

Article

Lifecycle Carbon Reduction Potential and Economic Valuation of Pumped Storage in a Multi-Energy Complementary System

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Abstract

Under international climate governance frameworks, including the Paris Agreement, the global decarbonization process has accelerated, imposing more stringent requirements on power system flexibility and low-carbon operation. Against this backdrop, pumped storage power stations, characterized by high flexibility and rapid response capability, serve as large-scale energy storage solutions that can replace thermal power for peak shaving, thereby enhancing renewable energy integration and delivering significant carbon reduction benefits in multi-energy complementary systems. A carbon reduction calculation model is developed within the framework of the Chinese Certified Emission Reduction (CCER) trading mechanism to quantify the annual contributions of pumped storage to carbon reduction. Using a Fractional-Order Gray Model (FGM) optimized via Particle Swarm Optimization (PSO), future carbon market prices are forecasted, facilitating a robust economic evaluation. The findings reveal that, over its lifecycle, pumped storage could achieve a total carbon reduction of approximately 23.27 million tons of CO₂, yielding approximately 7.981 billion CNY in carbon reduction value, with an initial 7-year CCER inclusion period contributing 254.0787 million CNY in carbon credits. It provides critical economic and policy insights, supporting the design of advanced power systems that position pumped storage as a central regulatory asset in carbon reduction strategies.

Keywords: pumped storage; carbon reduction; value assessment; CCER trading mechanism; fractional-order gray



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1. Introduction

Driven by global decarbonization efforts and the shift toward a low-carbon power sector, a multi-energy complementary system integrating wind, solar, pumped storage, and thermal power can effectively enhance overall system flexibility and renewable energy integration, while continuously reducing the carbon intensity of the power industry [1]. As a large-capacity low-carbon energy storage source, pumped storage can enhance the system's ability to integrate wind and solar power and improve the flexibility of power sources [2,3]. Within China's Emissions Trading System (ETS), two primary mechanisms exist: Cap-and-Trade (CaT) and the CCER [4]. The CCER scheme obtains quota income by promoting emission reduction projects to reduce carbon emissions effectively [5,6]. The carbon reduction research in the power industry can be divided into two main aspects: clean energy generation [7] and thermal power [8] emission reduction.

Research on carbon reduction in energy storage systems is divided into three main categories: integrated energy systems [9], new energy storage systems [10], and pumped storage [11]. For integrated energy systems, Liu et al. [12] developed a low-carbon dispatch model for multi-district integrated energy systems by jointly considering carbon emission trading and green certificate trading. Zhou et al. [13] proposed an optimal scheduling model for integrated energy systems considering combined weights between economic operation and carbon emission reduction. These studies indicate that coordinated energy dispatch and market-based mechanisms can effectively reduce system carbon emissions.

Energy storage has also been widely investigated as an important flexibility resource for carbon reduction. Mago and Luck [14] evaluated the potential reduction in CO₂ emissions by integrating electric energy storage with a power generation unit/organic Rankine cycle system. Hu et al. [15] proposed a bi-level low-carbon planning method for shared energy storage stations serving multiple integrated energy systems, showing that shared storage can improve both economic and low-carbon performance. For pumped storage, Li et al. [16] assessed its potential in reducing renewable energy curtailment and CO₂ emissions in Northwest China through an optimal dispatch model considering regional hydrological and operational characteristics. In addition, Shang et al. [17] proposed a fuzzy matter-element-based method for quantifying energy saving and emission reduction in renewable energy systems, while Wei et al. [6] calculated the carbon reduction effects of China's power industry at the provincial level. Wang et al. [18] and Gul Hameed et al. [19] further extended carbon reduction assessment to CCUS-EOR projects and integrated energy planning models, respectively.

As a crucial component of China's carbon market, the Chinese Certified Emission Reduction scheme provides a market-based mechanism for promoting emission reduction in the power sector [4]. Li et al. [20] investigated how the Chinese Certified Emission Reduction scheme can reduce the compliance cost of the national carbon trading system. He et al. [21] examined the promotion mechanism of the CCER scheme using a tripartite evolutionary game model, revealing the interactions among government regulation, enterprise participation, and project declaration. Existing CCER-related studies have mainly focused on renewable energy projects and general energy storage applications [22,23]. In parallel, Zhao et al. [24] analyzed China's provincial carbon emission transfer structure under the dual constraints of economic development and emission reduction targets, providing policy-oriented insights into regional carbon reduction coordination. In addition to CCER trading, green certificate mechanisms and carbon-electricity coupling have also been studied as market-based instruments for renewable energy valuation [25]. Xu and Xu [26] explored the optimal pricing decision of tradable green certificates for renewable power under carbon-electricity coupling. However, studies on CCER-based carbon emission reduction accounting and economic valuation for pumped storage remain limited [27]. Xu et al. [28] explored the carbon reduction mechanisms of pumped storage during generation and storage processes and established a CCER-based carbon reduction model.

Carbon trading price fluctuations are another key factor affecting the economic evaluation of carbon reduction benefits [29]. Existing studies have used deep learning algorithms to predict carbon prices over short- and long-term horizons [30,31]. However, the CCER market has a relatively short implementation history, and available historical CCER trading price data are limited. Therefore, gray models, which are suitable for small-sample and uncertain systems, have been applied in carbon emission and energy forecasting studies [32,33]. With the increasing demand for forecasting accuracy, improved gray models have been further developed [34]. Wang and Li [35] proposed a seasonal gray prediction model with fractional-order accumulation for energy forecasting. Ye et al. [36] developed an enhanced multivariable dynamic time-delay discrete gray forecasting model for predicting

China's carbon emissions. Gu et al. [37] applied a fractional gray model to construct a carbon emission prediction model.

Although previous studies have examined low-carbon dispatch, energy storage emission reduction, CCER mechanisms, and gray forecasting methods, these topics are mostly investigated independently. The role of pumped storage hydropower in achieving carbon emission reduction under the CCER mechanism has not been sufficiently quantified, especially in multi-energy complementary systems involving wind, solar, thermal power, and pumped storage. Moreover, few studies have linked the operational contribution of pumped storage to carbon emission reduction (CER) accounting and CCER-based lifecycle economic valuation. To fill this gap, this study develops an integrated assessment framework to evaluate the carbon reduction potential and CCER-based economic benefits of pumped storage in a multi-energy complementary system.

This paper investigates the carbon reduction potential and economic benefits of pumped storage in a multi-energy complementary system, integrating wind, solar, pumped storage, and thermal power. A system CER accounting model is developed to quantify carbon reductions under both baseline and actual scenarios. A low-carbon optimized operation model is constructed to simulate the scheduling of all power sources, while a Fractional-Order Gray Model (FGM) optimized via Particle Swarm Optimization (PSO) is employed to forecast future CCER carbon trading prices. Using these models, the study evaluates the lifecycle carbon emission reductions achieved by pumped storage, the associated economic value through the CCER market, and the contribution of pumped storage to peak shaving, renewable energy integration, and system flexibility. The primary contributions of this study are summarized as follows:

- (1) Based on the CCER mechanism, this study constructs a carbon reduction calculation model.
- (2) A carbon trading price prediction model is built using FGM, with the optimal order determined by the PSO optimization algorithm.
- (3) Construct a low-carbon optimized operation model to calculate the future annual carbon emission reductions.
- (4) Future CCER market carbon emission values are computed to assess substantial emission reduction benefits achievable by pumped storage in the energy base.

The remainder of this article is organized as follows: Section 2 presents the mechanisms and optimization methods underlying the proposed models. Section 3 details the development of the CER calculation model and the carbon trading price prediction model for low-carbon optimized operation. Section 4 presents the calculation results of CERs and evaluates the corresponding economic benefits. The overall research framework of this study, illustrating the methodology for evaluating the carbon reduction benefits of pumped storage, is shown in Figure 1.

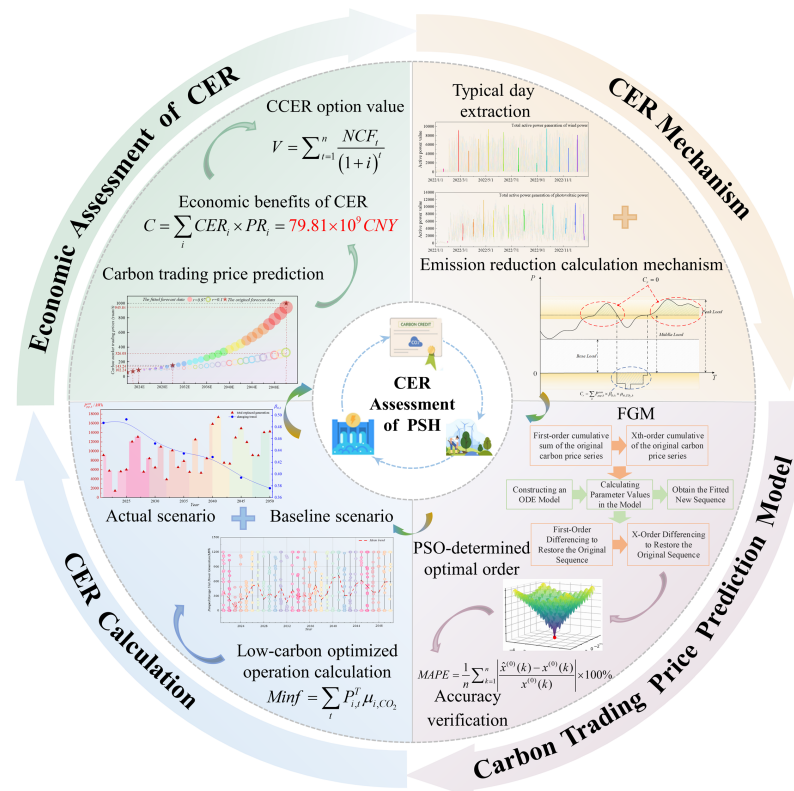


Figure 1. Research framework on the carbon reduction benefits of pumped storage.

2. Methodology

2.1. The 8760 h Data Feature Extraction

The traditional K-means algorithm heavily relies on the initial selection of cluster centers. However, based on the annual output characteristics of wind and solar, directly selecting cluster centers introduces significant uncertainty. This paper proposes an improved K-means algorithm to more effectively classify historical output data of wind and solar output. The steps are illustrated in the following Figure 2.

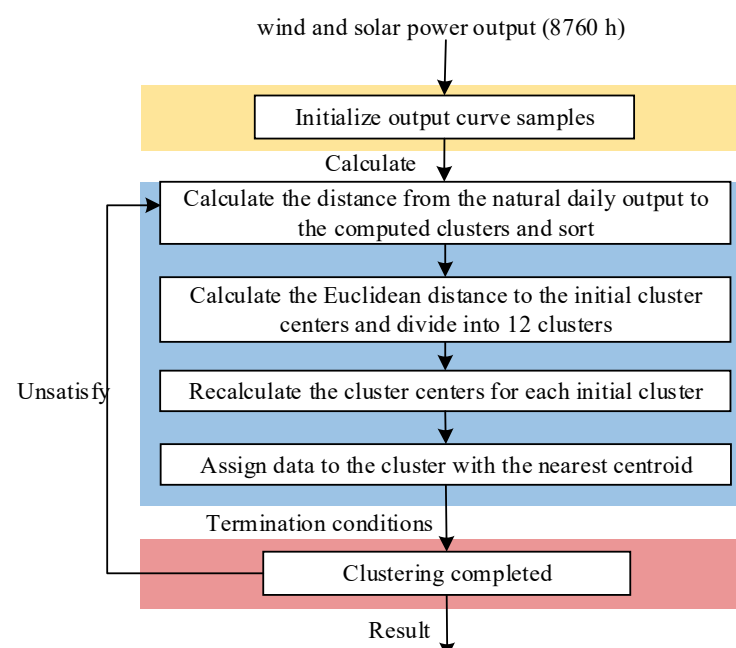


Figure 2. Flowchart for a typical day selection based on the improved K-means algorithm.

Based on dispatch data, input the total active power generation values of wind and photovoltaic energy in a certain province of western China in 2022, and perform internal clustering calculations. Finally, obtain 12 typical output scenarios for wind and solar power generation characteristics for each month, as illustrated in Figure 3 below.

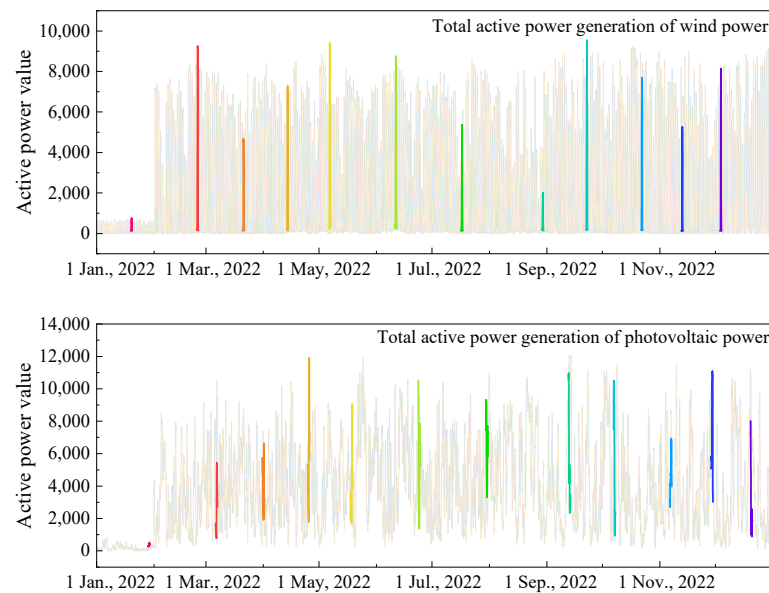


Figure 3. Typical day of wind and solar power generation for the year 2022 in a province in western China.

In Figure 3, the typical scenarios of wind and solar power generation exhibit complementary characteristics, with combined renewable energy output maintaining relatively high levels during the spring and autumn.

2.2. CCER Mechanism

China's carbon ETS is primarily divided into two main segments: the CaT mechanisms and the CCER [38]. CCER, derived from the International Clean Development Mechanism (CDM), is a unique Chinese-certified carbon emission reduction program. It is expected to have a profound impact on the decarbonization of China's economy [4,27]. The CCER, aimed at ensuring the economic viability of clean energy projects and energy-saving measures by issuing tradable emission allowances, allows participants to earn revenue by selling these allowances.

Nowadays, the CCER methodology is primarily applied to renewable energy power generation [22]. The mechanism for calculating CERs is subtracting the baseline scenario carbon emissions from the actual project carbon emissions, as shown in Equation (1):

$$\text{CER} = C_a - C_b \quad (1)$$

where CER represents system CERs based on CCER methodology. C_a and C_b represent the actual carbon emissions of the project and the carbon emissions under the baseline scenario, respectively.

The baseline carbon emissions of the project are calculated using the conventional method, as shown in the following Equation:

$$C_b = P_{b,y} \times \mu_{\text{CO}_2,y} \quad (2)$$

where $P_{b,y}$ represents the electricity generation of the power source in year y under the baseline scenario. $\mu_{\text{CO}_2,y}$ represents the regional carbon emission factor per unit of electricity in year y .

2.3. Carbon Trading Price Prediction Mechanism

2.3.1. Fractional-Order Gray Model

The first-order univariate GM (1,1) is suitable for data with limited samples and insufficient information. Based on the GM theory, the FGM introduces fractional-order accumulation to optimize its traditional modeling mechanism and enhance the effectiveness of the predictive model. Specifically, it transforms the traditional first-order accumulation into fractional-order accumulation, reducing the randomness in predicting the original data series and minimizing prediction range errors. The modeling process is illustrated in Figure 4.

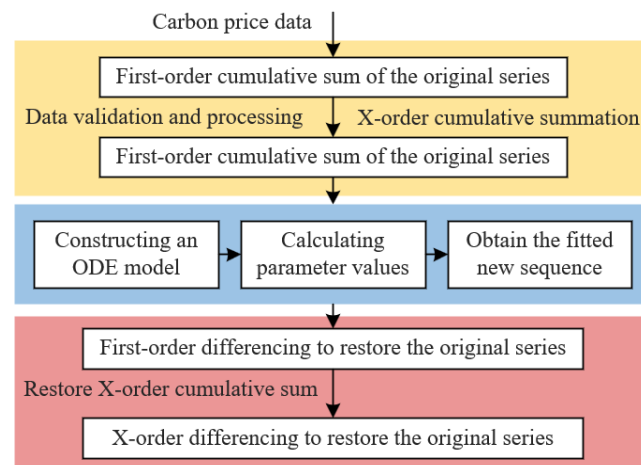


Figure 4. The calculation process of FGM.

2.3.2. Optimization of the Fractional Order

In the FGM, the determination of the optimal fractional order is formulated as a parameter optimization problem. Specifically, the fractional order r is treated as the decision variable, and the objective is to minimize the prediction error between the estimated values and the historical data. The optimization problem can be expressed as follows:

$$\min_r \text{MAPE}(r) \quad (3)$$

$$s.t. \ r \in [r_{\min}, r_{\max}] \quad (4)$$

where the feasible range of the fractional order is determined based on empirical gray system theory and numerical stability considerations.

To solve this optimization problem, the Particle Swarm Optimization (PSO) algorithm is employed. The PSO algorithm performs a population-based global search by iteratively updating candidate solutions, enabling efficient exploration of the solution space and avoiding local optima. Through multiple iterations, the optimal fractional order is obtained.

The prediction accuracy is often verified by using the Mean Absolute Percentage Error (MAPE), with its calculation formula and accuracy standards shown as follows:

$$\text{MAPE} = \frac{1}{n} \sum_{k=1}^n \left| \frac{\hat{x}^{(0)}(k) - x^{(0)}(k)}{x^{(0)}(k)} \right| \times 100\% \quad (5)$$

To further assess the quality of the fitting results, the corresponding evaluation criteria based on MAPE values are summarized in Table 1, which categorizes the prediction accuracy into different levels.

Table 1. Evaluation criteria for fitting results.

MAPE/%	<10	10~20	20~50	>50
Forecasting accuracy	Excellent	Good	Fair	Poor

In addition, the Standard Deviation of Errors (SDEs) is used to assess the dispersion of prediction errors, which is defined as follows:

$$SDE = \sqrt{MSE} = \sqrt{\frac{1}{n} \sum_{k=1}^n (x^{(0)}(k) - \hat{x}^{(0)}(k))^2} \quad (6)$$

where $x^{(0)}(k)$ is the known original data; $\hat{x}^{(0)}(k)$ is the predicted data.

3. Modeling

3.1. Low-Carbon Optimization Operation Model

3.1.1. Objective Function

The objective function is to minimize the total carbon emissions of the system:

$$\text{Min } f = \sum_i P_{i,t}^T \mu_{i,CO_2} \quad (7)$$

where $P_{i,t}^T$ represents the output of the i -th power source at time t , kWh. μ_{i,CO_2} represents the CEF of the i -th power source system, kgCO₂/kWh.

3.1.2. Constraints

(1) Power balance constraint

$$\sum_{t=1}^T P_{T,t} + P_{WT,t} + P_{PV,t} + P_{PS,t} = P_{D,t} \quad (8)$$

where $P_{T,t}$, $P_{D,t}$, $P_{PS,t}$ represent the total output of thermal power units at time t , system load value at time t , and pumped storage power generation at time t , MWh.

(2) Thermal power unit constraints

$$P_{T,t,i,min} \leq P_{T,t,i} \leq P_{T,t,i,max} \quad (9)$$

$$-v_{t,i}^{down} \Delta t \leq P_{T,t,i} - P_{T,t-1,i} \leq v_{t,i}^{up} \Delta t \quad (10)$$

where $P_{T,t,i,min}$ and $P_{T,t,i,max}$ respectively represent the lower and upper bounds of the output of the i -th thermal power unit at time t , MWh; $v_{t,i}^{down}$ and $v_{t,i}^{up}$ respectively represent the unload and ramp rate limits of the i -th thermal power unit during time period $t \sim (t-1)$, with a value of 2% per minute.

(3) Wind power generation constraint

$$0 \leq P_{WT,t,i} \leq P_{WT,t,i,max} \quad (11)$$

where $P_{WT,t,i}$ represents the output of the i -th wind turbine at time t , MWh. $P_{WT,t,i,max}$ represents the output limit of the i -th wind turbine at time t , MWh.

(4) Photovoltaic generation constraint

$$0 \leq P_{PV,t} \leq P_{PV,t,max} \quad (12)$$

where $P_{PV,t}$ represents the output of the photovoltaic power station at time t , MWh. $P_{PV,t,max}$ represents the output limit of the photovoltaic power station at time t , MWh.

(5) Pumped storage power station constraints

Pumped storage power station output:

$$0 \leq |P_{PS,t,i}| \leq P_{PS,t,i,max} \quad (13)$$

where $P_{PS,t,i}$ represents the actual output power of the i -th pumped storage unit at time t , MWh. $P_{PS,t,i,max}$ represents the upper limit of power generation and pumping power of the i -th pumped storage unit at time t , MWh.

Operating condition constraint, power generation constraint:

$$P_{gemin} \leq P_{ge,t,i} \leq \text{Min} \left(P_{gemax}, \frac{E_t}{t} \eta_{ge} \right) \quad (14)$$

$$E_{i+1} = E_i + t \left(\eta_{ps} P_{PS,t,i} - \frac{P_{\rho,i,i}}{\eta_{\rho}} \right) \quad (15)$$

$$0 \leq E_t \leq E_{max} \quad (16)$$

Power constraint during energy storage:

$$P_{psmin} \leq P_{ps,t,i} \leq P_{psmax} \quad (17)$$

The pumped storage unit has three operating modes: pumping, generating, and standby. These three modes cannot occur simultaneously:

$$\mu_{ps,t,i} \times \mu_{ge,t,i} \times \mu_{st,t,i} = \emptyset \quad (18)$$

where E_t represents the energy stored in the upper reservoir of the pumped storage power station at time t . η_{ps} and η_{ge} respectively represent the efficiency of energy storage during pumping and power generation during water discharge of the pumped storage power station. $\mu_{ps,t,i}$, $\mu_{ge,t,i}$, $\mu_{st,t,i}$ are all binary variables, where 0 indicates the state is not active and 1 indicates the pumped storage unit is operating in that state. Subscripts ps , ge , st represent pumping, generating, and standby states respectively.

The daily pumping and generation balance and reservoir capacity constraints are established according to the standard operational principles of pumped storage hydropower, including the energy conversion relationship between pumping and generation and the allowable storage range of the upper and lower reservoirs [39].

Daily pumping and generation balance:

$$\frac{\sum_{t=1}^T P_{ge,t,i} \eta_{ge}}{\eta_{ps}} = \sum_{t=1}^T P_{ps,t,i} \quad (19)$$

Upper and lower reservoir capacity constraint:

$$\frac{W_0 - W_{max}}{\eta_{ps}} \leq \sum_{t=1}^T \frac{P_{ge,t,i} \eta_{ge}}{\eta_{ps}} - \sum_{t=1}^T P_{ps,t,i} \leq \frac{W_0 - W_{min}}{\eta_{ps}} \quad (20)$$

where W_0 is the initial water volume in the upper reservoir, m^3 . W_{min} , W_{max} respectively represent the normal storage capacity and dead storage capacity.

3.2. Carbon Emission Reduction Model

Based on the low-carbon optimization operation model above, the baseline scenario for the project is set as a wind-solar-thermal combined power generation system without pumped storage power stations. The actual project scenario is the system with pumped

storage. A schematic diagram of the carbon emission reduction calculation for the actual project scenario is shown in Figure 5.

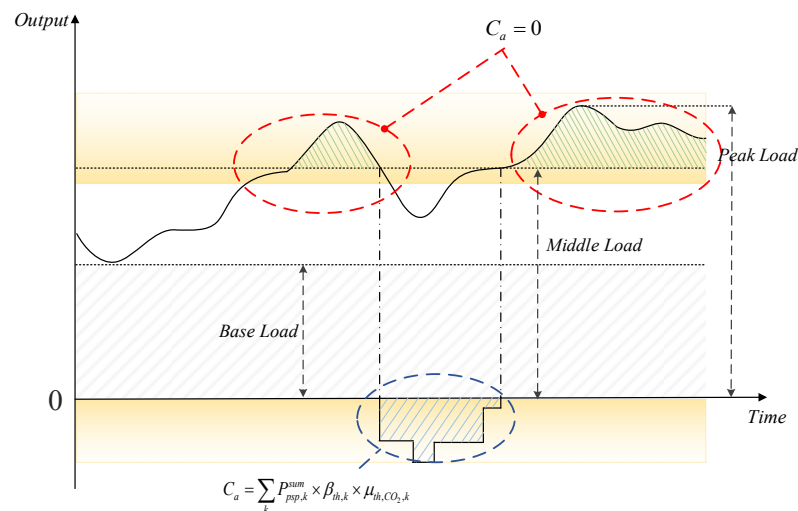


Figure 5. Actual scenario carbon emission reduction calculation scheme diagram.

A CER model for pumped storage is established based on the CCER methodology. The baseline and actual project scenarios are set, and the CE calculation methods for both scenarios are shown in Table 2.

Table 2. The setting of comparative scenarios for carbon emission calculations.

Scenario	Peak Load Phase	Off-Peak Load Phase
Baseline scenario (No Pumped Storage)	$P_{pst,k}^{sum} \times \mu_{CO_2,k}$	-
Actual scenario (With Pumped Storage)	-	$P_{psp,k}^{sum} \times \beta_{th,k} \times \mu_{th,CO_2,k}$

In the baseline scenario, without pumped storage units to regulate, the peak load needs to be handled by thermal power units. Therefore, the CE of the system at this time should be the portion that would have been dealt with by pumped storage units multiplied by the regional carbon emission factor.

In the actual scenario, during the off-peak load phase, the pumped storage units pump and store electricity, and the CE is calculated based on the pumped storage power multiplied by the corresponding CEF. Renewable energy generation in the system contributes to zero CE. Additionally, it is necessary to calculate the CE from thermal power units handling the base load during this phase. During the peak load phase, the pumped storage units handle the peak load output without generating CE.

The carbon emission reduction accounting model for the system is constructed as follows:

- (1) Calculation of CE in the baseline scenario:

$$C_0 = \sum_k P_{pst,k}^{sum} \times \mu_{th,CO_2,k} \quad (21)$$

where $P_{pst,k}^{sum}$ represents the thermal power generation capacity that can be replaced by pumped storage in the k -th year of the combined generation system with storage, kWh.

- (2) Calculation of CE in the actual scenario:

$$C_a = \sum_k P_{psp,k}^{sum} \times \beta_{th,k} \times \mu_{th,CO_2,k} \quad (22)$$

where $P_{psp,k}^{sum}$ represents the pumped storage energy in the k -th year of the combined generation system with storage, kWh. $\beta_{th,k}$ represents the percentage of electricity generated by thermal power during the pumping period of pumped storage power stations in year k , %. $\mu_{th,co_2,k}$ represents the CEF of thermal power generation in year k , assuming the CEF per kilowatt-hour remains constant throughout its lifecycle, $\mu_{th,co_2,k} = 937 \text{ gCO}_2/\text{kWh}$.

(3) Calculation of CERs using Equation (1):

The proposed low-carbon optimized operation model is formulated as a mixed-integer linear programming problem and implemented in MATLAB R2021a. The model is solved by the commercial solver CPLEX. The optimized dispatch results under the baseline and actual scenarios are then used for subsequent carbon emission reduction accounting. To facilitate a clearer understanding of the proposed modeling framework and solution process, Figure 6 illustrates the overall structure and main steps of the methodology.

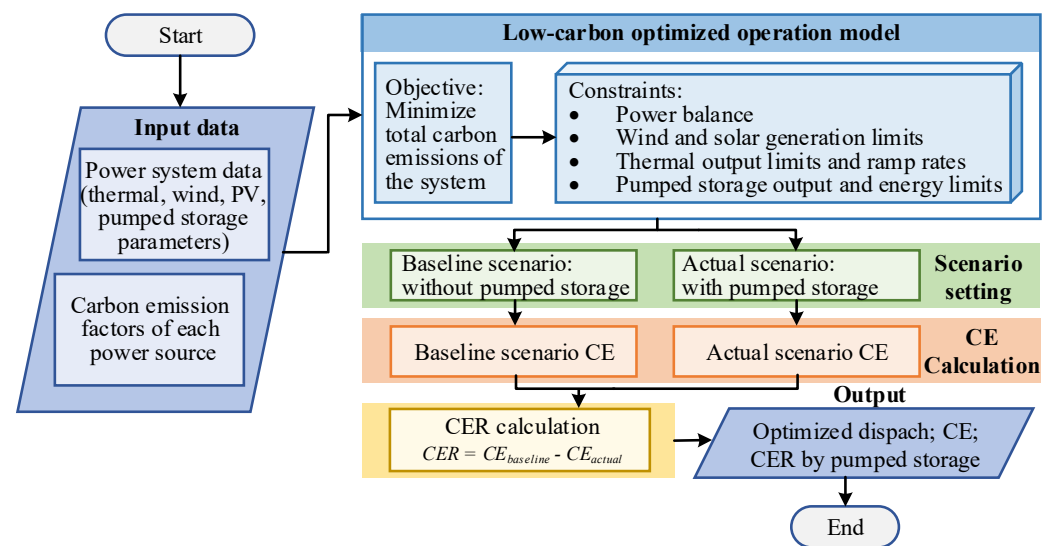


Figure 6. Framework of the proposed modeling.

4. Results and Discussion

This section presents and analyzes the results of the proposed lifecycle CER evaluation framework for integrated power generation systems with pumped storage. As the transition toward low-carbon power systems accelerates and the integration of renewable energy continues to expand, quantitatively assessing the carbon reduction potential and economic value of pumped storage becomes increasingly important. The analysis focuses on carbon emission calculation under different scenarios, carbon price forecasting based on the fractional-order gray model, and the evaluation of long-term economic benefits from carbon trading. The results provide valuable insights into the coordinated operation of multi-energy systems, the substitution effect of pumped storage on thermal power generation, and the role of carbon markets in enhancing the economic viability of low-carbon energy systems.

4.1. Basic Data

In this section, the installed capacities of wind power and photovoltaic power, as well as the load demand, are assumed to increase annually at a growth rate of approximately 1%. The installed capacities of various power sources in the comparative scenarios are listed in Table 3. These capacity values are selected based on the configuration of a pumped storage power station in Northwest China, together with its bundled wind-solar power generation system and supporting thermal power. The actual scenario represents the

system configuration with pumped storage, in which the installed capacity of pumped storage is 1200 MW. The baseline scenario excludes pumped storage, while the installed capacities of wind power, photovoltaic power, and thermal power are kept the same as those in the actual scenario. This setting is used to quantify the carbon reduction contribution of pumped storage by comparing the system operation results under the two scenarios.

Table 3. The installed capacity of various power sources in comparative scenarios.

Scenarios	Pumped Storage/MW	Wind/MW	Photovoltaic/MW	Thermal/MW
Actual scenario	1200	3000	2800	7200
Baseline scenario	0	3000	2800	7200

4.2. CER Calculation

4.2.1. CE in the Actual Scenario

Firstly, calculate the future load demand and output data of various power sources in the actual scenario for each year in the future. An example of output and demand curves for a summer month is shown in Figure 7.

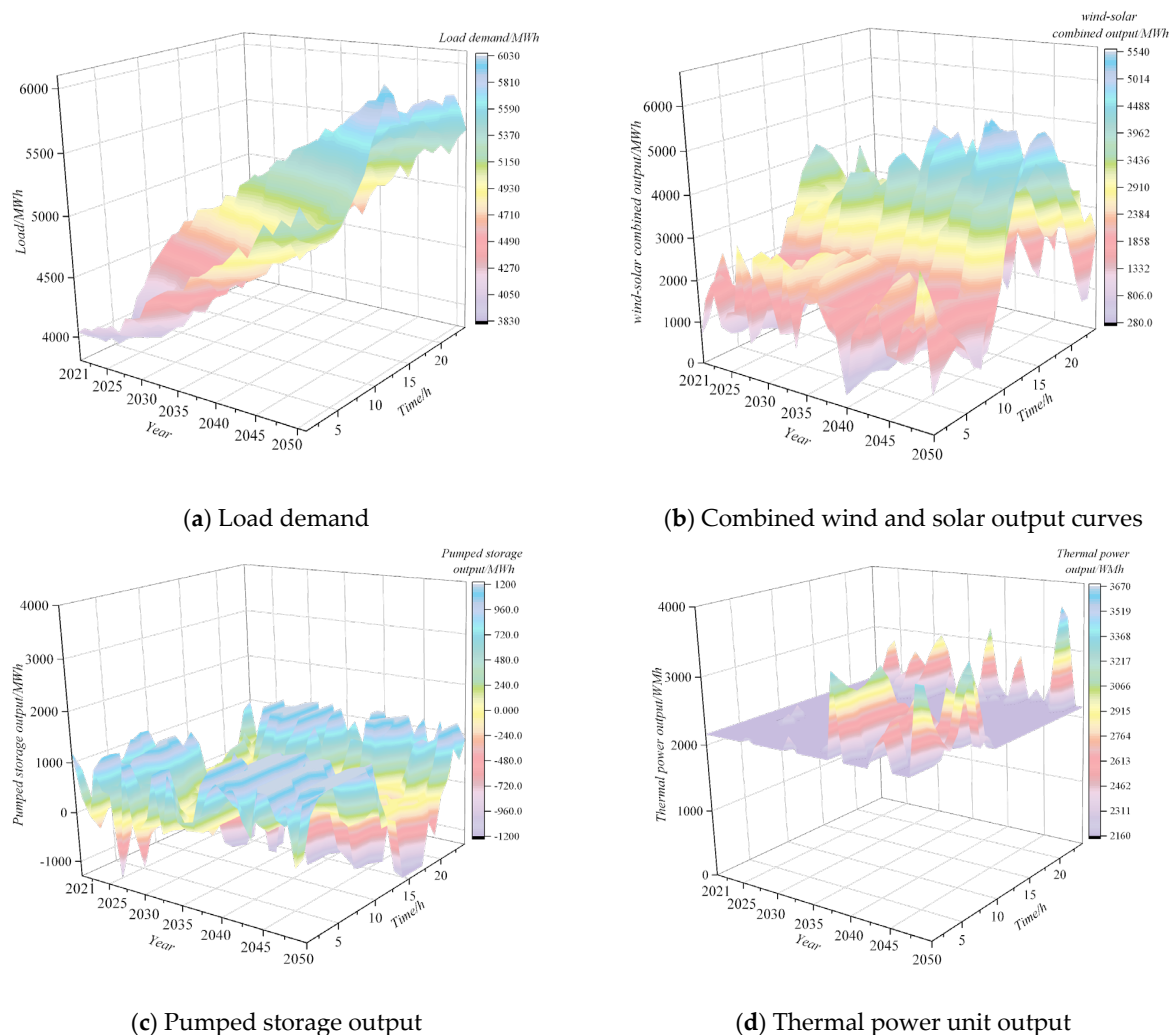


Figure 7. Load demand and output trends of various power sources for a typical day in the future.

Analyzing the daily load variation curve, it can be observed that the load variation trend is similar for the lifecycle of the same typical day. By 2050, the peak load will have nearly doubled compared to 2021. With the annual growth rate of wind and solar installed capacity remaining constant, the peak wind and solar output slightly increase, but the total

daily generation does not change significantly. In the baseline year (2021), the pumped storage output has few full pumping periods, and thermal power units mainly undertake the base load output throughout the day. After 2035, with the increase in wind and solar installed capacity, the full pumping periods increase significantly, especially during the peak hours of combined wind and solar output at midday, where the energy adjustment function of the pumped storage units is most evident.

To calculate the CERs in the actual scenario, it is necessary to compute the total energy stored by the pumped storage power stations and the proportion of electricity generated by thermal power units during the pumping periods of the pumped storage units. The calculation results are shown in Figure 8.

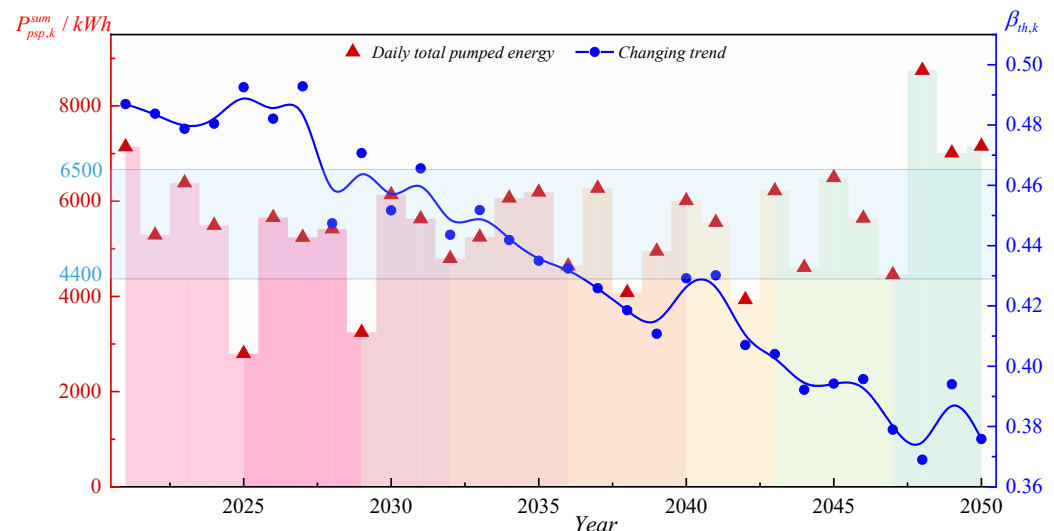


Figure 8. Total stored energy during the pumping periods of the pumped storage units and the proportion of electricity generated by thermal power units on typical days each year.

Due to the capacity limitations of pumped storage power stations, the total stored energy on a typical day each year fluctuates mostly within the range of [4400, 5600]. The proportion of electricity generated by thermal power units during the pumping periods decreases continuously, with an average annual decrease of 0.83% and a total decrease of 24.12%. Using Equation (4), the carbon emissions in the actual scenario can be calculated.

4.2.2. CE in the Baseline Scenario

The baseline scenario of the project does not include a pumped storage unit in the combined power generation system. According to Equation (3), the main task is to calculate the total power generation of the thermal power units replacing the pumped storage units in the actual scenario. The trend of thermal power replacing pumped storage power on a typical day is shown in Figure 9.

In the baseline scenario, the pumped storage units do not participate in flexible load regulation during peak and off-peak hours. In this case, only thermal power units undertake all the load regulation demands, participating in deep load regulation of the system. During peak times of combined wind and photovoltaic power output within a day, thermal power handles the base load output but cannot store energy. When renewable energy generation does not meet the load demand, thermal power units generate electricity to meet the system's load demand. Compared to the actual scenario, thermal power units start and stop more frequently within a day. After 2035, the average difference in extreme values of thermal power output within a day is 8.24 times.

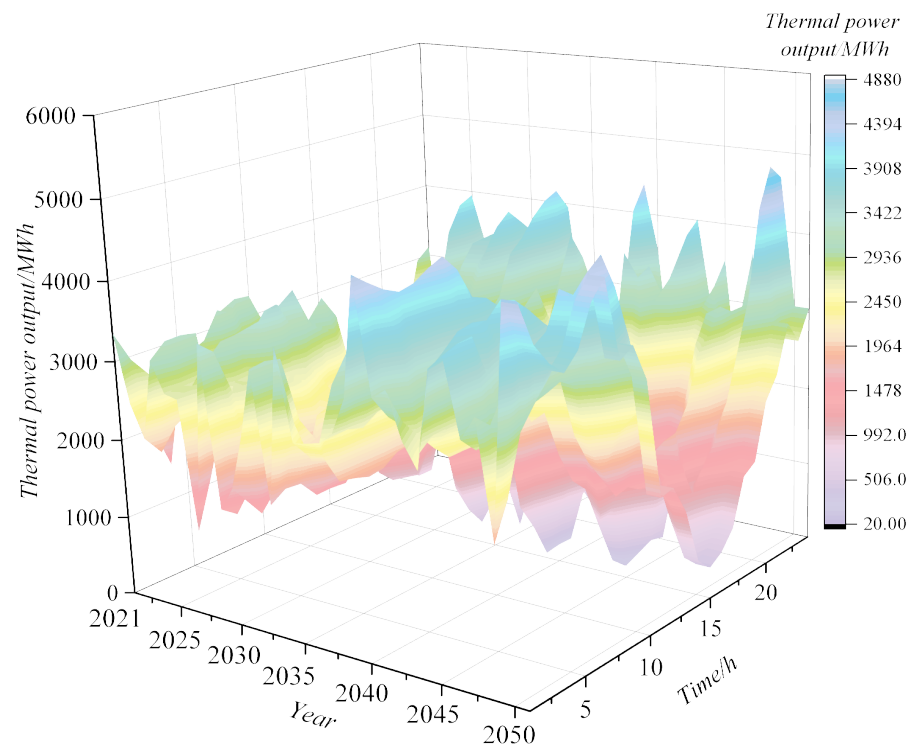


Figure 9. The power generation from thermal power units participating in load regulation on typical days each year.

Deep load regulation by thermal power units not only leads to a sharp increase in the system's CE but also reduces the overall system's flexibility to respond to load demand changes. This is because pumped storage units can quickly respond to load changes, providing flexibility regulation on a minute and second scale, whereas the start-up and shutdown of thermal power units, compared to systems with pumped storage units, require significant time and cost.

Calculate the total power generation of the pumped storage power stations in the actual scenario. The trend of daily power generation variation in a typical month during the summer of each year is shown in Figure 10.

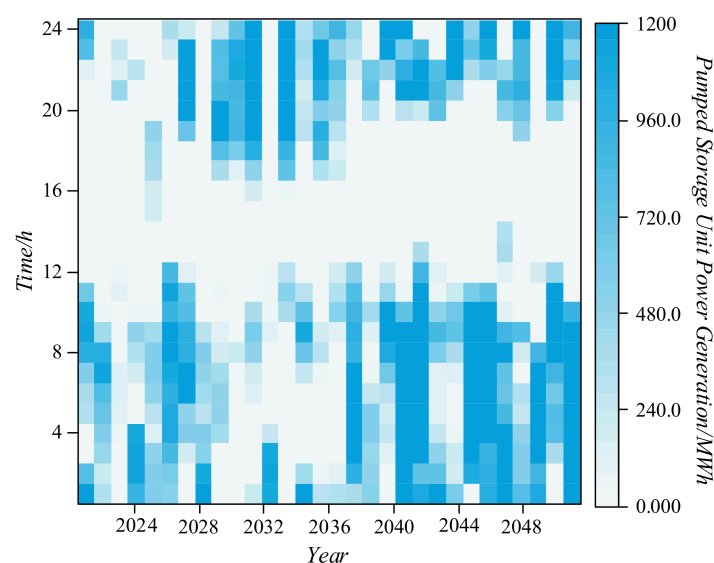


Figure 10. The daily power generation of pumped storage units on typical days each year.

Analysis reveals that the daily power generation shows a general trend of fluctuating increase over the years. The future power generation from pumped storage, replacing thermal power for load regulation, gradually increases. After 2035, the average replacement of thermal power generation is 1.47 times that of the previous 15 years, and the number of hours with full power generation from pumped storage within a day also increases.

4.2.3. CER of the System

According to the constructed CER model, the total power generation from pumped storage for load regulation in each baseline year and the total stored energy capacity in future years can be calculated. Some representative annual calculation results are shown in Tables 4 and 5.

The above tables only show partial calculation results. Based on the calculated peak load shaving capacity of pumped storage units replacing thermal power over a lifecycle of thirty years, the CE under the baseline scenario amounts to 437,800 t. Considering the annual pumping capacity of pumped storage and the proportion of thermal power generation during pumping in the actual scenario, the actual CE amounts to 23,709,600 t. Therefore, according to Equation (1), the CERs of the system amount to 23,271,800 t.

Table 4. The total power generation from pumped storage for load regulation in the reference year (representative year).

Representative Year	$P_{pst,k}^{sum}/\text{kWh}$
2021	3.34×10^9
2025	2.20×10^9
2030	2.37×10^9
2035	2.00×10^9
2040	1.41×10^9
2045	1.94×10^9
2050	3.01×10^9

Table 5. The total energy storage capacity from pumped storage over the reference year (representative year).

Representative Year	$P_{psp,k}^{sum}/\text{kWh}$
2021	2.61×10^9
2025	2.01×10^8
2030	2.24×10^9
2035	2.26×10^9
2040	2.19×10^9
2045	2.37×10^9
2050	2.61×10^9

4.3. Carbon Emission Reduction Value Assessment

4.3.1. Carbon Trading Price Forecasting

The national carbon emissions trading market was officially established in 2017 and began trading in July 2021. This research uses the average trading price of national carbon emissions trading as historical data, as shown in Table 6.

Using the existing national carbon emissions trading prices as initial data, input them into the FGM in Section 2.3.1. Using the PSO optimization algorithm in Python 3.8, solve for the optimal order, which is found to be 0.97. At this optimal order, the model achieves the highest accuracy in fitting the data and predicting future average electricity prices. The

following Figure 11 shows the fitting and prediction results of the model in the optimal order.

Table 6. The national carbon market trading prices and forecasts [40].

Representative Year	Price (CNY/t)	
2022	54.98	Annual average price
2023	68.15	
2024	85.19	
2030E	150	June
2050E	1000	Predicted value

Note: The letter “E” after the year indicates a predicted year.

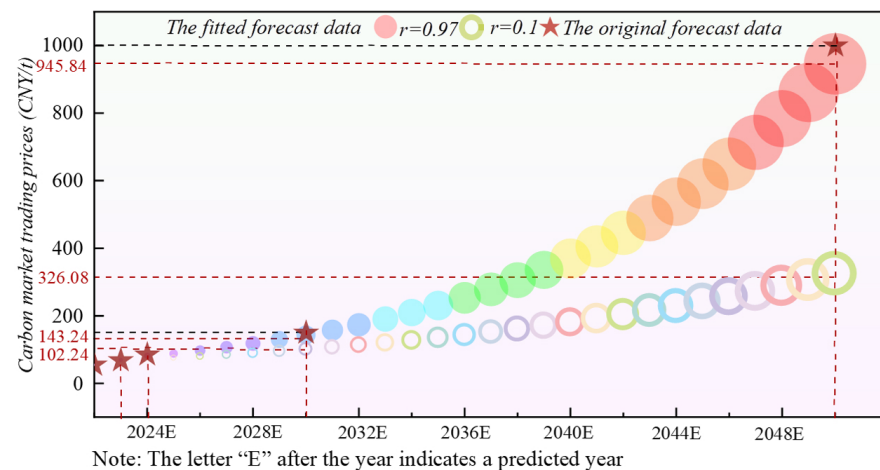


Figure 11. The trend of fitting and predicting future average carbon prices.

Due to the limited available data on average carbon market prices, there are only three years of actual data currently. The predicted future carbon prices show a stable increasing trend. Calculations using the optimal order indicate that the prices are estimated to be 143.24 CNY per ton in 2030 and 945.84 CNY per ton in 2050. These estimates are close to those forecasted in the report and demonstrate higher accuracy compared to predictions at an order of 0.1.

4.3.2. Prediction Accuracy Testing

To further compare the predictive effectiveness and estimation accuracy of the model at different fractional orders, the order was varied from $r = 0.1$ with a step size of 0.1. The simulated values and relative errors under different orders are shown in Figure 12, which is used to identify the order that best reflects the historical carbon price trend.

Analysis of Figure 12 indicates that the simulation performance of the model varies with different fractional orders. The MAPE values show notable variation when the order is greater than 1, indicating that inappropriate fractional orders may reduce the prediction accuracy of the model. Similarly, the SDE also increases under some non-optimal orders, suggesting that the dispersion of fitting errors becomes larger. These results show that the selection of the fractional order has an important influence on the fitting accuracy and stability of the FGM.

After applying the PSO algorithm, the optimal fractional order of the model was determined to be 0.9740. At this optimized order, the predicted relative errors are lower than those obtained under most other orders. Specifically, the MAPE is 3.25%, and the SDE is 2.23, demonstrating good model fit and small error deviation at the optimized order. Therefore, the PSO-optimized FGM under the optimal order of 0.9740 can provide a reliable basis for forecasting future CCER carbon price changes.

	$r = 0.1$		$r = 0.3$		$r = 0.5$		$r = 0.7$	
	fitted value	relative error	fitted value	relative error	fitted value	relative error	fitted value	relative error
2022	54.98	0.00%	54.98	0.00%	54.98	0.00%	54.98	0.00%
2023	69.37	-1.79%	69.33	-1.73%	69.55	-2.05%	70.07	-2.82%
2024	80.88	5.06%	81.08	4.82%	81.08	4.82%	80.76	5.20%
MAPE		2.38%		2.38%		2.42%		2.52%
SDE		2.110270125		2.065221538		2.071279798		2.196665655
	$r = 0.9$		$r = 0.97$ Optimal order		$r = 1.0$		$r = 1.1$	
	fitted value	relative error	fitted value	relative error	fitted value	relative error	fitted value	relative error
2022	54.98	0.00%	54.98	0.00%	54.98	0.00%	54.98	0.00%
2023	70.97	-4.14%	69.31	-1.70%	71.57	-5.02%	72.28	-6.06%
2024	79.96	6.14%	81.56	4.26%	79.32	6.89%	78.5	7.85%
MAPE		2.99%		3.25%		3.37%		3.93%
SDE		2.60989655		2.229237538		2.989080126		3.506950242
	$r = 1.3$		$r = 1.5$		$r = 1.7$		$r = 1.9$	
	fitted value	relative error	fitted value	relative error	fitted value	relative error	fitted value	relative error
2022	54.98	0.00%	54.98	0.00%	54.98	0.00%	54.98	0.00%
2023	74.08	-8.70%	76.39	-12.09%	79.27	-16.32%	54.98	19.33%
2024	76.18	10.58%	72.77	14.58%	68.01	20.17%	82.75	2.86%
MAPE		6.14%		9.15%		13.05%		17.92%
SDE		5.031570331		7.273696447		10.3436802		14.35974512

Figure 12. Comparison of simulated carbon price values and relative errors at different orders. Notes: Yellow shading indicates fitted values; red and blue highlights indicate negative and positive relative errors, respectively; green and orange bars represent MAPE and SDE, respectively.

4.3.3. Economic Benefits of CER

Based on the calculations from the previous sections, the future CERs over 30 years and the carbon trading prices for each year in a certain energy base in western China have been determined. Therefore, the economic benefits derived from CERs in the future can be computed using the following Equation:

$$C = \sum_k CER_k \times PR_k \quad (23)$$

where CER_k represents the predicted carbon emission reductions for the k -th year. PR_k represents the predicted carbon trading price for the k -th year.

Assuming that over the next 30 years, all CERs from this energy base will enter the carbon trading market, based on the predicted carbon trading price, it can be calculated that a total economic benefit of CNY 79.81 billion will be generated.

The value of CCER carbon emission reductions is typically evaluated using the revenue method, with the calculation formula as follows:

$$V = \sum_{NCF_k=1}^n \frac{NCF_k}{(1+\varepsilon)^k} \quad (24)$$

where V represents the enterprise's CCER carbon emission reduction value. NCF_k represents the net cash flow of CCER carbon emission reductions for the k -th year of the enterprise. NCF_k denotes the periods in which the enterprise obtains CCER carbon emission reduction revenue. ε denotes the discount rate. For the Chinese electric power industry, the Internal Rate of Return (IRR) after tax for all investments is 8%.

The net cash flow from CCER carbon emission reductions obtained by the enterprise is calculated based on the computed carbon emission trading prices and parameters such as consulting fees, verification fees, transaction fees, etc., as shown in the Table 7 below.

Table 7. Net cash flow from CCER carbon emission reductions.

Representative Year	2022	2023	2024	2025	2026	2027	2028
carbon price (CNY/t)	54.98	68.15	81.56	88.08	97.29	107.3	118.22
CER (t)	860,354	635,630	888,274	350,235	1,200,294	868,198	311,420
Net cash flow (ten thousand CNY)	3947	3493	6170	1809	10157	7502	1521

Based on the parameters from the Table 7 and using Equation (21), the carbon emission rights value for this energy base in the initial 7-year compliance period is calculated to be 254.07 million CNY.

5. Conclusions

This paper proposes a lifecycle CER evaluation model for pumped storage in integrated power generation systems under the CCER mechanism. A PSO-optimized FGM is employed for carbon price forecasting, and a low-carbon optimal operation model is developed to quantify both carbon reduction and economic benefits. The results demonstrate that the proposed framework can effectively capture the coordinated operation of multiple energy sources and the substitution effect of pumped storage on thermal power generation. Under the baseline scenario, the lifecycle carbon emissions reach 43.78 million tons, while they decrease to 23.71 million tons in the actual scenario with pumped storage, resulting in a total reduction of 23.27 million tons. The optimized FGM achieves a high prediction accuracy with an optimal fractional order of 0.9740, providing reliable carbon price forecasts. Based on these predictions, the total carbon trading revenue over a 30-year lifecycle is estimated to be 7.981 billion CNY, including 254.08 million CNY generated during the initial 7-year inclusion period. Compared with existing studies, the proposed method achieves further improvements in both carbon reduction and economic performance. The results indicate that promoting the grid integration of pumped storage and its participation in carbon markets can effectively enhance the regulation capability of the power system and realize a coordinated optimization of environmental and economic benefits.

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