27] Z. H. Zhang, F. Min, G. S. Chen, S. P. Shen, Z. C. Wen, and X. B. Zhou, "Tri-partition state alphabet-based sequential pattern for multivariate time series," *Cognitive Computation*, vol. 2021, no. 1, pp. 1–19, 2021.

[28] W. Deng, X. X. Zhang, Y. Q. Zhou et al., "An enhanced fast non-dominated solution sorting genetic algorithm for multi-objective problems," *Information Sciences*, vol. 585, no. 1, pp. 441–453, 2022.

[29] A. A. Abou El-Ela, R. A. El-Sehiemy, E. S. Ali, and A. M. Kinawy, "Minimisation of voltage fluctuation resulted from renewable energy sources uncertainty in distribution systems," *IET Generation Transmission & Distribution*, vol. 13, no. 12, pp. 2339–2351, 2019.

[30] M. W. Li, J. Geng, W. C. Hong, and Y. Zhang, "Hybridizing chaotic and quantum mechanisms and fruit fly optimization algorithm with least squares support vector regression model in electric load forecasting," *Energies*, vol. 11, no. 9, pp. 1–22, 2018.

[31] G. Kim, H. Shin, and H. Jin, "Probabilistic estimation of wind generating resources based on the spatio-temporal penetration scenarios for power grid expansions," *IEEE Access*, vol. 9, no. 1, pp. 15252–15258, 2021.

[32] K. Parker and P. Barooah, "A probabilistic method for reserve sizing in power grids with high renewable penetration," *IEEE Transactions on Power Systems*, vol. 36, no. 3, pp. 2473–2480, 2021.