Collaborative capacity planning method of wind–photovoltaic-storage equipment in microgrids considering different energy selling incomes

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A microgrid is a promising small-scale power generation and distribution system. The selling prices of wind turbine equipment (WT), photovoltaic generation equipment (PV), and battery energy storage equipment (BES) have a significant impact on microgrid profits, which, in turn, affects the planning capacity of renewable energy. However, existing research has not yet conducted in-depth modeling and analysis for different kinds of energy generation electricity prices. This paper proposes an optimal capacity planning method for wind–photovoltaic-storage equipment, considering different energy selling incomes in microgrids. Stochastic characteristics of renewable energy (WT and PV), selling prices of different types of energy, and timing coupling characteristic are considered in the proposed model. In addition, the configuration capacities of WT, PV, and BES are modeled as discrete decision variables, according to the type of specific equipment. The comprehensive life cycle cost (LCC) is considered an objective function. It can be found that the proposed collaborative capacity planning model is a mathematical programming problem with complex nonlinear constraints and integer variables. To solve this problem, a cultural gray wolf optimization algorithm (CGWO) is applied in this paper. The proposed method's efficiency, convergence, superiority, and effectiveness are verified through a case study. Moreover, the impact of different new energy sales prices on capacity planning results is also revealed in the article.

1 Introduction

1.1 Background

Global climate change has brought severe challenges to human survival. In the face of these challenges, China has put forward the "carbon emissions peak" and "carbon neutrality" policies (Wang Jiayu et al., 2022). The proposed policies insist on green and low-carbon development, tackling climate change actively. In this context, a novel power system with renewable energy is proposed as the main body of future power systems. Nowadays, Chinese

clean energies mainly contain wind and photovoltaic power generation, which are the most practical approaches and show great development potential.

In rural areas, industrial parks, or islands, there are often many distributed photovoltaic (PV) panels, wind turbines (WTs), and battery energy storage equipment (BES), which constitute a "microgrid" (Wei et al., 2014). In areas with abundant wind energy and light resources, how to optimize the capacity of different energy equipment in the microgrid, improving the economic profits, enhancing the reliability of the designed microgrid, and increasing the accommodation rate of clean energy, is a crucial but complicated problem (Wang et al., 2022b; Singh and Sharma, 2017).

1.2 Related work

Scholars around the world conducted research on the location and capacity of distributed generation (DG) in microgrids from different perspectives. Recent research studies can be summarized from model formulation and algorithms, as shown in Table 1.

1.2.1 Model formulation
The objective of a microgrid capacity planning model needs to consider economy, reliability, and environment protection (Kiptoo et al., 2023). Economic objectives mainly include costs (annual investment cost, maintenance cost, main grid electricity purchase cost, equipment operation cost, etc.) and profits (main grid electricity selling profits, environmental subsidies, etc.) (Yang et al., 2020a). Reliability objectives include time-based indicators (SAIDI and CAIDI), frequency-based indicators (SAIFI and CAIFI), and energy loss-based indicators (EENS). Environment objectives are related to emissions of greenhouse gases, which depend on the output of traditional thermal power and renewable energy

accommodation (Wang et al., 2022c). The constraints of a microgrid capacity planning model should consider the power flow equation and operation mode. It can be found that the capacity configuration of a microgrid is a nonlinear, multi-objective problem with complicated constraints (Singh and Sharma, 2017).

A cost-based formulation was performed to determine the optimal size of BES in the operation cost minimization problem of a MG under various constraints, such as the power capacity of distributed generators (DGs), power and energy capacity of BES, charge/discharge efficiency of BES, operating reserve, and load demand satisfaction (Sharma et al., 2016; Liu et al., 2016), focused on optimization of the power source capacity in the microgrid. In addition, a coordinated planning strategy is proposed with an integrated consideration of the characteristics of DG, ES, and load. Kiptoo et al. (2019) investigated the prospects of interlinking a short-term flexibility value into long-term capacity planning toward achieving a microgrid with a high renewable energy fraction. A pumped storage power station capacity planning method based on the full life cycle cost was proposed to describe a new sizing optimization methodology of a stand-alone hybrid photovoltaic/ wind/battery system, minimizing the levelized cost of energy (LCOE), the loss of power supply probability (LPSP), and the equivalent carbon dioxide (CO_2-eq) life cycle emission (Xiao et al., 2020). However, few studies have analyzed the impact of price (cost and profit) on the capacity allocation of a microgrid and carried out in-depth sensitivity analysis based on the proposed model, providing effective guidance for microgrid planners.

1.2.2 Algorithm
Existing solving algorithms of capacity configuration in a microgrid mainly include traditional analytical mathematical algorithms and heuristic optimization algorithms (Abou El-Ela et al., 2022). Some researchers tried to reformulate the original

TABLE 1 Summary of distributed generator planning models.

Reference	Investment cost	Reliability cost	Main grid interaction cost	Maintenance cost	RES sales profit	Scrapping profit
Hung et al. (2014)	√	√	×	×	×	×
Khoubseresht et al. (2023)	√	√	×	×	×	×
(Ali et al., 2023; Prakash et al., 2022)	×	√	√	×	×	×
Sharma et al. (2016)	√	×	√	√	√	×
Liu et al. (2016)	√	√	×	√	√	×
(Kiptoo et al., 2019; Borghei and Ghassemi, 2021)	√	√	×	×	×	×
Xiao et al. (2020)	√	×	√	√	√	√
Khemissi et al. (2021)	√	√	×	×	√	×
Abou El-Ela et al. (2022)	√	√	×	√	√	×
Coelho et al. (2016)	√	×	√	×	√	×
Kiptoo et al. (2023)	√	×	√	√	×	×
This paper	√	√	√	√	√	√

problem into a typical mixed-integer linear programming (MILP) with some approximate techniques (Borghei and Ghassemi, 2021; Kiptoo et al., 2023). Although these kinds of methods can obtain the optimal solution to the transformed problem, the obtained solution may have large deviations from practical solutions due to the approximation. Furthermore, these algorithms cannot accommodate to various scenarios, hindering their application in practical engineering. On the other hand, heuristic optimization algorithms can solve these complicated planning problems effectively. However, the selection and improvement of heuristic algorithms based on the variable form and constraint space of the specific problem is an urgent and promising research area (Coelho et al., 2016; Yang et al., 2020b).

1.3 Main purpose

From the aforementioned literature review, it can be found that existing research has not yet conducted in-depth modeling and analysis for different kinds of energy generation electricity prices, given that a significant portion of the revenue from microgrid operators comes from the selling income of renewable energy. In addition, the selling prices of different types of renewable energy are different, while existing research studies have not yet modeled, solved, and analyzed the differences in selling prices of different types of new energy. Microgrid planners or electricity market price setters also require corresponding theoretical basis and guidance when carrying out microgrid planning or setting electricity prices. Thus, it is necessary to model the differences in the selling prices of different types of renewable energy and integrate them into the microgrid planning model.

1.4 Main contribution

To tackle the aforementioned issues, this paper proposes a novel microgrid capacity planning model and an improved cultural gray wolf optimization algorithm. The major contributions of this paper can be summarized as follows:

(1) Novel microgrid capacity planning model. A novel wind-photovoltaic-storage microgrid capacity planning model considering comprehensive cost and profits is put forward. The different selling prices of WT, PV, and BES are considered in the paper, which is essential for the planning model.
(2) Improved cultural gray wolf optimization (CGWO) algorithm. An improved cultural gray wolf optimization algorithm (CGWO) is proposed to solve this problem efficiently. Compared with other heuristic optimization methods, the proposed method outperforms in convergence and calculation time when solving the proposed model.
(3) Impact of different energy sale prices and investment costs. The influence of different selling prices of WT, PV, and BES, and the investment cost of BES on the microgrid planning scheme is analyzed. The proposed model mainly focuses on the impact of the change in the electricity selling price on the planning results,
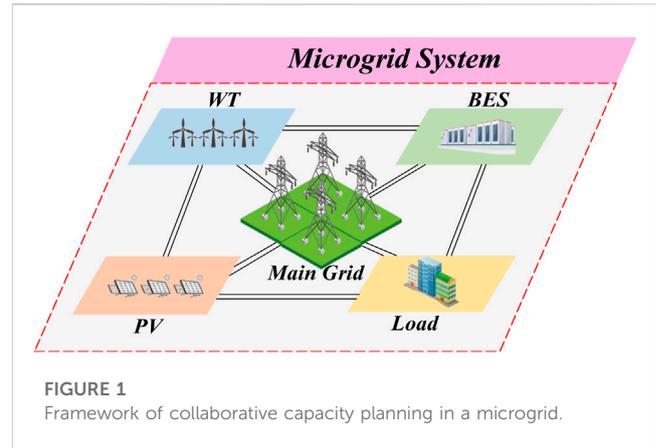

FIGURE 1
Framework of collaborative capacity planning in a microgrid.

which is conducive to microgrid planners to analyze the feasibility of the planning scheme from a new perspective.

1.5 Structure

The remainder of this paper is organized as follows: In Section 2, the overall architecture of collaborative capacity planning in a microgrid is presented. In Section 3, a capacity planning model of WT, PV, and BES in the microgrid is established. In Section 4, the solution algorithm CGWO is introduced. Subsequently, the testing of the proposed methods and the sensitivity study are presented in Section 5. Finally, conclusions and practical suggestions are summarized in Section 6.

2 Optimal capacity planning model of wind-photovoltaic-storage equipment in a microgrid

2.1 Architecture of collaborative capacity planning in a microgrid

Future smart DS will include various types of novel loads and DGs, including wind WT, PV, BES, and user load. From the perspective of optimal planning, DS planners should coordinate reliability and DS costs through an optimal design of the equipment capacity to accommodate these loads and DGs. Figure 1 shows the planning task of capacity planning in a microgrid.

The total objective function F of capacity planning of wind and solar storage equipment in the microgrid is formulated as follows.

$$F = \left(C_{Inv} + C_{EENS} + C_{Buy} + C_{Main}\right) - \left(I_{Sell} + I_{Drop}\right), \quad (1)$$

where F represents the comprehensive cost of the designed microgrid system. The objective function of this paper is to minimize the comprehensive cost of wind-photovoltaic-storage equipment in the microgrid system, which contains cost and profits. The cost of the capacity planning model includes the cost of equipment investment in the microgrid (WT, PV, and BES) C_{Inv}, cost of expected energy not supplied (EENS) C_{EENS}, cost of electricity purchased from the main grid C_{Buy}, and cost of

equipment maintenance C_{Main}. In addition, the profits of the designed microgrid system are composed of the profits obtained from selling electricity I_{Sell} and the scrapping of equipment I_{Drop}.

2.2 Annualized cost of investment

In the process of microgrid planning, the investment and construction cost of each piece of equipment (WT, PV, and BES in this paper) occupies an important part, which is shown as follows:

$$C_{Inv}^{EQ} = S^{EQ} p_{Inv}^{EQ} \frac{r}{(1+r)^{T^{EQ}} - 1}, \tag{2}$$

where C_{Inv}^{EQ} represents the investment cost of different equipment, including WT, PV, and BES. The investment and construction costs of each piece of equipment are closely related to the capacity of the equipment S^{EQ}. In addition, p_{Inv}^{EQ} represents the investment and construction costs per unit capacity of WT, PV, and BES.

2.3 Annual cost of outage compensation

If a power outage occurs due to insufficient power supply, the microgrid operator needs to compensate the corresponding users. In the planning and design of a high-reliability microgrid, it is necessary to consider the annual outage compensation cost of the microgrid, which can be written as follows:

$$C_{EENS} = k_{EENS} EENS, \tag{3}$$

$$\Delta P_t^{un} = D_t - P_t^W - P_t^S - (SOC_t - SOC_{min}), \tag{4}$$

$$EENS_t = \Delta P_t^{un} - P_t^{tie, max}; \Delta P_t^{un} > P_t^{tie, max}, \tag{5}$$

$$EENS = \sum_t (EENS_t), \tag{6}$$

where the annual outage compensation cost of planned equipment C_{EENS} is related to the annual shortage of power supply $EENS$ and power outage cost coefficient k_{EENS}. Based on the power balance equation, the unbalanced power ΔP_t^{un} is the part that is still insufficient after the wind, solar, and storage power output, as shown in Eq. 4. Then, the power shortage $EENS_t$ occurs at the current time t when the maximum power obtained from the main grid is added, which is shown in Eq. 5. Eq. 6 considers the power outage under all operating scenarios.

2.4 Annual cost of electricity purchased from the main grid

If the wind and solar storage resources are insufficient, the microgrid needs to purchase electricity from the main network to meet the load demand of the whole microgrid. The annual cost calculation formula of purchasing electricity from the main network is as follows:

$$C_{Buy} = k_{buy} P_t^{buy}, \tag{7}$$

$$P_t^{buy} = \begin{cases} 0; & \Delta P_t^{un} \leq 0 \\ \Delta P_t^{un}; & \Delta P_t^{un} > 0 \end{cases}, \tag{8}$$

where the annual cost of power purchase of the main grid C_{Buy} is related to the power obtained through the tie line/main grid P_t^{buy} and price coefficient of power purchase from the main grid k_{buy}. When the unbalanced power ΔP_t^{un} at time t is less than 0, it means that the current power of the microgrid is enough to be balanced by wind and solar storage in the microgrid. In this situation, there is no need to purchase electricity from main network, and the purchased power is 0 at this time. When the unbalanced power ΔP_t^{un} at time t is greater than 0, it means that the current wind and solar storage resources of the microgrid cannot meet the load demand in the microgrid. In this situation, it is necessary to purchase electricity from the main network at this time, and the purchased power of this part is P_t^{buy}.

2.5 Annual cost of equipment maintenance

The equipment invested and built by the microgrid needs to be operated and maintained in its life cycle. The specific calculation formula of the cost required for this part is as follows:

$$C_{Main}^{EQ} = S^{EQ} p_{Main}^{EQ} \frac{r}{(1+r)^{T^{EQ}} - 1}, \tag{9}$$

where C_{Main}^{EQ} represents the maintenance cost of WT, PV, and BES. The maintenance cost of each piece of equipment is closely related to the capacity of the equipment, S^{EQ}. In addition, p_{Main}^{EQ} represents the maintenance cost per unit capacity of WT, PV, and BES.

2.6 Annual profit of electricity sales

The microgrid can exchange energy with the main grid through the main grid bus, which can gain profits if the microgrid has extra power. The calculation formula of annual electricity sales income I_{Sell} of the microgrid, including the wind-photovoltaic-storage, is mainly composed of electricity sales income of wind power, photovoltaic, and battery energy storage.

$$I_{Sell} = p^W P_{Sell,t}^W + p^S P_{Sell,t}^S + p^B P_{Sell,t}^B, \tag{10}$$

where $\tilde{p}^W$, $\tilde{p}^S$, $\tilde{p}^B$ are the electricity sales prices of WT, PV, and BES, respectively. $P_{Sell,t}^W$, $P_{Sell,t}^S$, and $P_{Sell,t}^B$ are the sales power of WT, PV, and BES, respectively.

To calculate the wind selling power at each time, it is necessary to calculate the wind power PW_t.

$$P_t^W = \begin{cases} 0; & w_t \leq w_c \\ S^W (w_t - w_c)/k; & w_c \leq w_t \leq w_r \\ S^W; & w_t \geq w_r \end{cases}, \tag{11}$$

where P_t^W is the wind power, related to the wind speed at each time. If the wind speed w_t at the current moment is less than the cut-in wind speed w_c, the wind power cannot be output. If the current wind speed w_t is between the cut-in wind speed w_c and the cut-out wind speed w_r, the generated power can be calculated from a linear expression related to the wind speed and the capacity of WT. If the current wind speed w_t is greater than the cut-out wind speed w_r, the rated capacity S^W of WT is considered in this paper.

The calculation of solar power PS_t is formulated as follows:

$$P_t^S = S^S IT_t, \tag{12}$$

where P_t^S is the photovoltaic power generation related to the planned capacity of solar power generation equipment S^S and the radiation intensity of current illumination IT_t.

The renewable energy modeling in this paper considers the wind speed and irradiance in the planning area, establishes a mathematical relationship between wind or solar resources and power output under a given new energy installation capacity, and combines typical power output curves of wind and solar energy to construct a scenario-based modeling method.

This paper assumes that renewable energy is preferentially consumed in the system. Therefore, the power shortage at the current time ΔP_t can be expressed as follows.

$$\Delta P_t = P_t^W + P_t^S - D_t. \tag{13}$$

It can be found that if ΔP_t is greater than or equal to 0, indicating that the current wind power generation power P_t^W and the photovoltaic power generation power P_t^S are sufficient to supply the load D_t, the surplus power at the current time can be provided to the energy storage equipment for charging. If ΔP_t is less than 0, the current wind power generation power P_t^W and photovoltaic power generation power P_t^S cannot meet the current load D_t demand and need to be provided by the energy storage system.

SOC_t is the remaining capacity of the energy storage equipment at the current time, which is related to the capacity of the energy storage equipment. The minimum value of SOC_t is 30% of the planned capacity of BES. The maximum value of SOC_t is the value corresponding to the planned capacity of BES. In particular, the remaining capacity of the energy storage device needs to be limited between the maximum and minimum values of the remaining capacity.

$$SOC_t = \begin{cases} SOC_{\max}; & SOC_t \geq SOC_{\max}, \\ SOC_{\min}; & SOC_t < SOC_{\min}, \end{cases} \tag{14}$$

$$SOC_t = SOC_{t-1} + \Delta P_{t-1}\Delta t, \tag{15}$$

where SOC_t at the current time is the SOC at the previous time t-1 plus the charge/discharge power at the previous time. Then, the charge/discharge power of battery energy storage is expressed by the following formula.

$$\begin{cases} P_{Sell,t}^B = SOC_t - SOC_{t-1}; & SOC_t \geq SOC_{t-1}, \\ P_{Charge,t}^B = SOC_{t-1} - SOC_t; & SOC_t < SOC_{t-1}. \end{cases} \tag{16}$$

If the SOC at the current moment is larger than the SOC at the previous moment, the BES in the microgrid is in discharge and sells power to the main grid. Conversely, if the SOC at the current moment is larger than the SOC at the previous moment, the BES in the microgrid is in charge.

$$P_t^{c,\max} = D_t + P_t^{tie,\max} + P_t^B, \tag{17}$$

$$P_t^{MAR} = P_t^W + P_t^S - P_t^{c,\max}, \tag{18}$$

where $P_t^{c,\max}$ is the maximum consumable power at time t, $P_t^{tie,\max}$ is the maximum power of the tie line at time t, and P_t^B is the battery energy storage power at time t. It can be found that the maximum consumable power $P_t^{c,\max}$ at time t is composed of the load D_t, the maximum power of tie line $P_t^{tie,\max}$, and the battery discharge power

P_t^B at the current time. P_t^{MAR} is the remaining power margin after consuming wind power and photovoltaic, and its value is the surplus of wind power output P_t^W and photovoltaic output P_t^S after deducting the maximum consumable load power $P_t^{c,\max}$.

Combined with the power margin and the maximum consumable power calculated previously, the actual sales power of WT and PV can be calculated, which are shown as follows:

$$P_{Sell,t}^W = \begin{cases} P_t^W; & P_t^{MAR} \leq 0, \\ P_t^W(P_t^W + P_t^S)/P_t^{c,\max}; & P_t^{MAR} > 0, \end{cases} \tag{19}$$

$$P_{Sell,t}^S = \begin{cases} P_t^S; & P_t^{MAR} \leq 0, \\ P_t^S(P_t^W + P_t^S)/P_t^{c,\max}; & P_t^{MAR} > 0. \end{cases} \tag{20}$$

Therefore, when the residual power margin is less than 0, WT and PV power are the actual output power. If the power margin is greater than 0, WT and PV power can only be consumed proportionally.

2.7 Annual profit of equipment scrapping

Another part of the income of the wind-photovoltaic-storage microgrid comes from the scrapping income of wind-photovoltaic-storage equipment, and the specific calculation formula is as follows:

$$I_{Drop} = I_{Drop}^W + I_{Drop}^S + I_{Drop}^B, \tag{21}$$

$$I_{Drop}^{EQ} = S^{EQ} p_{Drop}^{EQ} \frac{r}{(1+r)^{T^{EQ}} - 1}, \tag{22}$$

where the annual scrapping income of planned equipment consists of the scrapping income of WT I_{Drop}^W, the scrapping income of PV I_{Drop}^S, and the scrapping income of BES I_{Drop}^B. The coefficient r is the discount rate. T^{EQ} are the life cycles of WT, PV, and BES, respectively. p_{Drop}^{EQ} represents the scrapping income per unit capacity of WT, PV, and BES.

3 Improvement in the cultural gray wolf optimization algorithm

The aforementioned problem is a planning model with complicated constraints and variables. It contains a large number of logical judgment constraints, which is intractable to most mathematical solvers. Furthermore, the traditional optimization algorithm has slow convergence speed. In addition, traditional mathematical optimization methods, such as branching-and-cut or cutting plane methods, need to approximate the non-convex and nonlinear parts, transforming the model into a tractable form of MILP. Although the precise solution of the model can be obtained, there is still some deviation between the transformed model and the original model. In this situation, the advantages of the heuristic optimization algorithm are more prominent.

This paper improves the GWO algorithm (Mirjalili and Seyed Mohammad Mirjalilib, 2014) and proposes an improved CGWO algorithm, which is suitable for the capacity planning model of wind-photovoltaic-storage equipment in the microgrid. The proposed CGWO algorithm enhances the gray wolf optimization method to effectively solve the capacity planning problem and optimize the performance of wind-photovoltaic-storage equipment in microgrids.

FIGURE 2
Framework of gray wolf optimization (GWO).
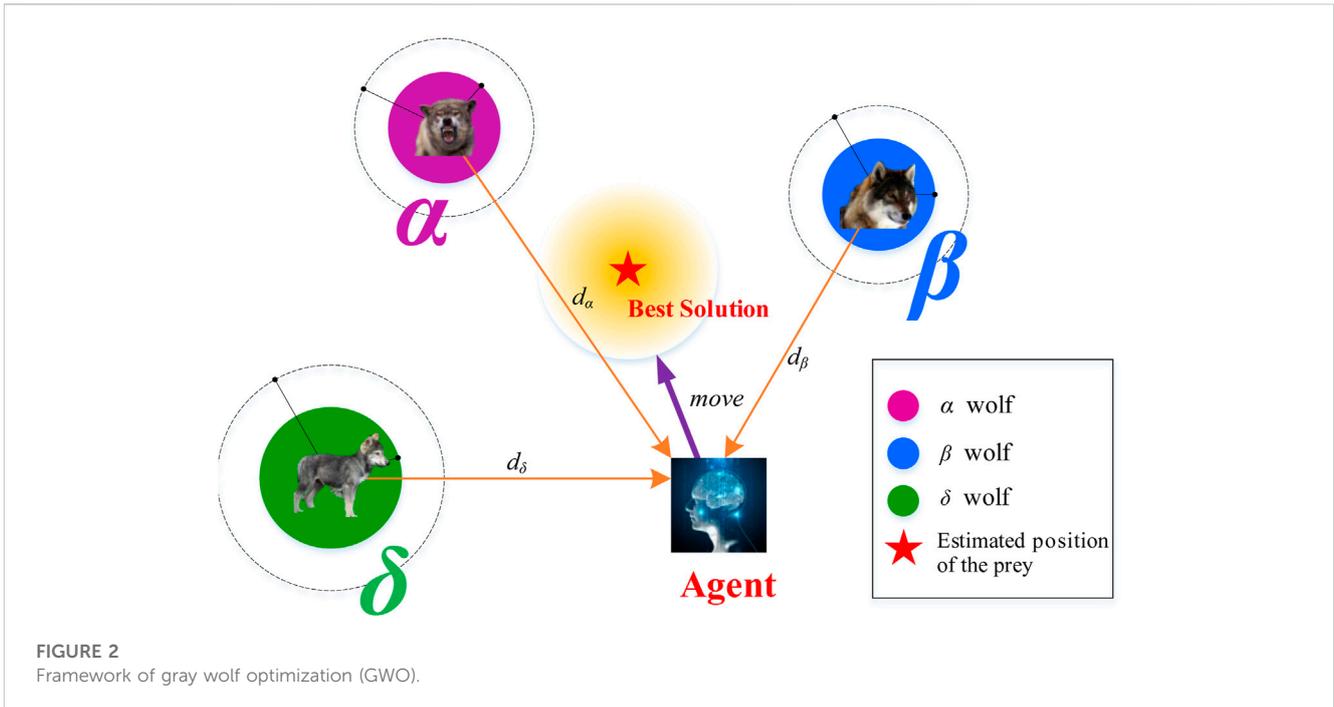
A traditional GWO algorithm is based on the classification of wolves. The weight of wolves with a high level is higher, and the weight of wolves with a low level is lower. The search range and target of different wolves are different. Finally, the search information on different wolves is summarized and synthesized, and the optimal search mode of the whole wolves is given. The framework of this algorithm is presented in Figure 2. With the iteration, the search range is continuously narrowed to achieve the optimal position. However, the iterative update mode of the traditional gray wolf optimization algorithm in the evolution process adopts the linear decreasing strategy to shrink, and the convergence factor calculation formula of the traditional gray wolf algorithm is as follows:

$$a = 2\left(1 - \frac{l}{T}\right), \tag{23}$$

where a is the convergence factor, l is the current iterative algebra, and T is the total number of evolutionary iterations.

Inspired by particle swarm optimization, slowing down the convergence rate of the convergence factor can enhance its global search ability and prevent the algorithm from falling into the local optimal solution. Therefore, to improve the global performance of algorithm contraction, this paper proposes a new convergence factor updating method based on exponential law change:

$$a = 2\exp\left(-l/T\right), \tag{24}$$

The convergence factor a will decrease in the form of a negative exponent, and its decreasing speed is lower than that of the linear decreasing strategy.

Second, to better carry out the global search and consider the performance of local utilization (the basic idea of the greedy algorithm), this paper proposes an adaptive search strategy, which makes the algorithm still attach importance to the role of the first wolf (α wolf), but at the same time, it does not take the average value of the positions of the three wolves. The specific expression is as follows:

$$X(l + 1) = \frac{X_1 + X_2 + X_3}{3}\left(1 - \frac{l}{T}\right) + X_1\frac{l}{T}, \tag{25}$$

where X_1 is the position of the α wolf, X_2 is the position of the β wolf, and X_3 is the position of γ wolf, which indicates the central position of the population after evolving from the previous generation to the next generation.

In addition, a better initial solution can significantly improve the initial search performance. Therefore, this paper is inspired by the cultural gene optimization algorithm to give full play to the global search performance of the genetic algorithm (GA). Before starting iteration, the initial solution is generated blindly and randomly. First, the high-quality initial solution is obtained based on GA, and then, the evolutionary iteration is carried out based on the gray wolf optimization algorithm.

The steps of the improved gray wolf optimization algorithm are summarized, as shown in Figure 3.

4 Case study

The following will be combined with the actual solution example for analysis, based on MatlabR 2020a. The processor parameter of the computer is Intel(R) Core(TM) i7-8565U CPU @ 1.80 GHz, 1.99 GHz.

4.1 Model parameter description

This paper takes a microgrid as a simulation example. Then, 8,760 h of the actual load demand in the microgrid, the wind speed, and the light intensity of the microgrid in a year for this area are collected and uploaded in Liang et al. (2023).
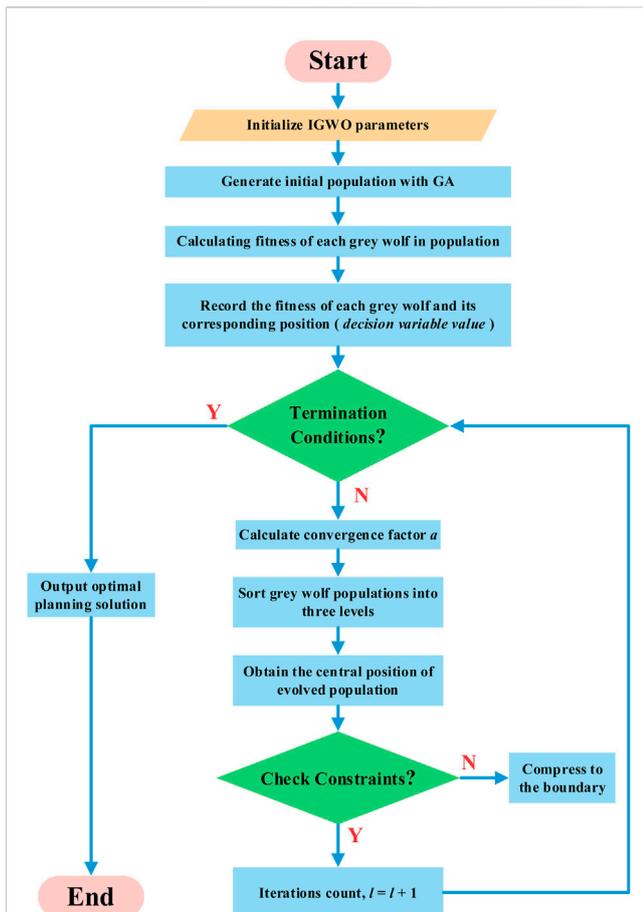
FIGURE 3
Framework of cultural gray wolf optimization (CGWO). (i) Initializing CGWO parameters, including the population number N and total iteration times T. (ii) Giving full play to the global optimization ability of GA, the initial solution is obtained by a genetic principle, and the initial gray wolf population is generated. (iii) Calculating the fitness function of each level of gray wolf in the population. For the calculation of fitness function in this paper, refer to the objective function of the optimal capacity planning model of wind and solar storage equipment in the microgrid, which is presented in Eq. 1. After the calculation, the fitness function of different gray wolves and its corresponding position (the value of decision variables) were recorded. (iv) Judging whether the condition of algorithm termination is met. For example, whether the algebra of convergence iteration is reached or not, the optimal solution does not change in K iterations. If the termination condition is satisfied, the optimal solution of the cycle output is proposed, and the optimal capacity planning scheme of wind–photovoltaic-storage equipment in the microgrid is obtained; otherwise, step (v) is performed. (v) The convergence factor a is calculated according to Eq. 24. (vi) The gray wolf population was sorted, and the gray wolf level was divided into three levels. (vii) The center position of the evolved population is obtained based on Formula 25, and it is checked whether the center position of the new population violates the relevant constraints of the model. If the constraint is violated, it is compressed to the boundary. (viii) The number of iterations plus 1, that is, $l = l+1$, return to step (iv).

4.2 Algorithm parameter setting

Before solving the model based on the heuristic/meta-heuristic optimization algorithm, it is necessary to set the memory of each parameter involved in each algorithm. In order to ensure the comparability of the algorithms, each heuristic optimization

TABLE 2 Parameter setting of particle swarm optimization (PSO).

Parameter	Name	Value
N	Population number	50
G	Maximum number of iterations	50
C_1	Learning factor 1	2.0
C_2	Learning factor 2	2.0
v_{max}	Maximum speed	0.8
v_{min}	Minimum speed	0.1

TABLE 3 Parameter setting of the genetic algorithm (GA).

Parameter	Name	Value
N	Population number	50
G	Maximum number of iterations	50
P_c	Crossover rate	0.8
P_m	Variation rate	0.05

TABLE 4 Parameter setting of the whale optimization algorithm (WOA).

Parameter	Name	Value
N	Population number	50
G	Maximum number of iterations	50

algorithm sets the same parameters in the population number and iteration times, and other algorithms determine the optimal parameter settings according to the grid search method (Bergh and Engelbrecht, 2003; Baker and Ayechew, 2003). The specific parameter settings of each algorithm are shown in Table 2; Table 3; Table 4; Table 5; Table 6.

4.3 Comparison of different optimization algorithms

To verify the convergence and convergence speed of the improved CGWO algorithm proposed in this paper, it is compared with PSO (Prakash et al., 2022), GA (Wang et al., 2022c, WOA (Singh and Sharma, 2017), and GWO algorithms (Ali et al., 2023). The convergence curves and convergence times of different algorithms are shown in Figure 4; Figure 5.

By using MATLAB, CGWO can converge to the optimal value of $-1.1908 * 10^6$ yuan at a faster speed. To verify the optimality of the convergence objective, this paper increases the number of population searches and iterations of other heuristic optimization algorithms and finally converges to the same objective function value. Therefore, it can be considered that the convergence value is the optimal objective function value of the wind-photovoltaic-storage microgrid planning model, and the specific decision variables obtained by the convergence of different algorithms are

TABLE 5 Parameter setting of the gray wolf optimization algorithm (GWO).

Parameter	Name	Value
N	Population number	50
G	Maximum number of iterations	50

TABLE 6 Parameter setting of the improved cultural gray wolf optimization algorithm (CGWO).

Parameter	Name	Value
N	Population number	50
G	Maximum number of iterations	50
P_c	Crossover rate	0.8
P_m	Variation rate	0.05

FIGURE 4
Convergence curves of different optimization algorithms.

FIGURE 5
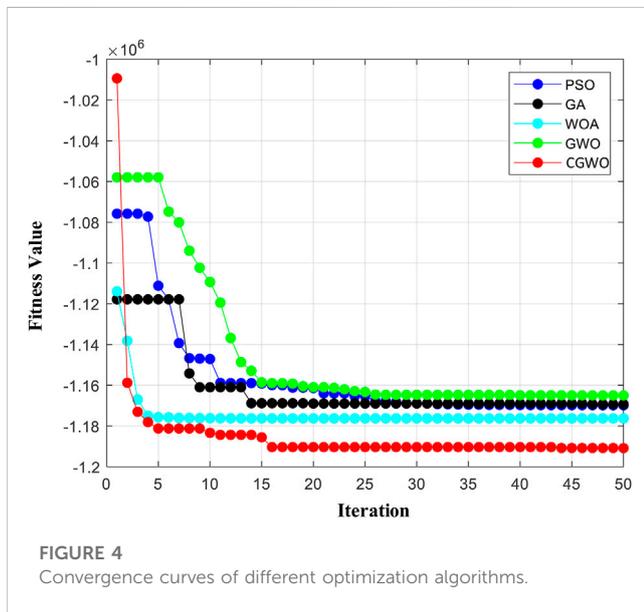Calculation time of different algorithms.
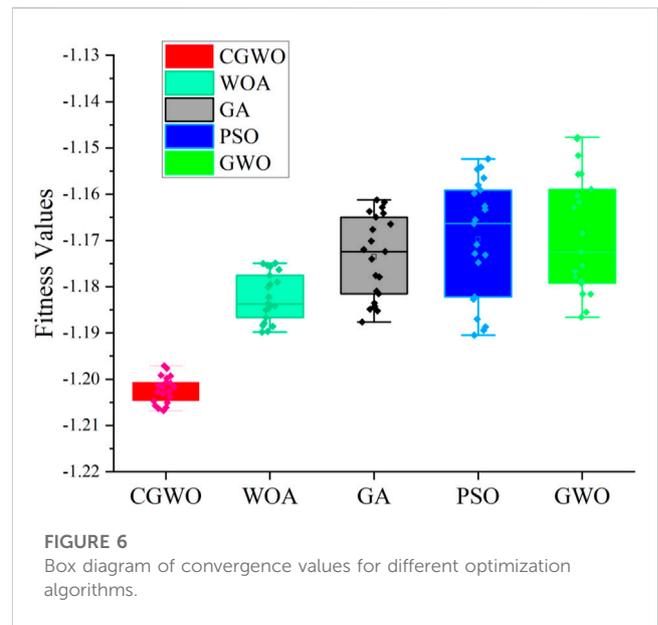
FIGURE 6
Box diagram of convergence values for different optimization algorithms.

395.8956, 397.6725, and 864.0066. The calculation time of different algorithms can be completed within 15 s, the solution efficiency can meet the requirements of planners for planning and design, and the efficiency is much higher than that of the manual scheme design and index comparison.

In this case study, the performance of several optimization algorithms to solve the planning model is compared. The key findings are as follows:

(1) PSO produced average initial solutions, eventually converging to a local optimal solution. PSO's optimization time was moderate, but its performance was sensitive to parameter settings, making it less adaptable and robust.

(2) GA had poor initial solutions and convergence speed, but its diverse and global solutions made it a valuable component of the improved GWO, which combined GA with the stable and powerful optimization performance of GWO.
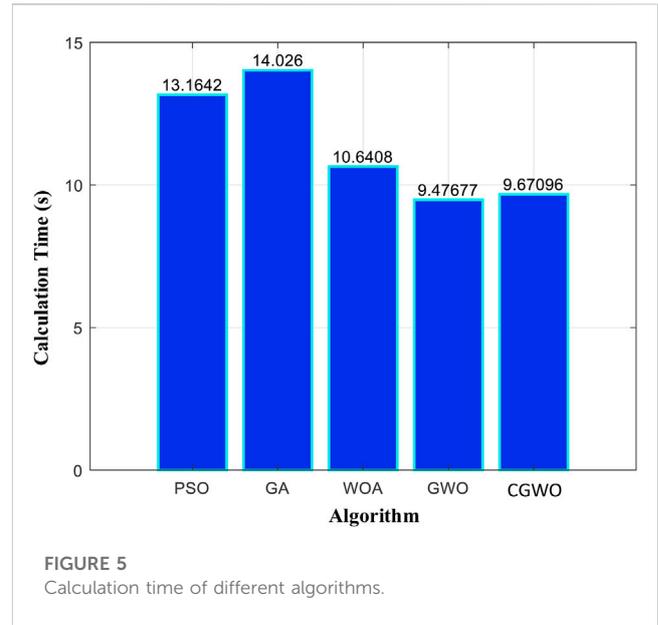
(3) WOA had better convergence and shorter calculation times compared to PSO. It is a meta-heuristic algorithm that is easier to apply and understand than PSO.

(4) CGWO outperformed all other algorithms in convergence speed and actual calculation time. Its combination of cultural genes enabled high-quality solutions to evolve and converge quickly.

To further verify the convergence of the algorithm, different optimization algorithms were repeated 20 times, and the curves were plotted in a boxplot, as shown in Figure 6. It can be found that CGWO has the best convergence, both in terms of the fluctuation of the boxplot (length of the boxplot) and the mean value of the boxplot, which are superior to other algorithms. Therefore, it can be

FIGURE 7
Optimal equipment capacity for different wind power selling prices.

FIGURE 8
Optimal equipment capacity for different solar power sale prices.
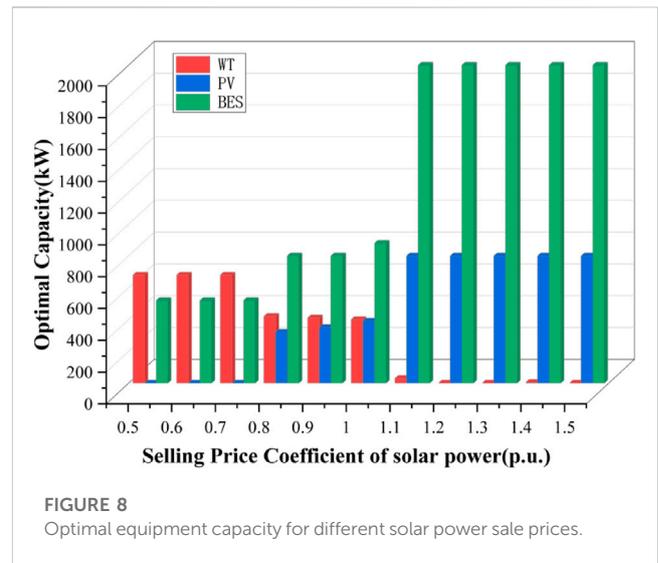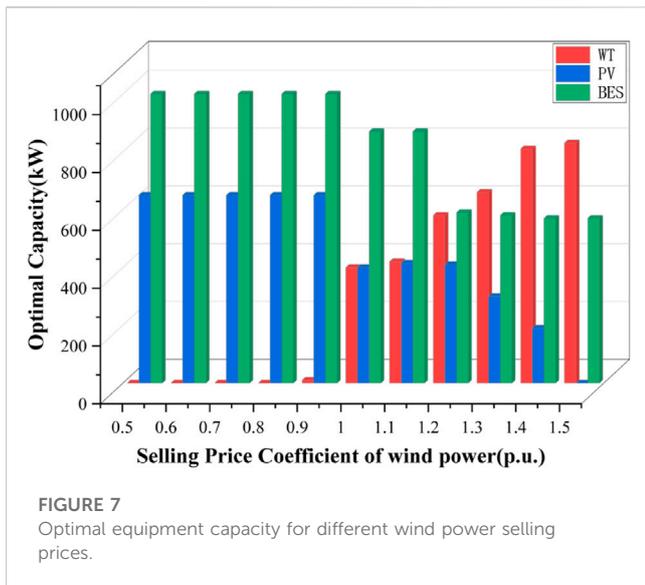
concluded that the algorithm proposed in this paper has better convergence compared to other optimization algorithms.

4.4 Sensitivity analysis of the model

4.4.1 Electricity price sensitivity analysis of different types of generators

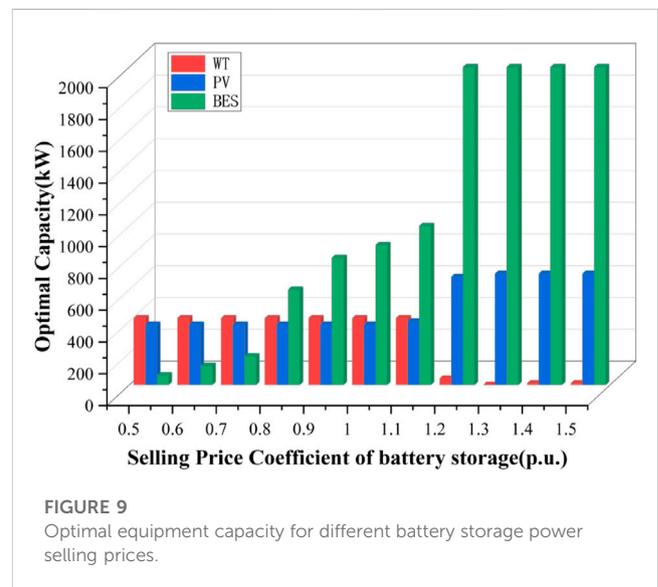#### 4.4.1.1 Sensitivity analysis of wind power selling prices

The sensitivity analysis of different wind power sales prices is performed and shown in Figure 7. A sensitivity analysis was conducted on wind power sales prices by multiplying the reference price with corresponding electricity price coefficients ranging from 0.5 to 1.5 in increments of 0.05.

Based on the findings presented in Figure 7, it can be inferred that an increase in the selling price of wind power will lead to an increase in the planned capacity of wind power equipment. When the electricity price coefficient exceeds 1 p. u., the planned capacity of wind power equipment increases, while the planned capacity of photovoltaic and energy storage equipment decreases. However, due to the ability of energy storage to smooth fluctuations, a certain capacity of energy storage equipment is still necessary.

4.4.1.2 Sensitivity analysis of solar power selling prices

The sensitivity analysis of different selling prices of photovoltaic power generation is performed, and the results are shown in Figure 8.

When revenue from photovoltaic electricity sales increases, it often leads to an increase in the construction of photovoltaic equipment. However, if the revenue from photovoltaic electricity sales continues to remain high, it may result in a decrease in the construction of wind power equipment and an increase in the construction of energy storage equipment. This is because high revenue from photovoltaic electricity sales may make wind power projects less financially attractive, and energy storage equipment becomes more important to balance the intermittency of renewable energy sources, such as wind and solar energy. Therefore, it is

FIGURE 9
Optimal equipment capacity for different battery storage power selling prices.

important to consider the overall energy mix and the balance between different renewable energy sources and energy storage technologies to ensure a sustainable and reliable energy system.

4.4.1.3 Sensitivity analysis of storage power selling prices

The sensitivity analysis is conducted on the selling price of different energy storage power generation, and the results are shown in Figure 9.

When the revenue generated by selling electricity from energy storage equipment increases, it incentivizes the expansion of the energy storage construction capacity. However, as the cost of selling electricity from energy storage equipment increases to a certain level, it may become more expensive to rely solely on energy storage to meet the load power demand. At this point, there may be an increased incentive to expand the construction capacity of photovoltaic equipment to help supplement the energy supply and lower costs.
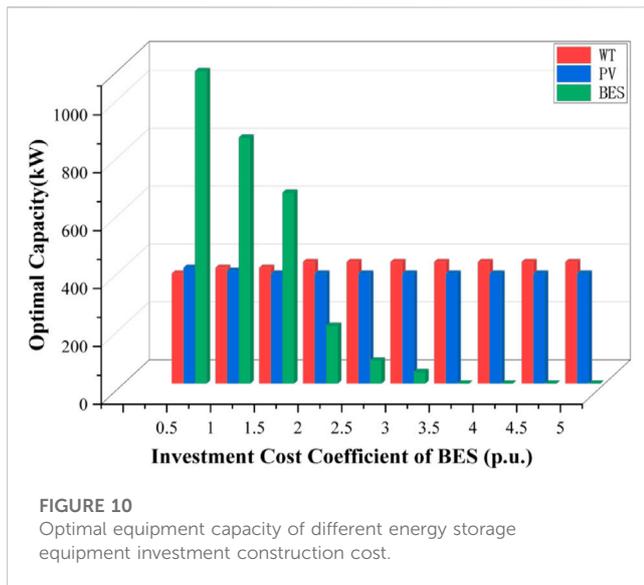
FIGURE 10
Optimal equipment capacity of different energy storage equipment investment construction cost.

4.4.2 Sensitivity analysis of the BES investment cost

The sensitivity analysis of investment and construction costs of different energy storage equipment is performed, and the results are shown in Figure 10.

Figure 10 demonstrates that a decrease in the investment cost of energy storage equipment results in a significant increase in its optimal planning capacity. This is because energy storage plays a vital role in stabilizing power fluctuations within a microgrid. As such, a reduction in the construction cost of energy storage equipment incentivizes its greater utilization and expansion within the system.

4.4.3 Discussion on the costs and benefits

Through sensitivity analysis, the costs and benefits of different types of renewable energy on the planning results can be summarized as follows:

① With the increase in the WT selling price, the WT installation capacity increases. In comparison to PV selling prices, the advantage of WT will squeeze out some of the PV installation capacity. However, due to the greater uncertainty of WT fluctuations compared to PV, the WT installation capacity rapidly decreases when the selling price is below 1 p. u.

② With the increase in the PV selling price, the PV capacity increases to a certain extent, but after reaching a certain point, PV also needs some energy storage support and will not increase further. In comparison to WT selling prices, the advantage of PV will squeeze out some of the WT installation capacity. Since the output of PV is relatively regular (high radiation intensity at noon and low radiation intensity at other times), the PV installation capacity is replaced by the WT installation capacity only when the price is below 0.8 p. u.

③ BES plays an important role in suppressing the volatility and uncertainty of wind and solar energy. Therefore, when the electricity price for energy storage and sales decreases, it is necessary to retain a certain degree of installed energy storage capacity to promote the consumption of wind and solar

resources. When the electricity price for energy storage and sales increases, the efficient combination of energy storage and photovoltaic will show "bundled growth."

5 Discussion and limitations

5.1 Advantages and disadvantages of the proposed method

The advantages of the proposed method for considering the selling income of renewable energy in microgrid capacity planning are summarized as follows:

(1) One of the key advantages of the proposed approach is its ability to capture the impact of varying electricity prices on microgrid capacity. By incorporating dynamic pricing models, different scenarios and the capacity planning solution can be obtained and analyzed. This allows microgrid operators to make more informed decisions and maximize their revenue potential.

(2) Another advantage is that the proposed method considers distributed power generation, which aligns with the growing trend of renewable energy integration in microgrids. By incorporating the revenue from selling excess power back to the grid, the deployment of DGs is incentivized.

(3) The proposed optimization algorithm is stable and has good convergence effect. Compared with traditional mathematical methods, such as branch-and-cut or cutting plane methods, the proposed algorithm can be applied easily to provide several satisfactory solutions for planners to select.

However, certain limitations are summarized as follows.

(1) Real-time volatility of electricity prices has not been considered. The uncertainties associated with price forecasting can indicate potential risks in the process of microgrid capacity planning. In future research, the uncertainty of prices can be accurately characterized through distributionally robust optimization (DRO) and integrated with the optimization model, fully considering the impact of price volatility on capacity planning (Zhou et al., 2021).

(2) Although feasible solutions can be provided, the optimal solution of the model cannot be guaranteed. Due to the non-convex and nonlinear nature of the proposed model, it can only be solved with the meta-heuristic optimization algorithm.

5.2 The potential impact of the communication mechanism

The intensity of communication among components has a significant impact on the microgrid system structure (Górski, 2022; Menniti et al., 2022). It is crucial to consider the area of information exchange, messaging patterns, and technologies employed. The use of messaging patterns in microgrid systems has gained significant attention due to their ability to facilitate efficient communication and coordination among various

components. Górski (2022) provided valuable insights into the use of messaging patterns in different domains. By leveraging messaging patterns, microgrid components can exchange information in a standardized and reliable manner, enabling effective coordination and control. Menniti et al. (2022) presented experimental use cases that highlight the potential of enabling technologies in energy communities. These technologies can be leveraged in microgrids to enhance information exchange, such as advanced metering infrastructure, smart sensors, and real-time data analytics.

Therefore, if the communication between different microgrids and the communication range constraints between different types of devices are considered, it may influence the planning result of the microgrid equipment capacity.

6 Conclusion

This paper proposes a capacity planning model for wind-photovoltaic-storage equipment in microgrids and solves the model using the CGWO algorithm. The paper presents the following conclusions.

(1) This paper analyzes the whole life cycle costs and profits that need to be considered in the planning of wind-photovoltaic-storage equipment in a microgrid. Then, a capacity planning model of wind, photovoltaic, and storage equipment considering LCC and profits in the microgrid is established. In terms of life cycle cost, annualized investment cost, annual power outage compensation cost, annualized main grid purchase cost, and annualized equipment operation and maintenance cost are considered. In terms of profits of the system, the electricity sales income and scrapping income are considered.

(2) CGWO is applied to solve the proposed model efficiently. From the simulation results, it can be seen that CGWO improves the solution efficiency and convergence characteristics without increasing too much computational complexity. In addition, the robustness and adaptability of the algorithm are obviously improved compared with the traditional heuristic optimization algorithms.

(3) Sensitivity analysis on electricity selling price and energy storage investment and construction cost in the model are conducted to analyze the influence of electricity selling price and energy storage construction cost on the planning scheme. Case studies reveal the impact of the planned capacity of WT, PV, and BES increases in varying degrees when the selling price of different equipment decreases. In addition, microgrid planners will rapidly increase the proportion of BES investment when the investment cost of BES decreases.

Future research can investigate the integration of multiple energy resources, dynamic demand response, multiple microgrid interaction, and digital techniques and their impact on the capacity planning of microgrid equipment. Additionally, uncertainty optimization algorithms that can accurately depict load, renewable energy, and electricity price fluctuations will be further studied and applied in depth (MirjaliliSeyedaliLewis, 2016).

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

Funding

Conflict of interest

LL, XZ, and WH are employed by the Digital Grid Research Institute of China Southern Power Grid. LS is employed by Guangzhou Shuimu Qinghua Technology Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Abou El-Ela, Adel A., Ragab, A. El-Sehiemy, and Shaheen, Abdullah M. (2022). A multi-objective equilibrium optimization for optimal allocation of batteries in distribution systems with lifetime maximization. *J. Energy Storage* 55, 2022. doi:10.1016/j.est.2022.105795

Ali, Selim, Kamel, Salah, Mohamed, Amal A., and Yu, J. (2023). Placement and sizing of distributed generations and shunt capacitors in radial distribution systems using hybrid optimization technique. *Electr. Power Components Syst.* 51, 421–437. doi:10.1080/15325008.2023.2173827

Baker, B. M., and Ayechew, M. A. (2003). A genetic algorithm for the vehicle routing problem. *Comput. Operations Res.* 30 (5), 787–800. doi:10.1016/S0305-0548(02)00051-5

Bergh, Fvd, and Engelbrecht, A. P. (2003). "A new locally convergent particle swarm optimiser," in IEEE International Conference on Systems, Man and Cybernetics IEEE, Prague, Czech Republic, October 1–4, 2023.

Borghei, M., and Ghassemi, M. (2021). Optimal planning of microgrids for resilient distribution networks. *Int. J. Electr. Power and Energy Syst.* 128, 106682. doi:10.1016/j.ijepes.2020.106682

Coelho, V. N., Coelho, I. M., Coelho, B. N., de Oliveira, G. C., Barbosa, A. C., Pereira, L., et al. (2016). A communitarian microgrid storage planning system inside the scope of a smart city. *Appl. Energy* 201, 371–381. sep.1. doi:10.1016/j.apenergy.2016.12.043

Górski, Tomasz (2022). UML profile for messaging patterns in service-oriented architecture, microservices, and internet of things. *Appl. Sci.* 12 (24), 12790. doi:10.3390/app122412790

Hung, D. Q., Mithulananthan, N., and Lee, K. Y. (2014). Optimal placement of dispatchable and nondispatchable renewable DG units in distribution networks for minimizing energy loss. *Int. J. Electr. Power and Energy Syst.* 55, 179–186. doi:10.1016/j.ijepes.2013.09.007

Khemissi, L., Khiari, B., and Sellami, A. (2021). A novel optimal planning methodology of an autonomous Photovoltaic/Wind/Battery hybrid power system by minimizing economic, energetic and environmental objectives. *Int. J. Green Energy* 18 (10), 1064–1080. doi:10.1080/15435075.2021.1891906

Khoubseresht, Omid, and Rajabinezhad, MohamadaminSeyyed Yousef Mousazadeh Mousavi (2023). An analytical optimum method for simultaneous integration of PV, wind turbine and BESS to maximize technical benefits. *IET Generation, Transm. Distribution*. doi:10.1049/gtd2.12801

Kiptoo, Mark Kipngetich, Elsayed Lotfy, M., Senjyu, T., Mandal, P., and Abdel-Akher, M.Oludamilare Bode Adewuyi (2019). Multi-objective optimal capacity planning for 100% renewable energy-based microgrid incorporating cost of demand-side flexibility management. *Appl. Sci.* 9 (18), 3855. doi:10.3390/app9183855

Kiptoo, Mark Kipngetich, Nakadomari, Akito, and Senjyu, TomonobuOludamilare Bode Adewuyi; Harun Or Rashid Howlader (2023). Optimal capacity and operational planning for renewable energy-based microgrid considering different demand-side management strategies. *Energies* 16, 4147. doi:10.3390/en16104147

Liang, Lingyu, Zhao, Xiangyu, and Huang, Wenqi (2023). *Collaborative capacity planning method of wind-photovoltaic-storage equipment in microgrid based on improved cultural gray wolf optimization algorithm*. Available at: https://drive.google.com/file/d/1WLDIC2-GerpFXQ6ngzzSC1lmFvKTS2hV/view?usp=sharing.

Liu, Z., Chen, Y., Luo, Y., Zhao, G., and Jin, X. (2016). Optimized planning of power source capacity in microgrid, considering combinations of energy storage devices. *Appl. Sci.* 6 (12), 416. doi:10.3390/app6120416

Menniti, D., Pinnarelli, A., Sorrentino, N., Vizza, P., Barone, G., Brusco, G., et al. (2022). Enabling technologies for energy communities: some experimental use cases. *Energies* 15 (17), 6374. doi:10.3390/en15176374

Mirjalili, SeyedaliSeyed Mohammad Mirjalilib (2014). Grey wolf optimizer. *Adv. Eng. Softw.* 69, 46–61. doi:10.1016/j.advengsoft.2013.12.007

MirjaliliSeyedaliLewis (2016). Grey wolf optimizer. *Adv. Eng. Softw.* 69, 46–61. doi:10.1016/j.advengsoft.2013.12.007

Prakash, P., Meena, D. C., Malik, H., Alotaibi, M. A., and Khan, I. A. (2022). A novel analytical approach for optimal integration of renewable energy sources in distribution systems. *Energies* 15, 1341. doi:10.3390/en15041341

Sharma, S., Bhattacharjee, S., and Bhattacharya, A. (2016). Grey wolf optimisation for optimal sizing of battery energy storage device to minimise operation cost of microgrid. *IET Generation Transm. Distribution* 10 (3), 625–637. doi:10.1049/iet-gtd.2015.0429

Singh, Bindeshwar, and Sharma, Janmejay (2017). A review on distributed generation planning. *Renew. Sustain. Energy Rev.* 76, 529–544. doi:10.1016/j.rser.2017.03.034

Wang, Jiayu, Han, Ding, Hu, Xiao, Liang, Hua, Xu, Zhongping, Zhang, Chengping, et al. (2022a). Research on application of "double-carbon power index" system based on delphi method. *MATEC Web Conf.* 356, 01006. doi:10.1051/matecconf/202235601006

Wang, Ziyao, Lin, Dan, Tao, Yu, Zeng, Guangxuan, and Pan, Zhenning (2022b). Explicit reliability incorporated switches planning of smart distribution system with high flexibility. *Int. J. Power Energy Syst.* doi:10.1016/j.ijepes.2022.108629

Wang, Ziyao, Zhong, Lipeng, Pan, Zhenning, Tao, Yu, and Qiu, Xingyu (2022c). Optimal double Q AC-DC hybrid distribution system planning with explicit topology-variable-based reliability assessment. *Appl. Energy* 322, 119438. doi:10.1016/j.apenergy.2022.119438

Wei, G., Zhi, W., Rui, B., Liu, W., Zhou, G., Chen, W., et al. (2014). Modeling, planning and optimal energy management of combined cooling, heating and power microgrid: A review. *Int. J. Electr. Power and Energy Syst.* 54, 26–37. jan. doi:10.1016/j.ijepes.2013.06.028

Xiao, B., Xing, S., Wang, T., Yang, Y., Dong, L., Yang, H., et al. (2020). Capacity planning of pumped storage power station based on the life cycle cost. *Electr. Power Components Syst.* 48 (3), 1263–1271. doi:10.1080/15325008.2020.1854383

Yang, B., Wang, J., Chen, Y., Li, D., Zeng, C., Chen, Y., et al. (2020b). Optimal sizing and placement of energy storage system in power grids: A state-of-the-art one-stop handbook. *J. energy storage* 32, 101814. doi:10.1016/j.est.2020.101814

Yang, B., Wang, J., Chen, Y., and Zeng, C. (2020a). Optimal sizing and placement of energy storage system in power grids: A state-of-the-art one-stop handbook. *J. Energy Storage* 32 (4), 101814. doi:10.1016/j.est.2020.101814

Zhou, Y., Zhai, Q., and Wu, L. (2021). Multistage transmission-constrained unit commitment with renewable energy and energy storage: implicit and explicit decision methods. *IEEE Trans. Sustain. Energy* 12 (2), 1032–1043. doi:10.1109/TSTE.2020.3031054

Nomenclature

Variables

F	Comprehensive cost of the designed microgrid system
C_{Inv}	Cost of the capacity planning model includes cost of equipment investment in the microgrid (WT, PV, and BES)
C_{EENS}	Cost of expected energy not supplied (EENS)
C_{Buy}	Cost of electricity purchased from the main grid
C_{Main}	Cost of equipment maintenance
I_{Sell}	Profits of selling electricity from the designed microgrid system
I_{Drop}	Profits of the scrapping of equipment from the designed microgrid system
$I_{Drop}^W/I_{Drop}^S/I_{Drop}^B$	Profits of the scrapping of WT/PV/BES
C_{Inv}^{EQ}	Investment cost of WT, PV, and BES
S^{EQ}	Capacity of WT, PV, and BES
C_{Main}^{EQ}	Maintenance cost of WT, PV, and BES
P_{Main}^{EQ}	Maintenance cost per unit capacity of WT, PV, and BES
$EENS_t$	Power shortage at time t
$EENS$	Annual shortage of power supply
ΔP_t^{un}	Unbalanced power at time t
P_t^W/P_t^S	Wind power/solar power generation power at time t
SOC_t	Energy storage value at time t
P_t^{buy}	Power obtained through the tie line/main grid at time t
$P_{Sell,t}^W/P_{Sell,t}^S/P_{Sell,t}^B$	Sales power of WT/PV/BES at time t
$P_{Charge,t}^B$	Charging power of BES at time t
S^W/S^S	Planned capacity of wind power/solar power generation equipment
ΔP_t	Power shortage at time t
$P_t^{c,max}$	Maximum consumable power at time t
P_t^B	Battery energy storage power at time t
P_t^{MAR}	Remaining power margin at time t
$X_1/X_2/X_3$	Position of α wolf, β wolf, and γ wolf
$X(l+1)$	Position of the next wolf

Parameters

P_{Drop}^{EQ}	Investment cost per unit capacity of WT, PV, and BES
r	Discounted rate
P_{Inv}^{EQ}	Investment and construction cost per unit capacity of WT, PV, and BES
T^{EQ}	Life cycle of WT, PV, and BES
k_{EENS}	Power outage cost coefficient
$\tilde{p}^W, \tilde{p}^S, \tilde{p}^B$	Electricity sales prices of WT, PV, and BES
D_t	Load at time t
k_{buy}	Price coefficient of power purchase from the main grid
IT_t	Radiation intensity of illumination at time t
SOC_{max}/SOC_{min}	Maximum/minimum energy storage value

$P_t^{tie,max}$	Maximum power of the tie line at time t
w_t	Wind speed at time t
w_c/w_r	Cut-in wind speed/cut-out wind speed
a	Convergence factor
l	Current iterative algebra
T	Total number of evolutionary iterations