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Research article

Model for sustainable carbon emission reduction energy development and smart grid technology strategy

Kangli Xiang, Keren Chen*, Simin Chen, Wanqing Chen and Jinyu Chen

Power Economic Research Institute of State Grid Fujian Electric Power Company, Fuzhou, 350000, China

* **Correspondence:** Email: 15076417446@163.com.

Abstract: In the context of sustainable energy development to reduce carbon emissions, the application of new energy sources and smart grid technologies in power systems is becoming more widespread. However, current research results on power system technology strategies for carbon emission reduction are not satisfactory. To address this problem, a model for optimal power system operation and scheduling based on the prediction error mechanism and synthetic fuel technology is proposed. The model used the carbon trading mechanism to further reduce carbon emissions and the carnivorous plant algorithm to optimize the scheduling strategy. The results indicate that the model demonstrates significant advantages in terms of carbon emission, total operating cost, prediction accuracy, and energy utilization efficiency, respectively, at 60.8 kg, 2517.5 yuan, 96.5%, and 90.2%, indicating that it utilizes energy more fully and helps to enhance the overall energy efficiency of the system. The calculation time of the optimized power system was only 12.5 s, the stability was as high as 98.7%, and the satisfaction rate was 95.6% in terms of user satisfaction. Compared to other contemporary designs, the proposed model can successfully reduce the system's carbon emissions while increasing energy efficiency. The model has positive implications for smart grid and sustainable development.

Keywords: sustainability; carbon emission reduction; smart grid; operation optimization; new energy; carbon trading

Abbreviations: CE: carbon emission; PG: power generation; IES: integrated energy system; RE: renewable energy; PS: power system; SOAs: swarm optimization algorithms; CPA: carnivorous plant algorithm; OS: optimization strategy; CT: carbon trading; EB: electric boiler; GSHP: ground source heat pump; MMV: maximum and minimum values; OF: objective function

1. Introduction

With the increasing global concern about climate change and environmental protection, the development of sustainable energy with carbon emission (CE) reduction has become an important issue for countries around the world. In this context, the importance of smart grid technology as a key tool to promote energy system transformation has become more and more prominent [1]. Priyanka E B et al. proposed an oil transportation monitoring system in an attempt to explore the application of smart grid technology in oil transportation. The system deliberately placed sensors, measurements, and instrumentation on a long transportation pipeline to locate the areas that needed to be cleaned for oil transportation through wireless communication combined with smart grid and the introduction of cloud computing technology. The method achieved 90% localization accuracy [2]. Pal R et al. addressed the rising cost of energy consumption and greenhouse gas emissions in the automotive industry by proposing an energy management strategy based on smart grid technology. To achieve the best scheduling for charging and discharging electric vehicles, the strategy made use of several intelligent systems and various integration strategies in a smart grid. The results indicated that the method was able to manage energy efficiently using sensor technology as well as communication technology [3]. Lopez J et al. suggested a network fault prediction and detection method considering context-aware capabilities and simulation techniques for protecting network security issues in smart grid systems. At the same time, it applied the digital twin technique to the formulation of access control policies. The results indicated that the method could realize long-term autonomous and self-learning grid security protection [4].

In recent years, governments worldwide have been actively taking measures to significantly improve the global energy structure. The world may achieve green development by utilizing an integrated energy system (IES) that is safe, secure, and efficient, which can be achieved through the organic combination of various energy sources [5]. With the rapid development of wind and solar power generation (PG) technologies, they have become an important part of renewable energy (RE). However, due to their high cost, they are also becoming more and more difficult to apply in practice [6]. Energy waste resulting from the unpredictable, erratic, and irregular character of solar and wind energy can be efficiently addressed by implementing the proper energy reserve technology [7]. To present the advantages as well as the performance of energy storage technologies utilizing hydrogen and metal hydrides, Tarasov B P et al. statistically analyzed the existing literature in the related field. The outcomes revealed that AB5-type and ab2-type intermetallic compounds have better storage in the hydrogen system. Moreover, it utilized this property to develop hydride-based energy storage components [8]. Diaz I U et al. suggested a methodology to ascertain the best way to choose and schedule distributed energy sources in order to evaluate their operational viability as an energy storage system in a microgrid. The findings showed that introducing hydrogen into microgrids was not practical due to the high investment costs at the moment. Microgrids may be made more affordable if environmental costs and commercial prospects are taken into account [9]. While new energy integration can mitigate CEs to some extent, an IES will optimize and co-manage fossil fuels to protect the demand for electricity and improve the quality of PG of the new energy grid-connected system [10]. Hydrogen, as a renewable, non-polluting, and sustainable energy source, has a very high energy efficiency and does not produce carbon dioxide. Abomazid A M et al. applied the method of water electrolysis to generate renewable hydrogen to the grid energy management system in an attempt to increase the utilization of RE. By incorporating a hydrogen production system, the strategy decreased the cost of producing hydrogen and achieved optimal scheduling of photovoltaic and battery storage systems. The results demonstrated that the method reduced the system operating costs by more than 10% [11]. In an integrated power and hydrogen system, Shao C et al. suggested a PHS optimal operation method that uses hydrogen tube trailers for transportation to increase the efficiency of hydrogen supply. The power system (PS), transportation system, and variable RE constraints were also combined to propose a strategic coordinated hydrogen generation scheme. The results indicated that the method could effectively coordinate hydrogen generation, transportation, and demand [12]. With the development of the Internet of Things, its application in the smart grid is becoming more and more extensive. To further explore the intelligent authorization based on B5G technology in the smart grid, Qays Moo et al. proposed the use of digital twin technology to enhance the safety and efficiency of the system. By simulating and analyzing the operating state of the power grid, the real-time monitoring and management of power grid devices were realized. The experimental results showed that the application of this technology was helpful to improve the reliability and security of the smart grid, and at the same time provided new ideas and methods for smart authorization [13]. In summary, the application of Internet of Things technology to smart energy systems will further improve the planning effect. Although hydrogen has high cleanliness and high efficiency, it still faces many challenges in production, storage, transportation, conversion, and utilization in practical applications [14].

To address this situation, the study uses synthetic fuel technology and swarm optimization algorithms (SOAs) to design the energy allocation and CE reduction methods in the smart grid. The study aims to overcome the further enhancement of the sustainable CE reduction energy capability of the PS. The novelty of the study lies in the mathematical modeling of CE reduction and equipment operation principles. An SOA is used to further optimize the operation of the PS. In addition, a new approach to CE reduction is proposed by introducing synthetic fuel technology from both economic and environmental perspectives. It further reduces the CE from the PG process while ensuring the stability of the PS. The novelty and contribution of this study are as follows: Based on a SOA, a model for reducing CEs in a smart grid is proposed. The objective is to optimize the operation of the PS, reduce CEs, and improve energy utilization efficiency. The introduction of synthetic fuel technology provides a new idea and method for CE reduction in smart grids. By comprehensively considering economic and environmental protection factors, an innovative CE reduction method is proposed, which provides a new solution for the sustainable development of smart grids. The specific research gaps are shown in Table 1.

The research is broken up into four parts. The first part is the introduction, which provides an overview of the direction and state of the research as well as a list of issues and potential paths for further investigation. The second part is the methodology section, which realizes CE reduction and energy management in the smart grid system by building mathematical models and artificial intelligence algorithms. The third part is the experimental section, which analyzes the performance of the designed methods. The fourth part is the conclusion section, which synthesizes the research methodology and experimental results, summarizes the research content, and proposes an outlook for future research work.

Table 1. Research gap.

Research field	Existing problems
Smart grid technology application	Accuracy needs to be improved, energy management methods need to be further optimized, and cybersecurity protection technologies need to be more autonomous and self-learning.
New energy grid-connected system	The power generation quality of grid-connected new energy systems is unstable, and the optimization and collaborative management of fossil fuels needs further research.
Hydrogen energy application and energy storage technology	Hydrogen production, storage, transportation, conversion, and utilization are facing challenges.
The application of Internet of Things technology in smart grid	The application of IoT technology in smart grids still needs to improve reliability and security.

2. Methods and materials

In the context of sustainable CE reduction energy development, the study proposes an integrated energy PS to further reduce CEs from fossil fuels. Based on this, the study introduces a prediction error mechanism and carnivorous plant algorithm (CPA) to optimize the energy system operation. The CE profile of the PS is then further optimized based on the synthetic fuel model.

2.1. Operational optimization strategy for introducing prediction error mechanism and improving CPA

New energy PG is very different from traditional thermal and gas PG in that its output is highly intermittent and random. This results in uncertainty surrounding network regulation, which in turn causes the issue of growing scheduling complexity and prediction difficulty in PS [15,16]. To address this problem, the study suggests an IES operation optimization strategy (OS) based on prediction error mechanism and CPA. To ensure the environmental friendliness of the IES, the study also takes the carbon trading (CT) mechanism into account in the OS. Figure 1 depicts the IES's organizational structure.

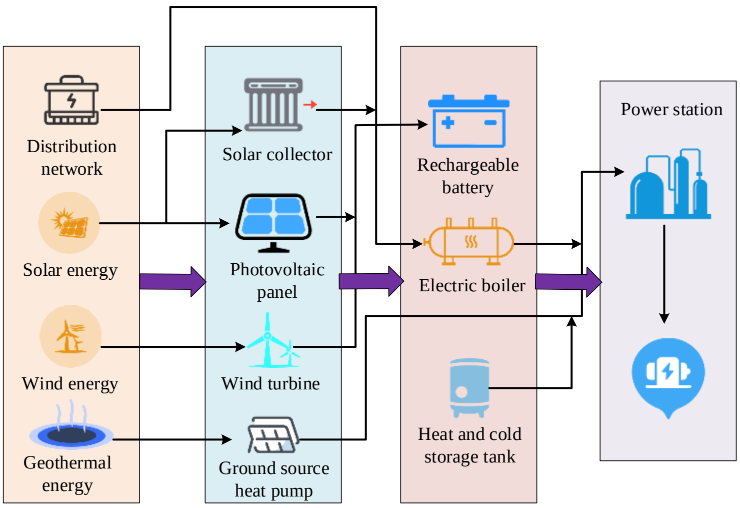

Figure 1. The proposed integrated energy system structure.

The research uses smart grid technology to track real-time PG in the IES in Figure 1 and then uses the tracking information to inform the operation optimization plan. In addition, the study takes wind, photovoltaic, and geothermal energy as non-primary power supply units based on the consideration of time-sharing tariffs, battery life, and other factors. Therefore, the PS's running costs are further decreased. The ground source heat pump (GSHP) and the electric boiler (EB) are the two components in the IES that the study suggests require regulation. Therefore, the study develops mathematical models for these two devices as well as a model for the prediction error mechanism. The energy conversion model of the EB is shown in Eq (1).

$$\begin{cases} H_{eb} = \beta P_{eb} \\ H_{eb}^{min} \le H_{eb} \le H_{eb}{}^{max} \end{cases} \tag{1}$$

In Eq (1), H_{eb} is the heat produced by the EB. P_{eb} is the input electric power of the EB. H_{eb}^{max} and H_{eb}^{min} are the maximum and minimum values (MMV) of heat produced by the EB, respectively. β is the electric heat conversion rate, which is set to 0.92 for this study. The calculation of the output electric energy and heat recovery energy of the GSHP is shown in Eq (2).

$$\begin{cases} P_{gt} = \begin{cases} \dfrac{H_g}{COP_h} Z_{gt} \\ \dfrac{L_g}{COP_1}\left(1 - Z_{gt}\right) \end{cases} \\ P_{gt}^{min} \le P_{gt} \le P_{gt}^{max} \\ H_{ge} = L_g \times \eta_h \end{cases} \tag{2}$$

In Eq (2), P_{gt} and P_{ge} are the output electrical energy and heat recovery energy of the GSHP, respectively. P_{gt}^{max} and P_{gt}^{min} are the MMV of output energy. COP_h is the heating efficiency ratio of the GSHP. Z_{gt} is the cooling and heating state of the GSHP. η_h is the heat recovery efficiency. Numerous factors influence the PG efficiency of RE including photovoltaics and wind power. Additionally, there are some mistakes in the expected output. Therefore, the study will segment the exponential distribution to represent its prediction error. The distribution probability density function is shown in Eq (3).

$$F(x) = \begin{cases} \dfrac{b_1}{b_1 + b_2} e^{\frac{x-\mu_0}{b_1}} & x < \mu_0 \\ 1 - \dfrac{b_2}{b_1 + b_2} e^{-\frac{x-\mu_0}{b_2}} & x \ge \mu_0 \end{cases} \tag{3}$$

In Eq (3), μ_0 is the standardized error value corresponding to the maximum probability density point of the probability density sequence. b_1 and b_2 are both shape parameters. $F(x)$ is the segmented exponential distribution probability. The study models the new energy-generating units based on the error values. Energy is lost when the real output power of RE exceeds the estimate. Therefore, the study introduces the deviation penalty cost, which is calculated as shown in Eq (4).

$$C_{dev} = \begin{cases} \alpha_1 \left(P_{new}^{plan} - P_{new} \right) & P_{new}^{plan} > P_{new} \\ \alpha_2 \left(P_{new} - P_{new}^{plan} \right) & P_{new}^{plan} \le P_{new} \end{cases} \tag{4}$$

In Eq (4), α_1 and α_2 are the overestimation and underestimation penalty cost coefficients, respectively, which are taken to be 0.58 in this study. P_{new}^{plan} and P_{new} are the predicted and actual outputs of RE sources, respectively. C_{dev} is the deviation penalty cost. Furthermore, to constrain the CEs, the study incorporates the CT mechanism into the objective function (OF). Equation (5) illustrates the CT cost calculation process.

$$C_{ctc} = \left(P_{buy} \times \eta_c - C_T \right) p_c^{price} \tag{5}$$

In Eq (5), C_{ctc} is the cost of CT. C_T is the free carbon credits allocated by the government. η_c is the CE coefficient of purchased electricity, which is taken as 0.285 in this study. P_{buy} is the amount of purchased electricity in the system. p_c^{price} is the price of carbon credits. The OF as well as the constraints of the optimization operation designed by the study are shown in Figure 2.

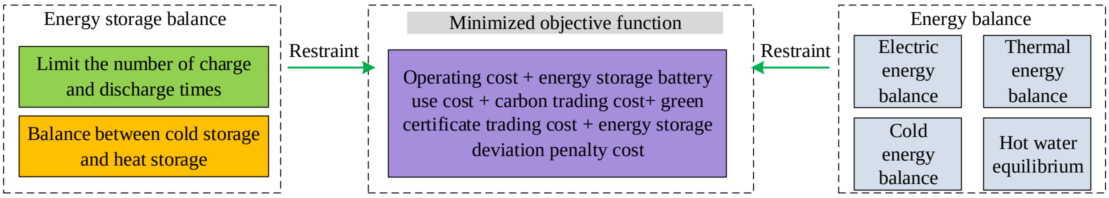

Figure 2. Objective function and constraints on the optimal operation of the research design.

In Figure 2, the study takes the energy balance constraints as well as the energy storage constraints as the constraints for the optimized operation strategy. Moreover, the minimization of operating cost by introducing the CT mechanism is taken as the optimization objective of the model [17,18]. In the weighting of operating cost, energy storage battery usage cost, and CT cost, the study adopts the combination of analytic hierarchy process (AHP) and expert scoring method. First, the relative importance of each cost item is determined through expert consultation or analysis of historical data. Each cost item is then assigned a weighting factor based on these rankings. Then, AHP is used to create a judgment matrix, and the rationality of the judgment is ensured by a consistency test. AHP decomposes complex problems into multiple component factors by pairwise comparison and ranks and quantifies the relative importance of these factors. After determining the weight coefficients of each cost item, the research multiplies these weight coefficients by the corresponding cost items to obtain the weighted cost value. The study uses the CPA to determine the optimization of the model's scheduling scheme after creating the IES's optimal scheduling model. By attracting, catching, and breaking down prey, the CPA heuristic optimization algorithm mimics the actions of carnivorous plants, based on the predatory nature of these plants. The algorithm first initializes the possible solutions to the problem to be solved and sets these solutions as the positions of the carnivorous plants and prey individuals. The CPA then enters an iterative process that simulates the three phases of the predatory behavior of carnivorous plants: luring, capturing, and digesting. In the luring phase, the algorithm guides the prey to the carnivorous plant using specific strategies. Entering the capture phase, the algorithm then focuses on the screening and retention of high-quality solutions. In the digestion phase, the algorithm further processes the captured solutions to extract useful information from them and use it to guide the subsequent search [19]. However, the initial population of CPAs is highly uncertain due to its random generation within a specific range. Therefore, to enhance the optimization and convergence of the algorithm, it needs to be improved so that it can achieve better performance in both local exploitation and global exploration. To increase the algorithm's search efficiency and prevent local optimization, the study presents two new search strategies: reverse learning and adaptive search. The computation of the reverse solution is shown in Eq (6).

$$Individual'_{i,j} = a_j + b_j - Individual_{i,j} \tag{6}$$

In Eq (6), $Individual'_{i,j}$ and $Individual_{i,j}$ are the inverse and forward solutions, respectively. a_j and b_j are the upper and lower limits of the solution range, respectively. The study is carried out to adaptively regulate the growth rate of CPA through an adaptive search strategy, which is calculated as shown in Eq (7).

$$growth = growth^{max} - \left(growth^{max} - growth^{min}\right) \times \left(N_1 / N_2\right)^2 \tag{7}$$

In Eq (7), N_1 and N_2 are the current and maximum iteration numbers, respectively. $growth^{max}$ and $growth^{min}$ are the MMV of the growth rate. $growth$ is the solution result of growth rate. The improved CPA process is shown in Figure 3.

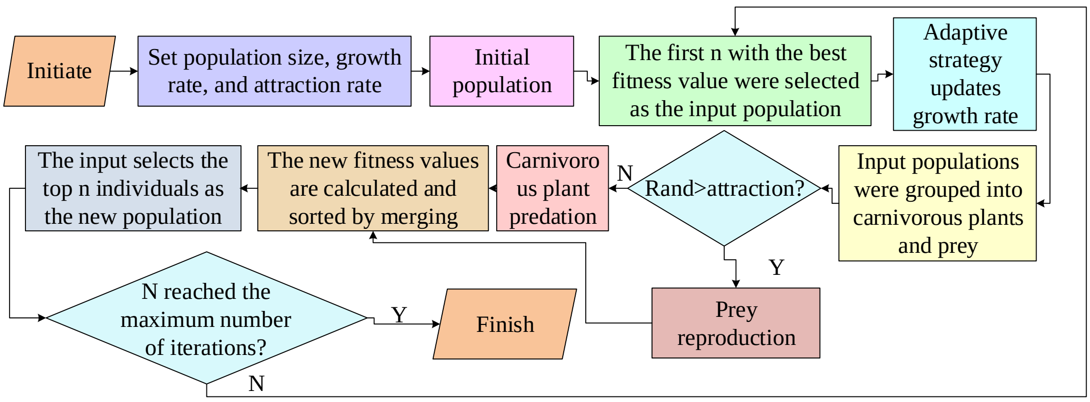

Figure 3. The improved CPA flow.

2.2. Carbon emission reduction method for power system based on synthetic fuel modeling

After developing an operational OS for the IES, the study finds that the system still produces a high amount of CEs. To further deal with this, the study considers the chemical synthesis of captured carbon dioxide and hydrogen energy. Its ability to produce zero-carbon synthetic materials further reduces the CEs in the PG system. The study is conducted by regulating the proportion of wind power and photovoltaic power used to provide the electrical load for the electrolysis of water to produce hydrogen. The oxygen produced during the electrolysis of hydrogen is then used for coal gasification, reducing the electricity consumption of the oxygen generator and further reducing electricity costs.

The obtained oxygen is applied to the combustion system, and the carbon dioxide and hydrogen energy from combustion are combined to make a synthetic fuel. The flow of the proposed CE reduction method for PS based on the synthetic fuel model is shown in Figure 4.

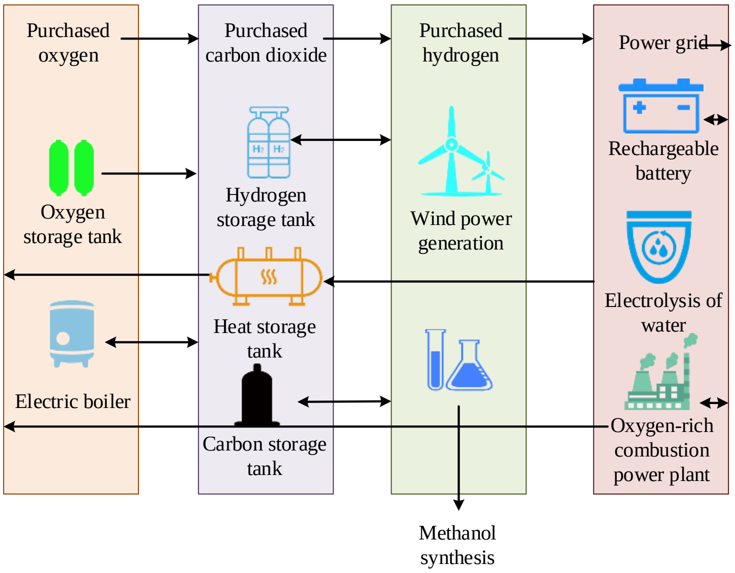

Figure 4. Carbon emission reduction method for power systems based on synthetic fuel modeling.

In Figure 4, the study modifies the conventional power to gas (P2G) process by coupling it with oxygen-enriched combustion technology and renewable fuel synthesis. The study then replaces the air by a mixture of oxygen and recycled carbon dioxide, applied in combustion chambers. In the oxygen-enriched combustion chamber, the introduction of an air-split oxygen generation unit with a carbon capture and compression purification unit is evaluated to further improve the gas flow in the chamber. Hydrogen energy from electrolytic hydrogen production is then combined with the remaining carbon dioxide to obtain a new fuel. The study uses zinc oxide-zirconium dioxide bimetallic solid solution oxide as a catalyst to prepare methanol from hydrogen. The methanol synthesis system synthesizes methanol under a catalyst by complementing the strengths and weaknesses between the new technologies, using green hydrogen, hydrogen from coal gasification, and captured CO_2. On the one hand, it can be supplied locally to chemical companies in the park. On the other hand, since methanol is a relatively stable chemical, it can utilize the current mature oil and gas storage and transportation system. Combined with the above, the study introduces a synthetic fuel model to optimize the IES. The structure of the optimized scheduling model introduced synthetic fuel model designed by the study is shown in Figure 5.

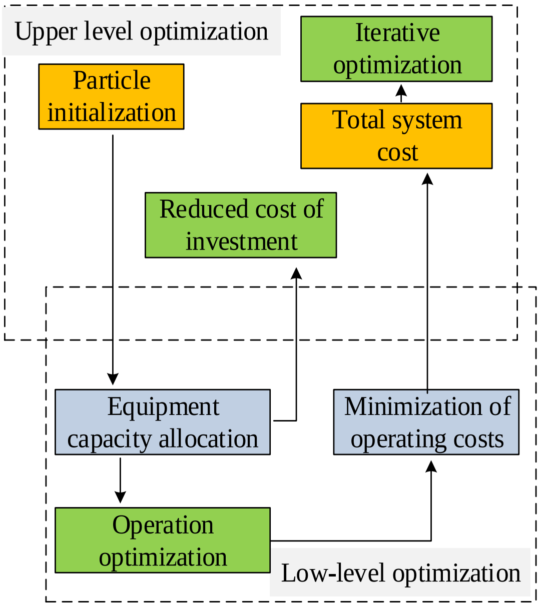

Figure 5. Optimized scheduling model structure for synthetic combustion models.

In Figure 5, the study establishes a two-layer optimization scheduling model. The upper layer optimization result of this model mainly combines the weighted annual cost of equipment initial investment discounted annual cost as well as fuel cost to obtain the annual cost index of the system, which is used as the OF. The operating cost used in the lower layer optimization structure is an operating cost function that considers the CT mechanism and the forecast error penalty cost. Based on this, the lower-tier equipment capacity is optimally allocated. CT schemes provide economic incentives for the integration and utilization of RE sources in the electricity system by establishing a price on CEs. CT schemes establish a market environment conducive to the reduction of greenhouse gas emissions. This is achieved by establishing a cap on CEs and facilitating the purchase and sale of CE rights. To reduce the cost of CEs, companies will tend to invest in cleaner and more efficient energy technologies. This economic incentive drives companies to seek alternatives to fossil fuels, thereby driving the development and deployment of RE technologies. Second, CT indirectly reduces the relative cost of renewable electricity generation by increasing the cost of fossil fuel generation. As a result, the share of RE in the electricity market will gradually increase, contributing to the transformation of the energy structure.

Nevertheless, it is possible that CT schemes may present certain challenges to the advancement of RE. For instance, if the initial distribution of carbon permits is excessively lenient or if the cost of carbon is set at an unduly low level, the motivation for CT schemes to diminish CEs will be significantly diminished. In addition, the CT market can be subject to speculation, leading to fluctuations in the price of carbon, which in turn affects the expected return on investment for RE projects. The CT mechanism is considered as an important object in the scheduling optimization process, and it is introduced into the OF of the lower tier. Figure 6 illustrates the CT principle as well as the connection between trading volume and CT pricing.

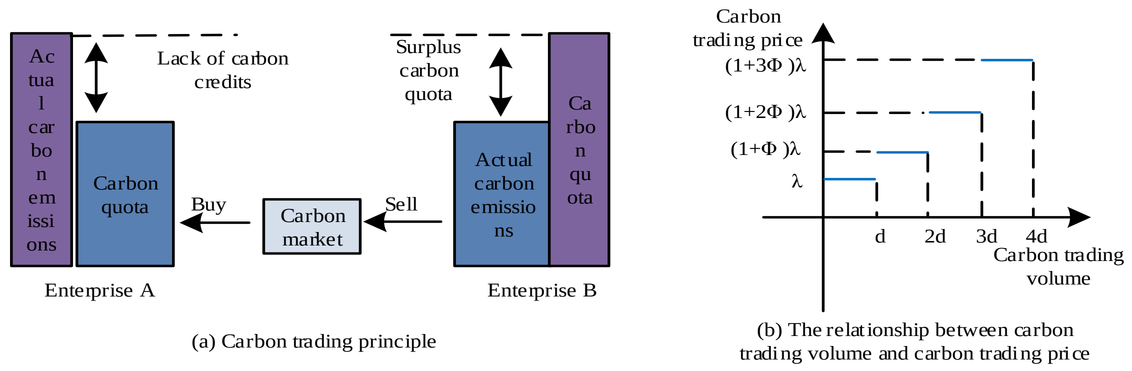

Figure 6. The principle of carbon trading and the relationship between carbon trading price and trading volume.

In Figure 6(a,b), the government usually provides an initial carbon allowance. However, if firms' actual emissions are lower than this limit, they have the option to sell the remainder to the market. If firms' actual emissions exceed the limit provided by the government, they have to buy additional carbon allowances in the CT market. The amount of CT increases as the price of CT rises. The calculation method of the transaction model in Figure 6(b) is shown in Eq (8).

$$C_{co2} = \begin{cases} \lambda(1+\Phi)(C_p - C_l), \quad C_p \le C_l \\ \lambda(C_p - C_l), C_l \le C_p \le C_l + d \\ \lambda d + (1+\Phi)\lambda(C_p - C_l - d), C_l + d \le C_p \le C_l + 2d \\ \lambda d(2+\Phi) + (1+2\sigma)\lambda(C_p - C_l - 2d), C_l + 2d \le C_p \le C_l + 3d \\ \lambda d(3+\Phi) + (1+3\sigma)\lambda(C_p - C_l - 3d), C_l + 3d \le C_p \le C_l + 4d \\ \lambda d(4+\Phi) + (1+4\sigma)\lambda(C_p - C_l - 4d), C_l + 4d \le C_p \end{cases} \tag{8}$$

In Eq (8), Φ is the increase coefficient of carbon price in each ladder. λ is the carbon price in the CT market. d is the length of each CE interval. C_p and C_l are the total CE and system CE quota respectively. C_{CO2} is the CT cost. To address this, the study constructs a stepped CT model, which categorizes the difference between CEs and carbon allowances into a number of levels. This method can regulate the CT market. To summarize the above, the study introduces the prediction error mechanism and CPA to propose an integrated energy PG system to further reduce the CE of fossil fuels. Subsequently, the synthetic fuel model is utilized to further enhance the PS's CE profile. Finally, the study establishes a stepped CT model based on CT characteristics to further regulate the CT market.

The overall process of researching and proposing the method is shown in Figure 7.

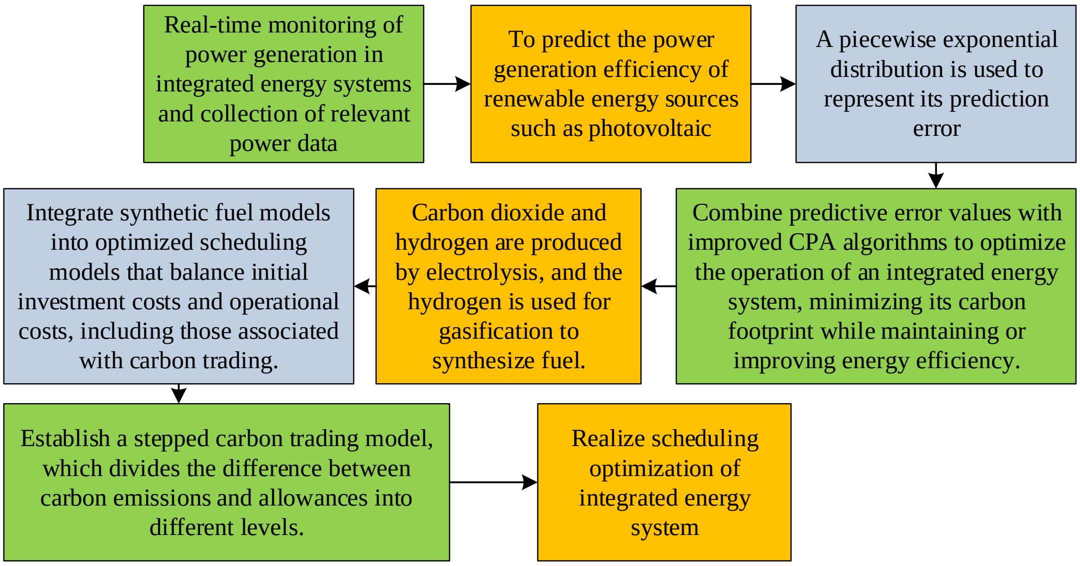

Figure 7. The overall process of the proposed method.

As shown in Figure 7, the research first predicts the PG efficiency of RE sources such as photovoltaic and will segment the exponential distribution to represent its prediction error. Based on this, an improved CPA algorithm is used to optimize the operation of the IES, which could minimize the carbon footprint while maintaining or improving energy efficiency. The synthetic material is then synthesized from the captured carbon dioxide and hydrogen produced by electrolysis of water using RE sources such as wind and solar power. The oxygen produced in the electrolysis process is employed in the gasification process, which not only diminishes the energy consumption associated with oxygen production but also contributes to the comprehensive carbon reduction strategy, integrating synthetic fuel models into optimized planning models that balance initial investment costs and operating costs, including those associated with CT. The final stage of the approach is to create a tiered CT model that divides the difference between CEs and allowances into different tiers. This model aims to provide a structured approach to CT, making the market more controlled and predictable. In conclusion, the study proposes a comprehensive approach to reduce CEs from PSs by combining predictive error mechanisms, optimization algorithms, synthetic fuel production, and structured CT models.

3. Results

To examine the application value of the proposed method in CE reduction and optimal scheduling of PS operation, the study designs a series of experiments to analyze its performance.

3.1. Prediction error mechanism and CPA application rationalization analysis

The study uses simulation software to model the experiments in order to verify the reasonableness and superiority of the method proposed. This study introduces the prediction error mechanism and CPA in the optimal scheduling of the IES. To test the reasonableness of the method in the optimal scheduling strategy, the study compares the changes in the prediction accuracy of each unit in the system before and after the introduction of the prediction error mechanism. The details are shown in Figure 8.

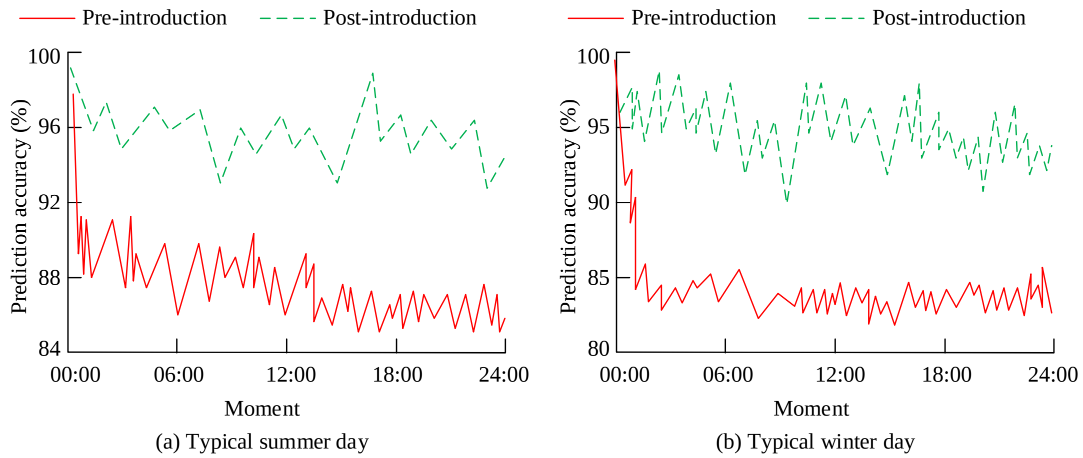

Figure 8. The change of prediction accuracy of each unit in the system before and after the introduction of prediction error mechanism.

In Figure 8(a,b), after the introduction of the prediction error mechanism, the prediction accuracy of the units in the system is significantly improved for both typical winter and summer days. The prediction accuracy of each unit is improved by about 10% on average for typical winter days, while it is improved by about 8% on average for typical summer days. This suggests that the introduction of a forecast error mechanism can more accurately predict the load demand of the system, thereby reducing energy waste and CEs due to inaccurate forecasts.

Further, the study utilizes CPA for optimization of the running scheme and introduces the inverse solving strategy and adaptive search strategy to improve the CPA. To check the improvement effect of the algorithm, the study compares the fitness value of the algorithm before and after the improvement as well as the training of the solution accuracy. Figure 9 presents the findings.

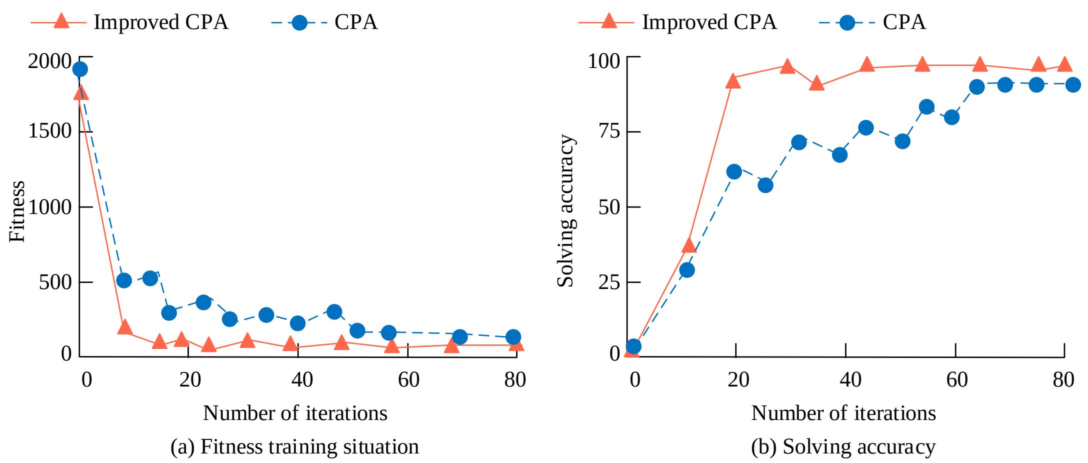

Figure 9. Fitness value and solving accuracy of CPA before and after improvement.

In Figure 9(a), before the improvement, the fitness value of CPA fluctuates greatly and converges slowly, which means that the algorithm is less efficient in the process of finding the optimal solution. After the improvement, the fitness value of CPA becomes significantly more stable, and the convergence speed is significantly improved, which starts to converge after only 18 iterations. In Figure 9(b), the solution accuracy of the improved algorithm rises rapidly at the beginning of training and remains at a high level.

To test the reasonableness of the study in applying the CT cost as well as the deviation penalty cost to the OF in the model, the study compares the CE situation and energy consumption of the scheduling only applying the deviation penalty cost (Scenario 1) and considering the CE cost (Scenario 2), as well as applying the two at the same time (Scenario 3). The results are shown in Figure 10.

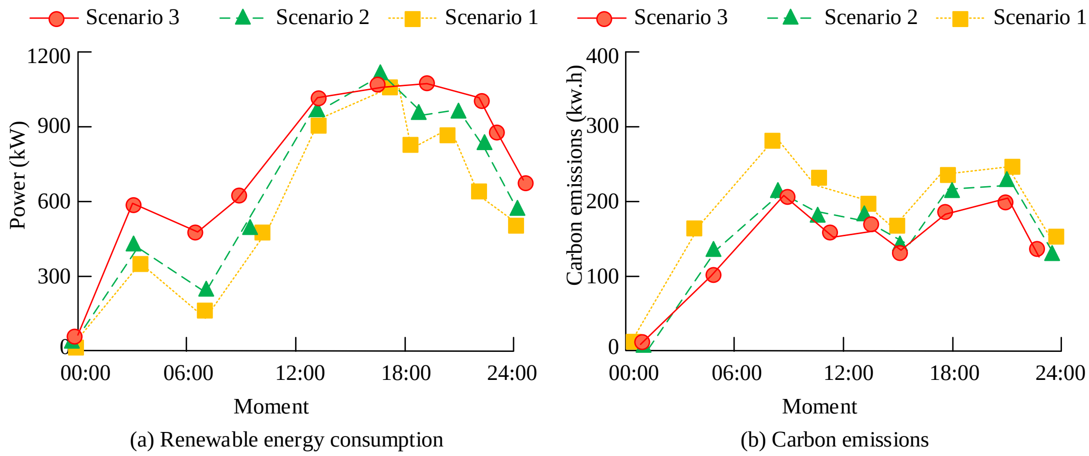

Figure 10. Effect analysis of carbon trading cost and deviation penalty cost in the objective function.

In Figure 10(a), Scenario 3 also shows significant superiority in terms of energy consumption. Since both CT cost and deviation penalty cost are taken into account, the system is able to allocate various energy resources more reasonably, ensuring efficient utilization and maximizing energy consumption. In Figure 10(b), among the three scenarios, the CE content of Scenario 3 is significantly lower compared with Scenario 2 and Scenario 1, and the difference between Scenario 3 and Scenario 2 is relatively small. The total CE of Scenario 3 is 455 kWh.

3.2. Improved training of optimized scheduling models for integrated energy systems

In order to further reduce CEs in the IES and to ensure lower operating costs, a system scheduling balance is achieved. The study introduces a synthetic fuel model to optimize the scheduling of the PS. To test the performance of the improved CE reduction and scheduling optimization model, the study takes a typical industrial park in A as an example and inputs its parameters into the simulation model for simulation analysis. To examine the reasonableness of introducing the synthetic fuel model into the improved model, the study compares the capacity optimization results of the model before and after the improvement. The details are shown in Figure 11.

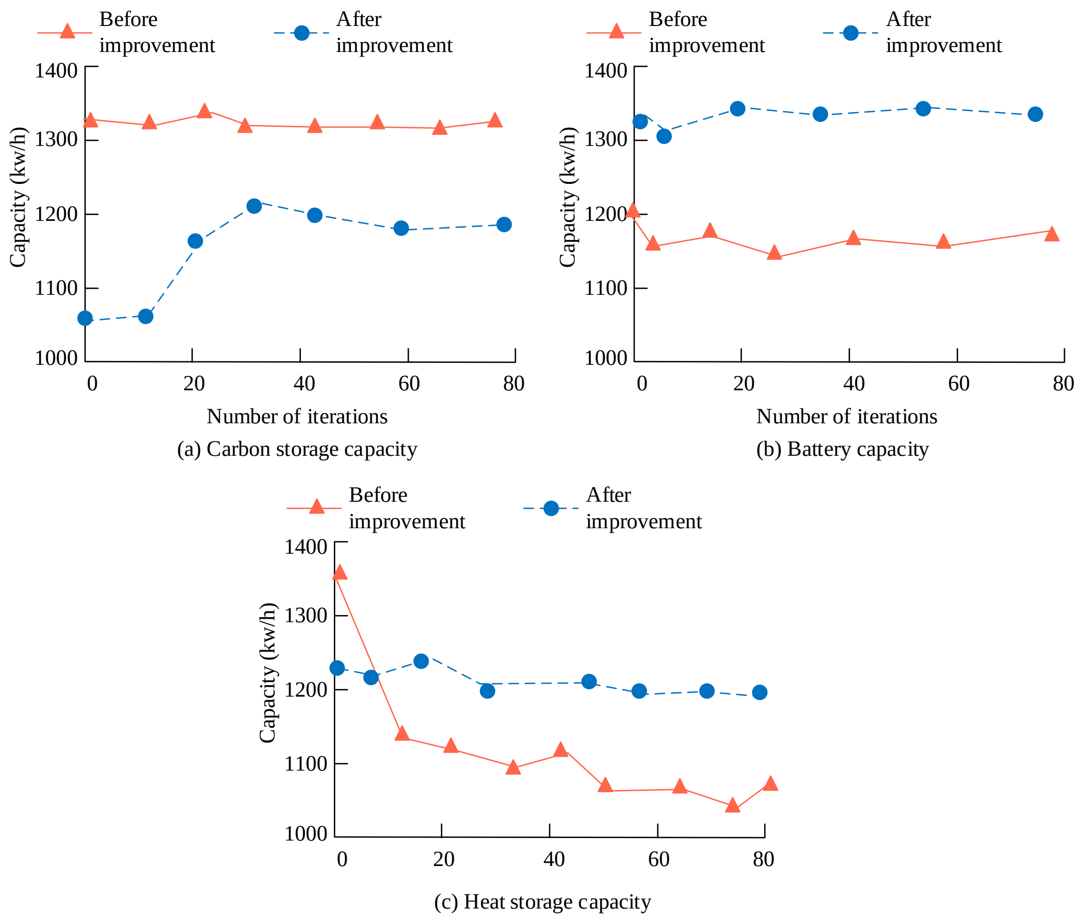

Figure 11. The capacity optimization results are compared before and after the improvement.

In Figure 11(a), the pre-improved model has a higher carbon storage tank capacity because it is not able to consume carbon dioxide in the system since it does not introduce the synthetic fuel model. In Figure 11(b,c), the improved model fully utilizes the carbon dioxide and oxygen produced in the system after introducing the synthetic fuel model. This produces more electrical and thermal energy, so the electrical and thermal capacity is higher. This indicates that the improved optimized dispatch model of the IES achieves effective utilization of carbon dioxide and oxygen in the system by introducing the synthetic fuel model. This significantly improves the electrical and thermal energy production capacity of the system. The results of the operation in the system before and after the introduction of the synthetic fuel model improvement are compared in Table 2.

Table 2. Comparison of operation results of the model before and after improvement.

Project	Total cost (yuan)	Wind power consumption (kWh)	Photoelectric consumption (kWh)	Power to gas input power (kWh)	Carbon emission (kg)
Before improvement	3065.4	15947.2	5798.2	6853.4	2058.0
After improvement	2517.5	16898.4	7377.3	5188.4	60.8
Decline range	−547.9	+951.2	+1579.1	−1665.0	1997.2

In Table 2, the total cost of the system decreases significantly by 17.8% after the introduction of the synthetic fuel model. Meanwhile, wind and photovoltaic power consumption increased by 951.2 kWh and 1579.1 kWh, respectively, showing the higher acceptance of RE in the system. The power to natural gas input decreased by 1665.0 kWh. This may be attributed to the fact that the production process of synthetic fuels directly utilizes carbon dioxide and oxygen in the system, reducing the dependence on the power of the natural gas conversion process. The CE of the system plummeted from 2058.0 to 60.8 kg, a reduction of 97.0%. This result demonstrates the great potential of the synthetic fuel model in reducing CEs.

To further examine the performance of the PS optimization model (Model 1) proposed in the study, the study compares it with several more popular models. The comparison model includes the model in [20] (Model 2), the model in [21] (Model 3), the model in [22] (model 4), the model in [23] (model 5), and the model in [24] (model 6). The comparison metrics include CE, total operating cost, prediction accuracy, and energy utilization efficiency. Table 3 displays the outcomes of the comparison.

Table 3. Performance comparison between the proposed model and existing models.

Model	Carbon emission (kg)	Total operating cost (yuan)	Prediction accuracy (%)	Energy utilization efficiency (%)
Model 1	60.8	2517.5	96.5	90.2
Model 2	1200.0	2800.5	92.0	85.0
Model 3	850.4	2650.2	93.8	87.4
Model 4	900.5	2699.9	93.5	86.0
Model 5	610.7	2600.3	93.9	88.0
Model 6	928.5	2712.6	92.1	85.4

As shown in Table 3, Model 1 performs particularly well in terms of CE, which is only 60.8 kg, which is about 53.3%, 92.8%, 93.2%, 54.6%, and 93.5% lower than the other five models, respectively. This indicates that Model 1 has significant advantages in reducing CE during PS operation. In terms of total operating cost, Model 1 also performs well, with a cost of 2,517.5 yuan, which is about 10.1%, 5.4%, 6.8%, 3.6%, and 7.6% lower than Model 2, Model 3, Model 4, Model 5, and Model 6, respectively. This shows that Model 1 also has certain advantages in terms of economy. In terms of prediction accuracy, Model 1 is 96.5%, higher than Model 2, Model 3, Model 4, and Model 6, and only slightly lower than Model 5, at 96.7%. This indicates that Model 1 has a high accuracy in predicting future electricity demand and supply. Finally, in terms of energy use efficiency, Model 1 has an efficiency of 90.2%, which is higher than the other five models by 5.2%, 2.8%, 4.2%, 2.2%, and 4.8%, respectively. This shows that Model 1 also has obvious advantages in improving energy efficiency. In summary, Model 1 is superior to the other comparison models in terms of CEs, total cost of ownership, prediction accuracy, and energy utilization efficiency, demonstrating its superior performance in PS optimization.

To further highlight the advantages of the proposed method (Method 1), the method in reference [25] (Method 2) and the method in reference [26] are added. The comparison metrics include calculation speed, system stability, user satisfaction, and scalability. The results of the comparison are shown in Table 4.

Table 4. Performance comparison between the proposed method and existing methods.

Method	Calculation speed (seconds)	System stability (%)	User satisfaction (%)	Scalability
Method 1	12.5	98.7	95.6	Excellent
Method 2	25.3	95.4	90.2	Good
Method 3	18.6	97.1	93.4	Good

As shown in Table 4, in terms of calculation speed, Method 1 has the best performance, and its calculation time is only 12.5 s, which is 50.6% and 32.8% higher than Method 2 and Method 3, respectively. This shows that Method 1 is more efficient when dealing with large amounts of data. In terms of system stability, Method 1 also performs well, with a stability of 98.7%, which is higher than the 95.4% and 97.1% of Methods 2 and 3, respectively. This shows that Method 1 can maintain high stability over a long period of time. In terms of user satisfaction, Method 1 also achieved a high rating, with a satisfaction rate of 95.6%, higher than Method 2 and Method 3 (90.2% and 93.4%). This indicates that users are more satisfied with the experience of using Method 1. Finally, in terms of scalability, Method 1 is rated “excellent”, better than the “good” ratings for both Methods 2 and 3. This indicates that Method 1 is more adaptable to system expansion and upgrades.

4. Discussion and conclusions

Aiming at the poor energy utilization and high CE in the current PS, the study proposed a PS dispatch optimization model based on the prediction error mechanism and CPA and synthetic fuel technology. The model aimed to improve energy utilization in the PS, maintain the stability of the PS, and reduce the CE. The experimental results indicated that with the introduction of the prediction error mechanism, the prediction accuracy of each unit in the system was significantly improved for both typical winter and summer days. The introduction of the synthetic fuel model in the improved model fully utilized the carbon dioxide and oxygen produced in the system. It produced more electrical and thermal energy, resulting in higher electrical and thermal capacity. The improved IES optimal dispatch model achieved effective utilization of carbon dioxide and oxygen in the system by introducing the synthetic fuel model. With the introduction of the synthetic fuel model, the total cost of the system decreased significantly by 17.8%. Meanwhile, the consumption of wind power and photovoltaic power increased by 951.2 and 1579.1 kWh, respectively. In addition, the CE of the system decreased 97.0%, from 2058.0 to 60.8 kg. Compared with other existing models, the CE, total operating cost, prediction accuracy, and energy utilization efficiency of Model 1 were 60.8 kg, 2517.5 yuan, 96.5%, and 90.2%, respectively. The calculation time of Method 1 was only 12.5 s, and the system stability reached 98.7%. The integration of PS with other energy systems such as heat and cold energy could achieve comprehensive utilization and optimal allocation of energy. To further enhance the performance and sustainability of PSs, future research could investigate the development of a multi-energy system integration framework to optimize the efficiency and sustainability of the overall energy system.

Use of AI tools declaration

In the preparation of this manuscript, no artificial intelligence (AI) tools were used for any aspect of the research.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

Author contributions

Kangli Xiang: Study design, data collection, statistical analysis, visualization, writing the original draft; Keren Chen: Study design, data collection, statistical analysis, funding, writing, and revision of the original draft; Simin Chen: Visualization, writing the article; Wanqing Chen: Data collection, statistical analysis; Jinyu Chen: Supervise and revise the manuscript.

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