

Special Issue Reprint

Modeling, Design and Engineering Optimization of Energy Systems

Edited by
Yamin Yan, Qi Liao, Jie Yan, Haoran Zhang and Wanshui Yu

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Contents

Preface	vii
-------------------	-----

Yamin Yan, Qi Liao, Jie Yan, Haoran Zhang and Wanshui Yu Special Issue on “Modeling, Design and Engineering Optimization of Energy Systems” Reprinted from: <i>Processes</i> 2025 , <i>13</i> , 1980, https://doi.org/10.3390/pr13071980	1
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Feng Yan, Kaituo Jiao, Chaofei Nie, Dongxu Han, Qifu Li and Yujie Chen Fast Prediction of the Temperature Field Surrounding a Hot Oil Pipe Using the POD-BP Model Reprinted from: <i>Processes</i> 2023 , <i>11</i> , 2666, https://doi.org/10.3390/pr11092666	4
---	----------

Jiangyan Zhao, Tianyi Zhang, Siwei Tang, Jinhua Zhang, Yuerong Zhu and Jie Yan Optimal Scheduling Strategy of Wind Farm Active Power Based on Distributed Model Predictive Control Reprinted from: <i>Processes</i> 2023 , <i>11</i> , 3072, https://doi.org/10.3390/pr11113072	23
--	-----------

Kunyi Wu, Jianying Yang, Yu Lin, Pan Zhou, Yanli Luo, Feng Wang, et al. A Multi-Period Model of Compressor Scheme Optimization for the Shale Gas Gathering and Transportation System Reprinted from: <i>Processes</i> 2023 , <i>11</i> , 3101, https://doi.org/10.3390/pr11113101	45
--	-----------

Jinhua Zhang, Xinzhi Xue, Dongfeng Li, Jie Yan and Peng Cheng Optimization of Energy Storage Allocation in Wind Energy Storage Combined System Based on Improved Sand Cat Swarm Optimization Algorithm Reprinted from: <i>Processes</i> 2023 , <i>11</i> , 3274, https://doi.org/10.3390/pr11123274	64
--	-----------

Yue Zhang and Chenchen Song A Novel Design of Centrifugal Pump Impeller for Hydropower Station Management Based on Multi-Objective Inverse Optimization Reprinted from: <i>Processes</i> 2023 , <i>11</i> , 3335, https://doi.org/10.3390/pr11123335	84
---	-----------

Jinhua Zhang, Tianyi Zhang, Peng Cheng, Dongzheng Yang, Jie Yan and Xinpei Tian Optimal Allocation of Hybrid Energy Storage System Based on Smoothing Wind Power Fluctuation and Improved Scenario Clustering Algorithm Reprinted from: <i>Processes</i> 2023 , <i>11</i> , 3407, https://doi.org/10.3390/pr11123407	104
---	------------

Yue Zhang and Chenchen Song Economical Design of Drip Irrigation Control System Management Based on the Chaos Beetle Search Algorithm Reprinted from: <i>Processes</i> 2023 , <i>11</i> , 3417, https://doi.org/10.3390/pr11123417	136
---	------------

Guanglei Li, Tengqi Luo, Ran Liu, Chenchen Song, Congyu Zhao, Shouyuan Wu and Zhengguang Liu Integration of Carbon Dioxide Removal (CDR) Technology and Artificial Intelligence (AI) in Energy System Optimization Reprinted from: <i>Processes</i> 2024 , <i>12</i> , 402, https://doi.org/10.3390/pr12020402	154
---	------------

Xiaobin Liang, Fan Fei, Lei Wang, Daibin Mou, Weifeng Ma and Junming Yao An Integrated Risk Assessment Methodology of In-Service Hydrogen Storage Tanks Based on Connection Coefficient Algorithms and Quintuple Subtraction Set Pair Potential Reprinted from: <i>Processes</i> 2024 , <i>12</i> , 420, https://doi.org/10.3390/pr12020420	172
--	------------

Jiaoyang Lu, Shan Liu, Jing Zhang, Shuang Han, Xingyuan Zhou and Yongqian Liu Charging and Discharging Optimization of Vehicle Battery Efficiency for Minimizing Company Expenses Considering Regular User Travel Habits Reprinted from: <i>Processes</i> 2024 , 12, 435, https://doi.org/10.3390/pr12030435	189
Yuelong Wang, Weiqing Wang, Xiaozhu Li and Weiwei Yu Enhanced Management of Unified Energy Systems Using Hydrogen Fuel Cell Combined Heat and Power with a Carbon Trading Scheme Incentivizing Emissions Reduction Reprinted from: <i>Processes</i> 2024 , 12, 1358, https://doi.org/10.3390/pr12071358	213
He Chang, Ying Xing, Bo Miao, Li Li, Chao Liu, Kangli Xiang, et al. A Quantitative Method of Carbon Emission Reduction for Electrochemical Energy Storage Based on the Clean Development Mechanism Reprinted from: <i>Processes</i> 2024 , 12, 2472, https://doi.org/10.3390/pr12112472	237

Preface

The global energy landscape faces unprecedented challenges, driven by the imperative to mitigate climate change, enhance energy efficiency, and integrate renewable sources at scale. This Reprint, titled “Modeling, Design and Engineering Optimization of Energy Systems”, responds to these critical needs by compiling cutting-edge research on advanced methodologies for sustainable energy transitions.

Our motivation stems from the urgency to bridge theoretical innovation with practical engineering solutions. As Guest Editors, we recognize that optimizing complex energy systems—spanning storage, conversion, hydrogen technologies, and grid integration—demands interdisciplinary collaboration and computational advancements. This Reprint specifically addresses gaps in scalable optimization frameworks, AI-driven design, and techno-economic analysis, which are essential for decarbonization.

The scope encompasses five pivotal domains: (1) innovations in energy storage and conversion for grid stability; (2) hydrogen and fuel cell systems for hard-to-abate sectors; (3) computational and AI-driven optimization tools; (4) renewable integration and smart grid management; and (5) policy-responsive modeling. Each contribution offers actionable insights for minimizing costs, maximizing efficiency, and enhancing system resilience.

This work is intended for researchers developing next-generation energy models, engineers designing deployable solutions, and policymakers crafting evidence-based decarbonization strategies. We acknowledge the authors whose pioneering studies help accelerate the progress toward a sustainable energy future.

Yamin Yan, Qi Liao, Jie Yan, Haoran Zhang, and Wanshui Yu

Guest Editors

Editorial

Special Issue on “Modeling, Design and Engineering Optimization of Energy Systems”

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The global energy landscape is undergoing a transformative shift, driven by the urgent need to address climate change, enhance energy efficiency, and integrate renewable energy sources [1–3]. Advanced modeling, innovative design, and engineering optimization are pivotal to achieving these goals [4]. This Special Issue of *Processes* on “Modeling, Design, and Engineering Optimization of Energy Systems” presents cutting-edge research that explores novel methodologies, computational tools, and optimization strategies to tackle the complexities of modern energy systems.

1. Innovations in Energy Storage and Conversion

Energy storage systems are critical for balancing supply and demand, especially with the increasing penetration of intermittent renewable energy sources [5]. This Special Issue features several studies focused on optimizing energy storage technologies. One article [6] proposed a framework to quantify the environmental benefits of electrochemical storage systems, providing policymakers and industry stakeholders with data-driven insights to support sustainable deployment. Meanwhile, another article [7] addressed the challenges of wind power variability by integrating hybrid storage solutions. This not only enhanced grid reliability but also reduced the need for fossil-fuel-based balancing reserves. Collectively, the study underscored how technological advancements in energy storage can bolster system resilience, support higher renewable penetration, and accelerate progress toward a sustainable energy future.

2. Hydrogen and Fuel Cell Technologies

Hydrogen energy and fuel cell technologies are rapidly emerging as critical enablers of a sustainable and decarbonized energy future [8]. As nations worldwide strive to meet ambitious climate targets, hydrogen—particularly when produced via renewable-powered electrolysis (“green hydrogen”)—offers a versatile solution for sectors that are challenging to electrify directly, such as heavy industry, long-haul transportation, and seasonal energy storage [9]. Fuel cells, which convert hydrogen into electricity with high efficiency and zero emissions, further enhance this potential, making hydrogen a cornerstone of the future energy mix [10]. In this Special Issue, cutting-edge research highlights the multifaceted advancements in hydrogen-based systems. One standout article [11] introduced an innovative Integrated Energy System approach by enhancing conventional Power-to-Gas (P2G) systems. To overcome the operational dependency of existing P2G, hydrogen fuel cells (HFCs) were integrated, enabling autonomous dual-phase operation that strengthened renewable energy integration. A tiered penalty–reward

carbon trading mechanism, with differentiated emission pricing, incentivized energy suppliers to reduce emissions. Further, flexible heat-to-power ratio adjustment in cogeneration significantly boosted energy efficiency. The proposed P2G-HFC co-optimization model minimizes total costs—including carbon trading and renewable integration expenses—across the combined system.

3. Computational and AI-Driven Optimization

Artificial intelligence (AI) and computational modeling are fundamentally transforming the design, operation, and optimization of modern energy systems [12]. One article [13] synthesized the current AI-CDR integration research, articulating the following four principal implementation dimensions: precision carbon quantification, adaptive energy system reconfiguration, the dynamic spatiotemporal orchestration of CDR infrastructure, and symbiotic mechanism design—collectively demonstrating AI's tripartite value proposition in environmental mitigation, economic optimization, and efficiency augmentation. Future advancement necessitates next-generation computational frameworks for optimization, unified cross-domain data fusion architectures, robust decision-risk analytics under uncertainty, and policy-informed interdisciplinary collaboration.

4. Renewable Energy Integration and Smart Systems

The seamless integration of intermittent renewable energy sources into legacy power grids demands increasingly sophisticated optimization techniques [14], particularly as global renewable penetration targets exceed 60% by 2040. One article [15] in this Special Issue addressed the challenges of variability and demand-side management. This study employed a coordinated charging–discharging strategy for balancing user mobility patterns and charger operational efficiency. A spatiotemporal probability model with Monte Carlo simulations generates EV mobility trajectories, informing a linear programming framework that minimizes the dual costs of charger operation expenses and user charging fees. Empirical validation shows that corporate costs reach a minimum at specific charger deployment levels under routine travel patterns. Crucially, user-centric optimization objectives heighten sensitivity to battery degradation, drastically reducing discharge participation willingness.

5. Conclusions

The research presented in this Special Issue reflects the diverse and dynamic nature of energy system optimization. From hydrogen technologies to AI-driven solutions, these contributions pave the way for a more sustainable and efficient energy future. We hope this collection inspires further innovation and collaboration in the field, ultimately accelerating the transition to a low-carbon economy.

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Article

Fast Prediction of the Temperature Field Surrounding a Hot Oil Pipe Using the POD-BP Model

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Abstract: The heat transfer assessment of a buried hot oil pipe is essential for the economical and safe transportation of the pipeline, where the basis is to determine the temperature field surrounding the pipe quickly. This work proposes a novel method to efficiently predict the temperature field surrounding a hot oil pipe, which combines the proper orthogonal decomposition (POD) method and the backpropagation (BP) neural network, named the POD-BP model. Specifically, the BP neural network is used to establish the mapping relationship between spectrum coefficients and the preset parameters of the sample. Compared with the classical POD reduced-order model, the POD-BP model avoids solving the system of reduced-order governing equations with spectrum coefficients as variables, thus improving the prediction speed. Another advantage is that it is easy to implement and does not require tremendous mathematical derivation of reduced-order governing equations. The POD-BP model is then used to predict the temperature field surrounding the hot oil pipe, and the sample matrix is obtained from the numerical results using the finite volume method (FVM). In validation cases, both steady and unsteady states are investigated, and multiple boundary conditions, thermal properties, and even geometry parameters (different buried depths and pipe diameters) are tested. The mean errors of steady and unsteady cases are 0.845~3.052% and 0.133~1.439%, respectively. Appealingly, almost no time, around 0.008 s, is consumed in predicting unsteady situations using the proposed POD-BP model, while the FVM requires a computational time of 70 s.

Keywords: POD prediction; BP neural network; temperature field; hot oil pipe

1. Introduction

In 2022, oil accounted for the largest proportion of global energy consumption, approximately 31% [1]. Pipeline buried under the surface of the ground is the main method of transporting oil; e.g., pipeline transportation occupies 68% of domestic petroleum shipments in the United States [2]. If the oil has a high pour point or high viscosity, it should be heated to reduce friction loss and ensure the reliability of pipe transportation [3,4]. The continuous heat exchange between oil and the surrounding soil lowers the oil temperature, but the oil temperature is supposed to be kept higher than the gel point at all times during transportation, leading to great energy consumption and carbon emission from the oil heating. Therefore, efficient and accurate prediction of the temperature field around the hot oil pipe has important implications for the economical, safe, and environmentally friendly operation of the pipeline system.

In recent years, much numerical research has been carried out to investigate the temperature field surrounding the hot oil pipe, mostly based on direct numerical simulation [5], such as the finite element method (FEM) [6] and finite volume method (FVM) [7,8]. Nevertheless, direct numerical simulation has high computational complexity when solving

discretization systems, resulting in large memory requirements and a long computational time. These defects make it difficult to apply to optimal design and risk assessment of the pipeline system, which requires the calculation of different conditions containing a great number of combinations of operation and structure parameters [9]. Herein, this work tends to adopt the proper orthogonal decomposition (POD) method to improve the simulation efficiency [10].

POD can abstract large amounts of data about one mathematical model into a series of basis functions to represent the main characteristics of this model [11,12]. It is always combined with the Galerkin projection method to construct the POD reduced-order model that can predict the physical field distribution [13]. The spectrum coefficients system with lower degrees of freedom is solved in the POD reduced-order model [14], rather than all discretized grids, as in direct numerical simulation, and thus the POD reduced-order model can significantly improve the simulation speed. Researchers have paid extensive attention to the POD reduced-order model, and it is widely applied to various engineering projects, including turbulent flow [15,16], and pipe flow [17]. Recently, some applications of the POD reduced-order model to predict the temperature field surrounding the hot oil pipe have been published. Yu et al. [18] established the POD reduced-order model for the pipe cross section based on the unstructured grid, in which comprehensive boundary conditions of the physical domain were considered, and the boundary treatments in the POD reduced-order model were discussed in detail. To make the POD reduced-order model suitable for different geometry parameters (i.e., buried depth, pipe diameter, and pipe wall thickness), the body-fitted coordinates (BFCs) of the pipe cross section were combined with the POD reduced-order model in [19]. This model effectively expanded the application scope of POD, but only a steady situation was studied. Furthermore, Han et al. [20] proposed a BFC-based POD reduced-order model for the unsteady heat conduction of crude oil pipelines and applied it to the cold and hot oil batch transportation as well as pipe shutdown.

The classical POD reduced-order model requires many numerical simulation results to extract the basis functions, which are then used for predicting the temperature field. However, this approach has two drawbacks: (1) There is a mapping relationship between spectrum coefficients and preset parameters of the predicted sample, described by reduced-order governing equations [20]; solving reduced-order governing equations with spectrum coefficients as variables still needs a certain amount of computation. (2) The Galerkin projection method used to derive the reduced-order governing equations from the POD basis functions requires high mathematical complexity and is tedious to implement [21]; if the assumptions underlying the heat transfer processes, such as steady or unsteady states, constant or variable thermal properties, and boundary conditions, are changed, the reduced-order governing equations must be rederived [18].

In another way, using neural networks to fit mapping relationships has high flexibility and adaptability [22,23]. The training process of neural networks does not require any complex mathematical derivation, and the application of neural networks has almost no computational effort. Hence, to address the two drawbacks of the classical POD reduced-order model mentioned above, this work uses the backpropagation (BP) neural network to establish the mapping between spectrum coefficients and preset parameters of the sample. The present model is named the POD-BP model, and it can efficiently predict the temperature field surrounding the hot oil pipe in both steady and unsteady situations. A variety of boundary, thermal property, and geometry parameters are also considered in validation cases to illustrate the applicability of the POD-BP model.

2. Methodology

This section first presents the physical model and governing equations for the temperature field surrounding the hot oil pipe. Then, the meshing of the computational domain is introduced to ensure that the POD-BP model applies to various geometry parameters. Subsequently, the POD basis function calculation is briefly described and the POD-BP model is established to predict the temperature field.

2.1. Physical Model for Heat Conduction Surrounding the Hot Oil Pipe

Figure 1 shows the schematic of the computational domain and boundary conditions for the heat conduction surrounding the hot oil pipeline. The deposited wax, steel layer, and corrosion protection layer are considered for the pipe wall, and the surrounding soil accounts for the primary area. The following assumptions are made to simplify this problem.

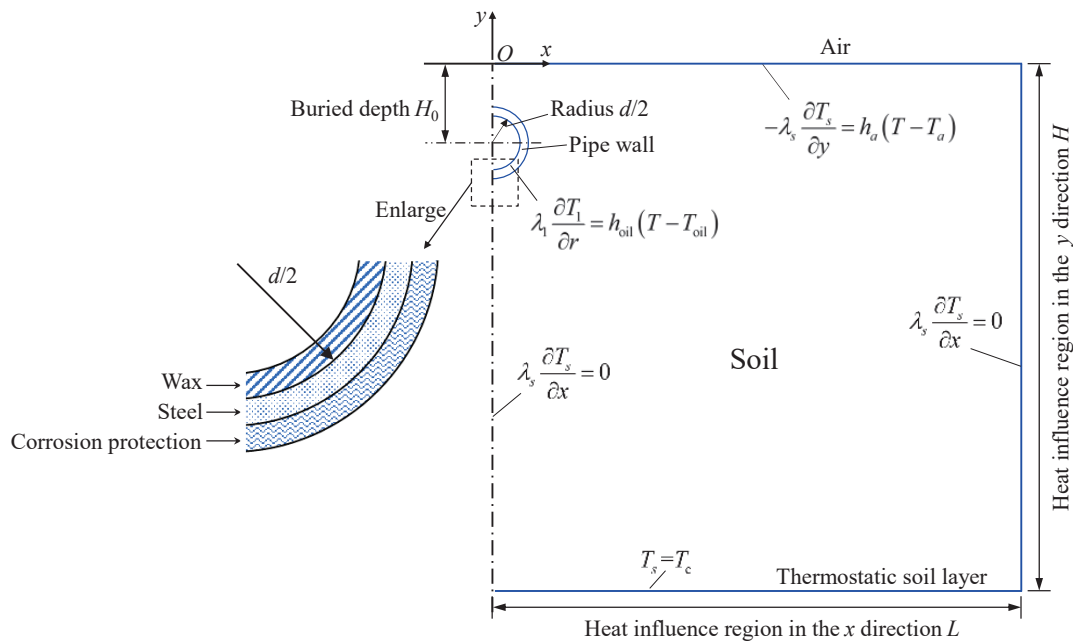


Figure 1. Computational domain and boundary condition.

- The thermal properties of the soil and pipe wall are isotropy and homogeneous. Hence, the physical problem is symmetry along the vertical centerline of the pipe, and only half of the domain is investigated here.
- The axial temperature variation of the surrounding soil is slight compared with the radial direction and is thus neglected. A two-dimensional pipeline cross section is studied here.
- The temperatures of hot oil inside the pipe and atmosphere air and the thickness of wax deposition remain unchanged with time.
- According to the literature and engineering applications, the thermal influence regions in the x and y directions are both 10 m [5]. It is assumed that the temperature response outside the thermal influence region is neglected.

The governing equations of heat conduction in the pipe wall and surrounding soil are expressed as follows:

$$\frac{\partial(\rho_i c_{p,i} T_i)}{\partial t} = \nabla \cdot (\lambda_i \nabla T_i) \quad (1)$$

where T is the temperature in the physical domain; t is the time; ρ is the density; c_p is the specific heat capacity; λ is the thermal conductivity; and subscripts 1, 2, 3, and s denote the wax layer, steel layer, corrosion protection layer, and soil, respectively.

For the boundary conditions, the left boundary (except the wax layer boundary) is subjected to the symmetrical boundary condition as follows:

$$\lambda_i \frac{\partial T_i}{\partial x} = 0 \text{ at } x = 0 \text{ and } y \in \left[-\left(H_0 - \frac{d}{2} + \delta_1 \right), 0 \right] \cup \left[-H_0, -\left(H_0 + \frac{d}{2} - \delta_1 \right) \right] \quad (2)$$

where H_0 is the buried depth; d is the inner diameter of the steel pipe; and δ_1 is the thickness of the wax layer. The wax layer boundary and upper boundary are subjected to the convection boundary condition:

$$-\lambda_s \frac{\partial T}{\partial y} = h_a(T - T_a) \text{ at } y = 0 \quad (3)$$

$$\lambda_1 \frac{\partial T_1}{\partial r} = h_{oil}(T - T_{oil}) \text{ at } r = \frac{d}{2} - \delta_1 \quad (4)$$

where T_a is the atmosphere temperature; h_a is the heat transfer coefficient between the soil and air; T_{oil} is the hot oil temperature inside the pipe; and h_{oil} is the heat transfer coefficient between the oil and the wax layer. The right boundary is assigned as the adiabatic boundary and the lower boundary is regarded as the thermostatic soil layer and maintained at a constant value:

$$\lambda_s \frac{\partial T_s}{\partial x} = 0 \quad (5)$$

$$T_s = T_c \quad (6)$$

where T_c is the temperature of the thermostatic layer.

2.2. Meshing of the Computational Domain

Figure 2 presents the mesh of the computational domain. All areas tend to use the structured grid division. The geometry parameters of the computational domain, such as buried depth, wall thickness, and pipe diameter, might change in different samples. It is worth noting that the number of grids at the specific boundary is fixed even if geometry parameters are changed. This limitation can ensure that the connection relationship for grid cells is unchanged, even though the geometry parameters are different. Hence, the POD basis functions discussed below apply to the various geometry structures of the computational domain.

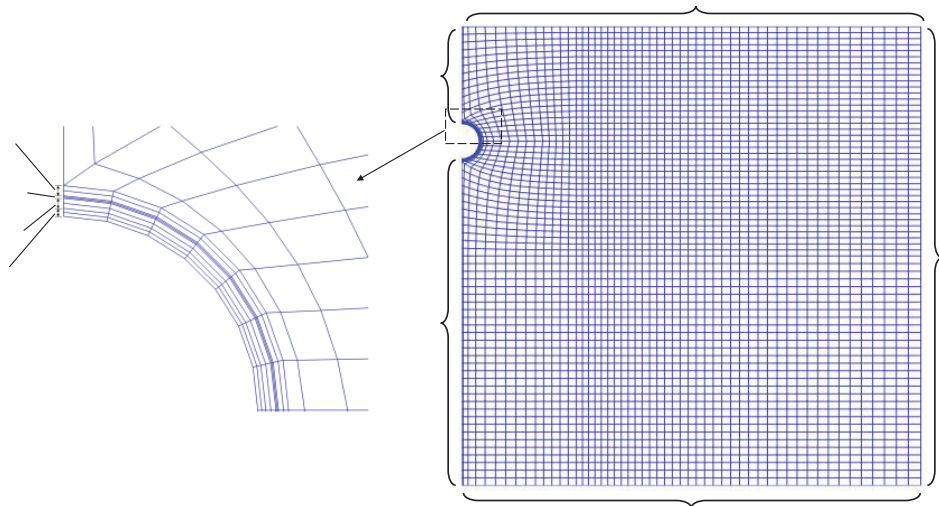


Figure 2. Mesh of the computational domain.

Specifically, the total number of grid cells is 3846, and the upper, lower, and right boundaries have 53, 53, and 68 grids, respectively, as presented in Figure 2. The left-upper, wax layer, and left-lower boundaries have 12, 14, and 42 grids, respectively. The wax, steel, corrosion protection, and virtual soil layers each have two grids for the pipe wall. The virtual soil layer is the meshing transition from the pipe wall to the soil, and its thermal properties are the same as the soil.

2.3. Calculation of the POD Basis Functions

POD can extract the characteristic information of the physical problem through its basis functions [24]. The POD basis functions are derived from the accurate results of multiple sampling conditions, which are calculated by the finite volume method (FVM) in this work [25]. The calculation of POD basis functions may need a large amount of computation, but it is a one-off effort.

Suppose the computational domain has N grid cells, the matrix of a single sample for the steady situation or unsteady situation with K recorded moments is constructed, as shown in Equation (7). The temperature values of all grid cells and moments in a certain sampling condition are saved in the same matrix, marked as $\mathbf{Q}$.

$$\mathbf{Q} = \begin{cases} \begin{bmatrix} T(\mathbf{x}_1) \\ T(\mathbf{x}_2) \\ \vdots \\ T(\mathbf{x}_{N-1}) \\ T(\mathbf{x}_N) \end{bmatrix} & \text{(Steady situation)} \\ \begin{bmatrix} T(\mathbf{x}_1, \tau_1) & T(\mathbf{x}_1, \tau_2) & \cdots & T(\mathbf{x}_1, \tau_{K-1}) & T(\mathbf{x}_1, \tau_K) \\ T(\mathbf{x}_2, \tau_1) & T(\mathbf{x}_2, \tau_2) & \cdots & T(\mathbf{x}_2, \tau_{K-1}) & T(\mathbf{x}_2, \tau_K) \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ T(\mathbf{x}_{N-1}, \tau_1) & T(\mathbf{x}_{N-1}, \tau_2) & \cdots & T(\mathbf{x}_{N-1}, \tau_{K-1}) & T(\mathbf{x}_{N-1}, \tau_K) \\ T(\mathbf{x}_N, \tau_1) & T(\mathbf{x}_N, \tau_2) & \cdots & T(\mathbf{x}_N, \tau_{K-1}) & T(\mathbf{x}_N, \tau_K) \end{bmatrix} & \text{(Unsteady situation)} \end{cases} \quad (7)$$

where τ is the simulation time step and $\mathbf{Q}$ is generated by FVM simulations. Furthermore, POD always applies to investigate various conditions, thus the $\mathbf{Q}$ of various sampling conditions should be assembled into the same matrix $\mathbf{S}$ to superimpose the influences of various conditions. It can be derived from Equation (7) that the matrix $\mathbf{Q}$ for the steady situation has only one column to describe one steady temperature field, while for the unsteady situation with K recorded moments, the matrix $\mathbf{Q}$ consists of K columns to describe multiple temperature fields. Considering that there are L kinds of sampling conditions, an entire sample matrix is constructed:

$$\mathbf{S} = [\mathbf{Q}_1 \quad \mathbf{Q}_2 \quad \cdots \quad \mathbf{Q}_{L-1} \quad \mathbf{Q}_L] \quad (8)$$

The basis functions are obtained by applying the singular-value decomposition method [26] to $\mathbf{S}$. When the row number N_r of $\mathbf{S}$ is smaller than its column number N_c , the basis functions are calculated by the following steps:

- Calculate the matrix $\mathbf{R}_{N_r \times N_r} = \frac{1}{N_c} \mathbf{S}_{N_r \times N_c} (\mathbf{S}_{N_r \times N_c})^T$;
- Orthogonally decompose the matrix $\mathbf{R}_{N_r \times N_r}$ and obtain a series of eigenvectors $\mathbf{w}_i$ ($i = 1, 2, 3, \dots, N_r$). Sort eigenvectors $\mathbf{w}_i$ by their corresponding eigenvalues.
- The basis functions are $\boldsymbol{\varphi}_i = \mathbf{w}_i$;
- If N_r is larger than N_c , the following steps are conducted:
 - Calculate the matrix $\mathbf{R}_{N_c \times N_c} = \frac{1}{N_r} (\mathbf{S}_{N_r \times N_c})^T \mathbf{S}_{N_r \times N_c}$;
 - Orthogonally decompose the matrix $\mathbf{R}_{N_c \times N_c}$ and obtain a series of eigenvectors $\mathbf{w}_i$ ($i = 1, 2, 3, \dots, N_c$). Sort eigenvectors $\mathbf{w}_i$ by their corresponding eigenvalues.
 - The basis functions are $\boldsymbol{\varphi}_i = \mathbf{S} \mathbf{w}_i$;
- In general, the matrix of basis functions is expressed as follows:

$$\Phi = \begin{cases} [\varphi_1 \ \varphi_2 \ \cdots \ \varphi_{L-1} \ \varphi_L] = \begin{bmatrix} \varphi_1(\mathbf{x}_1) & \varphi_2(\mathbf{x}_1) & \cdots & \varphi_{L-1}(\mathbf{x}_1) & \varphi_L(\mathbf{x}_1) \\ \varphi_1(\mathbf{x}_2) & \varphi_2(\mathbf{x}_2) & \cdots & \varphi_{L-1}(\mathbf{x}_2) & \varphi_L(\mathbf{x}_2) \\ \vdots & \vdots & \cdots & \vdots & \cdots \\ \varphi_1(\mathbf{x}_{N-1}) & \varphi_2(\mathbf{x}_{N-1}) & \cdots & \varphi_{L-1}(\mathbf{x}_{N-1}) & \varphi_L(\mathbf{x}_{N-1}) \\ \varphi_1(\mathbf{x}_N) & \varphi_2(\mathbf{x}_N) & \cdots & \varphi_{L-1}(\mathbf{x}_N) & \varphi_L(\mathbf{x}_N) \end{bmatrix} & \text{(Steady situation)} \\ \\ [\varphi_1 \ \varphi_2 \ \cdots \ \varphi_{L \times K-1} \ \varphi_{L \times K}] = \begin{bmatrix} \varphi_1(\mathbf{x}_1) & \varphi_2(\mathbf{x}_1) & \cdots & \varphi_{L \times K-1}(\mathbf{x}_1) & \varphi_{L \times K}(\mathbf{x}_1) \\ \varphi_1(\mathbf{x}_2) & \varphi_2(\mathbf{x}_2) & \cdots & \varphi_{L \times K-1}(\mathbf{x}_2) & \varphi_{L \times K}(\mathbf{x}_2) \\ \vdots & \vdots & \cdots & \vdots & \cdots \\ \varphi_1(\mathbf{x}_{N-1}) & \varphi_2(\mathbf{x}_{N-1}) & \cdots & \varphi_{L \times K-1}(\mathbf{x}_{N-1}) & \varphi_{L \times K}(\mathbf{x}_{N-1}) \\ \varphi_1(\mathbf{x}_N) & \varphi_2(\mathbf{x}_N) & \cdots & \varphi_{L \times K-1}(\mathbf{x}_N) & \varphi_{L \times K}(\mathbf{x}_N) \end{bmatrix} & \text{(Unsteady situation)} \end{cases} \quad (9)$$

where Φ is the matrix of basis functions and the number of basis functions is the same as the number of columns of $\mathbf{S}$; the single basis function φ_i follows orthogonality, i.e., $(\varphi_i, \varphi_j) = \delta_{ij}$. Based on the POD basis functions, the original sample sequence is expressed as follows:

$$\begin{cases} \begin{bmatrix} T(\mathbf{x}_1) \\ T(\mathbf{x}_2) \\ \vdots \\ T(\mathbf{x}_{N-1}) \\ T(\mathbf{x}_N) \end{bmatrix} = \sum_{m=1}^L a_m \varphi_m & \text{(Steady situation)} \\ \\ \begin{bmatrix} T(\mathbf{x}_1, \tau_j) \\ T(\mathbf{x}_2, \tau_j) \\ \vdots \\ T(\mathbf{x}_{N-1}, \tau_j) \\ T(\mathbf{x}_N, \tau_j) \end{bmatrix} = \sum_{m=1}^{L \times K} a_m(\tau_j) \varphi_m & \text{(Unsteady situation)} \end{cases} \quad (10)$$

where a_m is the spectrum coefficient and is equal to the following:

$$a_m = \begin{cases} ([T(\mathbf{x}_1) \ T(\mathbf{x}_2) \ \cdots \ T(\mathbf{x}_{N-1}) \ T(\mathbf{x}_N)]^T, \varphi_m) & \text{(Steady situation)} \\ \\ ([T(\mathbf{x}_1, \tau_j) \ T(\mathbf{x}_2, \tau_j) \ \cdots \ T(\mathbf{x}_{N-1}, \tau_j) \ T(\mathbf{x}_N, \tau_j)]^T, \varphi_m) & \text{(Unsteady situation)} \end{cases} \quad (11)$$

The POD basis functions can be arranged in descending order of eigenvalues, which represents the energy or necessities of each basis function. The front POD basis functions possess the most energy and are selected to characterize the physical problem. If the first M basis functions were used to approximately construct the temperature field, the original sequence is rewritten as follows:

$$\begin{cases} \begin{bmatrix} T(\mathbf{x}_1) \\ T(\mathbf{x}_2) \\ \vdots \\ T(\mathbf{x}_{N-1}) \\ T(\mathbf{x}_N) \end{bmatrix} \approx \sum_{m=1}^M a_m \varphi_m, M \leq L & \text{(Steady situation)} \\ \\ \begin{bmatrix} T(\mathbf{x}_1, \tau_j) \\ T(\mathbf{x}_2, \tau_j) \\ \vdots \\ T(\mathbf{x}_{N-1}, \tau_j) \\ T(\mathbf{x}_N, \tau_j) \end{bmatrix} \approx \sum_{m=1}^M a_m(\tau_j) \varphi_m, M \leq L \times K & \text{(Unsteady situation)} \end{cases} \quad (12)$$

2.4. Establishment of the POD-BP Prediction Model

In the classical POD reduced-order model, the spectrum coefficients are solved by the reduced-order governing equations when the basis functions are attempted to represent the predicted sample. In other words, there is a mapping between the predicted sample and its related spectrum coefficients, described by the reduced-order governing equations in the classical POD reduced-order method. However, the BP neural network substitutes the reduced-order governing equations to establish the mapping in this work. The following firstly introduces the construction of the dataset for the neural network, and then the entire calculation process of the POD-BP model is presented.

After obtaining the sample matrix and the POD basis functions, we can construct the spectrum coefficient matrix as the target data of the BP neural network. It is computed by the projection of the sample matrix to the basis functions matrix:

$$\mathbf{A} = [\boldsymbol{\varphi}_1 \quad \boldsymbol{\varphi}_2 \quad \cdots \quad \boldsymbol{\varphi}_{M-1} \quad \boldsymbol{\varphi}_M]^T \mathbf{S} = \begin{cases} \begin{bmatrix} a_{1,Q_1} & a_{1,Q_2} & \cdots & a_{1,Q_{L-1}} & a_{1,Q_L} \\ a_{2,Q_1} & a_{2,Q_2} & \cdots & a_{2,Q_{L-1}} & a_{2,Q_L} \\ \vdots & \vdots & \cdots & \vdots & \vdots \\ a_{M-1,Q_1} & a_{M-1,Q_2} & \cdots & a_{M-1,Q_{L-1}} & a_{M,Q_L} \\ a_{M,Q_1} & a_{M,Q_2} & \cdots & a_{M,Q_{L-1}} & a_{M,Q_L} \end{bmatrix} & \text{(Steady situation)} \\ \begin{bmatrix} a_{1,Q_1,\tau_1} & a_{1,Q_1,\tau_2} & a_{1,Q_1,\tau_3} & \cdots & a_{1,Q_L,\tau_{K-2}} & a_{1,Q_L,\tau_{K-1}} & a_{1,Q_L,\tau_K} \\ a_{2,Q_1,\tau_1} & a_{2,Q_1,\tau_2} & a_{2,Q_1,\tau_3} & \cdots & a_{2,Q_L,\tau_{K-2}} & a_{2,Q_L,\tau_{K-1}} & a_{2,Q_L,\tau_K} \\ \vdots & \vdots & \vdots & \cdots & \vdots & \vdots & \vdots \\ a_{M-1,Q_1,\tau_1} & a_{M-1,Q_1,\tau_2} & a_{M-1,Q_1,\tau_3} & \cdots & a_{M-1,Q_L,\tau_{K-2}} & a_{M-1,Q_L,\tau_{K-1}} & a_{M-1,Q_L,\tau_K} \\ a_{M,Q_1,\tau_1} & a_{M,Q_1,\tau_2} & a_{M,Q_1,\tau_3} & \cdots & a_{M,Q_L,\tau_{K-2}} & a_{M,Q_L,\tau_{K-1}} & a_{M,Q_L,\tau_K} \end{bmatrix} & \text{(Unsteady situation)} \end{cases} \quad (13)$$

where every column of $\mathbf{A}$ is regarded as a set of outputs of neural networks.

On the other hand, the input data of the BP neural network are derived from the preset parameters of samples, including boundary parameters, thermal property parameters, geometry parameters, and the simulation time step if there is an unsteady situation. It is apparent that, for all samples, the preset parameters and the associated output spectrum coefficients have a mapping and form a dataset. Then, a typical BP neural network [27,28], which usually has a two-layer feed-forward framework, sigmoid hidden neurons, and linear output neurons, is established, as shown in Figure 3. For the training process of the BP neural network, the dataset is split into training, validation, and testing sets in a ratio of 7:1.5:1.5, and the Levenberg–Marquardt algorithm is implemented [29,30].

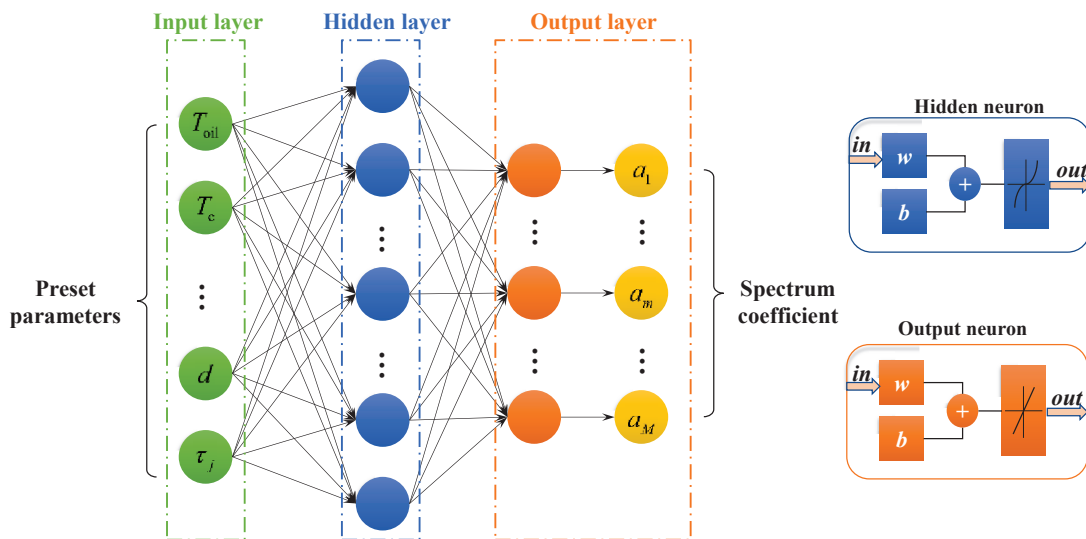


Figure 3. The BP neural network used to predict the spectrum coefficients through the input of preset parameters of the sample.

The predicted spectrum coefficients of the BP neural network can be used to reconstruct the temperature field by substituting them into Equation (12). The entire calculation process of the POD-BP model is presented in Figure 4.

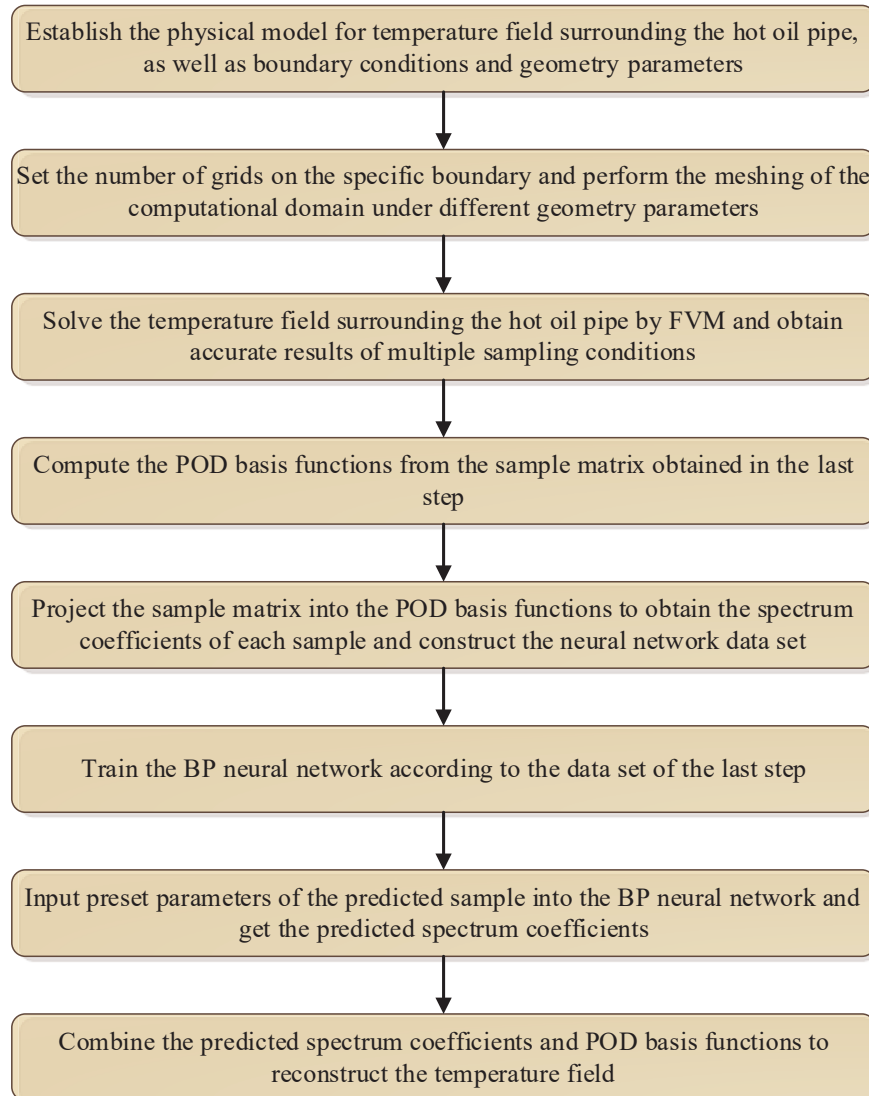


Figure 4. The entire calculation process of the POD-BP model to predict the temperature field surrounding the hot oil pipe.

3. Results and Discussion

This section employs the POD-BP model to predict the soil temperature field for both steady and unsteady situations. The accuracy of the prediction results is testified by comparing them with the results of FVM.

First, the parameters, which are constant for all sampling conditions, are given. The wax layer, steel layer, corrosion protection layer, and virtual soil layer thicknesses are fixed at 0.016 m, 0.02 m, 0.005 m, and 0.02 m, respectively. The specific heat capacities of wax, steel, corrosion protection, and soil are $2100 \text{ J}\cdot\text{kg}^{-1}\cdot^\circ\text{C}^{-1}$, $465 \text{ J}\cdot\text{kg}^{-1}\cdot^\circ\text{C}^{-1}$, $1670 \text{ J}\cdot\text{kg}^{-1}\cdot^\circ\text{C}^{-1}$, and $1010 \text{ J}\cdot\text{kg}^{-1}\cdot^\circ\text{C}^{-1}$, respectively, and their densities are $910 \text{ kg}\cdot\text{m}^{-3}$, $7800 \text{ kg}\cdot\text{m}^{-3}$, $1200 \text{ kg}\cdot\text{m}^{-3}$, and $1700 \text{ kg}\cdot\text{m}^{-3}$, respectively. The thermal conductivities of wax, steel, and corrosion protection are $2.5 \text{ W}\cdot\text{m}^{-1}\cdot^\circ\text{C}^{-1}$, $48.0 \text{ W}\cdot\text{m}^{-1}\cdot^\circ\text{C}^{-1}$, and $0.15 \text{ W}\cdot\text{m}^{-1}\cdot^\circ\text{C}^{-1}$, respectively. For the boundary parameters, the convective heat transfer coefficients of oil and atmosphere are fixed at $100 \text{ W}\cdot\text{m}^{-2}\cdot^\circ\text{C}^{-1}$ and $20 \text{ W}\cdot\text{m}^{-2}\cdot^\circ\text{C}^{-1}$, respectively.

Tables 1 and 2 list the sampling conditions, which are also the preset parameters of samples. They are solved by FVM with an algebraic multigrid solver, and the results are used to form the sample matrix. There are three boundary parameters, three values of soil heat conductivity, and eight kinds of geometry structures with different buried depths and pipe internal diameters. The sampling conditions are generated by the permutation and combination of parameters, with 648 cases in total.

Table 1. Boundary and property parameters of samples.

Boundary Parameters			Property Parameter	Geometry Parameter
T_{oil} (°C)	T_c (°C)	T_a (°C)	λ_s (W·m ⁻¹ ·°C ⁻¹)	
30	−5	−20	0.8	Geo 1–Geo 8 (See Table 2)
50	5	0	1.4	
70	15	20	2.0	

Table 2. Geometry parameters of samples in Table 1.

Geo No.	Geo 1	Geo 2	Geo 3	Geo 4	Geo 5	Geo 6	Geo 7	Geo 8
H_0 (m)	1.0	1.0	1.5	1.5	1.5	2.5	2.5	2.5
d (m)	0.5	0.8	0.5	0.8	1.0	0.5	0.8	1.0

The five validation cases supposed to be predicted by the POD-BP model are presented in Table 3. The values of preset parameters are all different from Tables 1 and 2. In particular, Cases 3–5 involve the parameters out of the sampling range, increasing the prediction difficulty. The two boundary parameters and one property parameter are out of the sampling range in Case 3, the two geometry parameters are out of the sampling range in Case 4, and the two boundary parameters and one geometry parameter are out of the sampling range in Case 5.

Table 3. Preset parameters of the validation cases.

Case No.	T_{oil} (°C)	T_c (°C)	T_a (°C)	λ_s (W·m ⁻¹ ·°C ⁻¹)	H_0 (m)	d (m)
Case 1	45	−3	−10	0.9	2.0	0.9
Case 2	60	0	8	1.0	1.5	0.6
Case 3	80 *	10	25 *	2.5 *	1.7	0.7
Case 4	35	−4	15	1.6	0.8 *	0.4 *
Case 5	75 *	−10 *	12	1.8	2.8 *	0.8

* means that this value is outside the sampling range.

The error is defined to evaluate the accuracy of the proposed model quantitatively:

$$\varepsilon_i = \left| \frac{T^{\text{POD-BP}}(\mathbf{x}_i) - T^{\text{FVM}}(\mathbf{x}_i)}{T_{\max}^{\text{FVM}} - T_{\min}^{\text{FVM}}} \right| \times 100\% \quad (14)$$

where ε_i is the error of the i th grid cell; superscripts ‘POD-BP’ and ‘FVM’ mean the results calculated by the POD-BP model and FVM, respectively; and superscripts ‘max’ and ‘min’ are maximum and minimum values, respectively, of the temperature field.

3.1. Steady Situation

With the singular-value decomposition method, 648 basis functions are obtained for the steady situation. The eigenvalue λ_n , energy contribution ζ_n , and accumulative energy ω_n of the first eight basis functions are presented in Table 4. It can be observed that the first six basis functions account for more than 99.9% of the total energy. However, they can only capture the main characters of the physical problem, and the subsequent basis functions are also necessary to capture the exact information in local places. Figure 5 can illustrate this point. The first and second basis functions have continuous and regular contours

covering the entire area, while the fifteenth and twenty-fifth represent the heterogeneity and randomness of the temperature field. For this physical problem, the first twenty-five basis functions are employed in the POD-BP model after the independent test of the selected basis function number, as presented in Table 5. The projected spectrum coefficients of samples are used to reconstruct the approximate temperature field. If the difference between the approximate temperature field and FVM results of samples is small enough, the number of basis functions is sufficient.

Table 4. Eigenvalues of the first eight POD basis functions in the steady situation.

n	1	2	3	4	5	6	7	8
λ_n	9.47×10^8	1.73×10^8	4.55×10^7	2.46×10^7	2.45×10^6	1.13×10^6	1.51×10^5	3.85×10^4
ζ_n	79.338	14.475	3.810	2.058	0.205	0.0950	0.0127	0.00323
ω_n	79.338	93.813	97.623	99.681	99.886	99.981	99.994	99.997

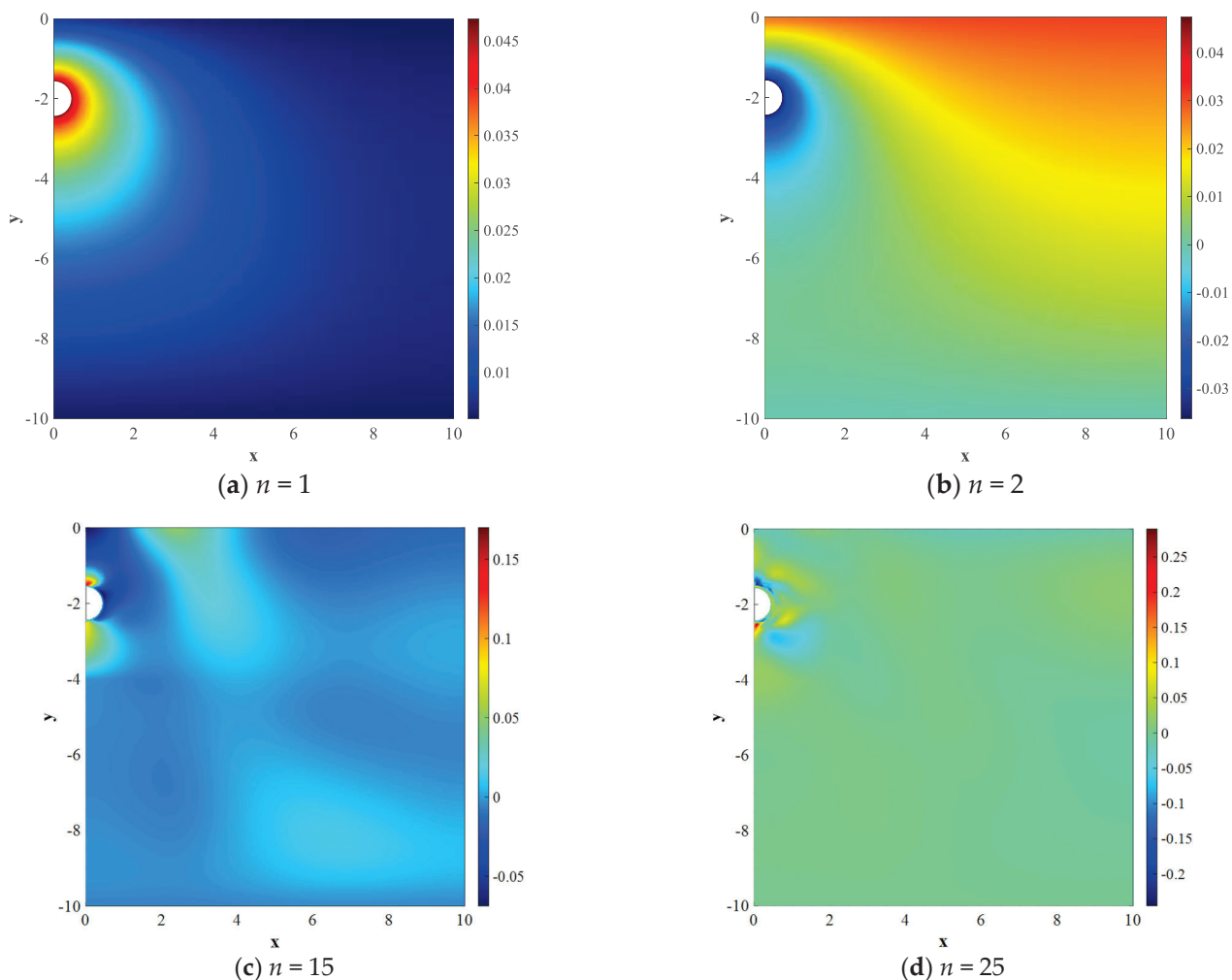


Figure 5. Distributions of the typical POD basis functions applied to the steady situation.

Table 5. Independency test of the selected basis function number.

Number of Basis Functions	5	10	20	25
Average approximation error of all samples through Equation (12)	0.4629 °C	0.0370 °C	0.0011 °C	3.2972×10^{-4} °C

Fifteen hidden neurons and twenty-five output neurons are used to construct the two-layered BP neural network, and the BP neural network is trained according to the

spectrum coefficients and preset parameters of samples. The training process takes 345 s. The decay of the mean squared error with epochs and the regression plot of the testing set are shown in Figure 6. The mean squared error is from the sum of all grid cells and finally becomes approximately invariant. The correlation coefficient approaches one, thus the trained BP neural network can fit well with the mapping relationship between the input and output. Then, the preset parameters of five validation cases are inputted into the BP neural network to obtain the predicted spectrum coefficients. After that, substituting the predicted spectrum coefficients into the basis functions can reconstruct the predicted temperature field. Figure 7 presents the comparison of predicted temperature fields and accurate results. The POD-BP model successfully captures the temperature distribution trends of cases with different boundary conditions, thermal properties, and geometry parameters. It can be seen that the contours of the predicted temperature field are very consistent with the accurate results around the hot oil pipe, where the high-temperature gradient lies. The deviation of contours is larger on the region far from the pipe because the temperature changes are slight and hard to capture. There is no distinct regularity of error distribution among cases, as shown in the right subgraphs of Figure 7.

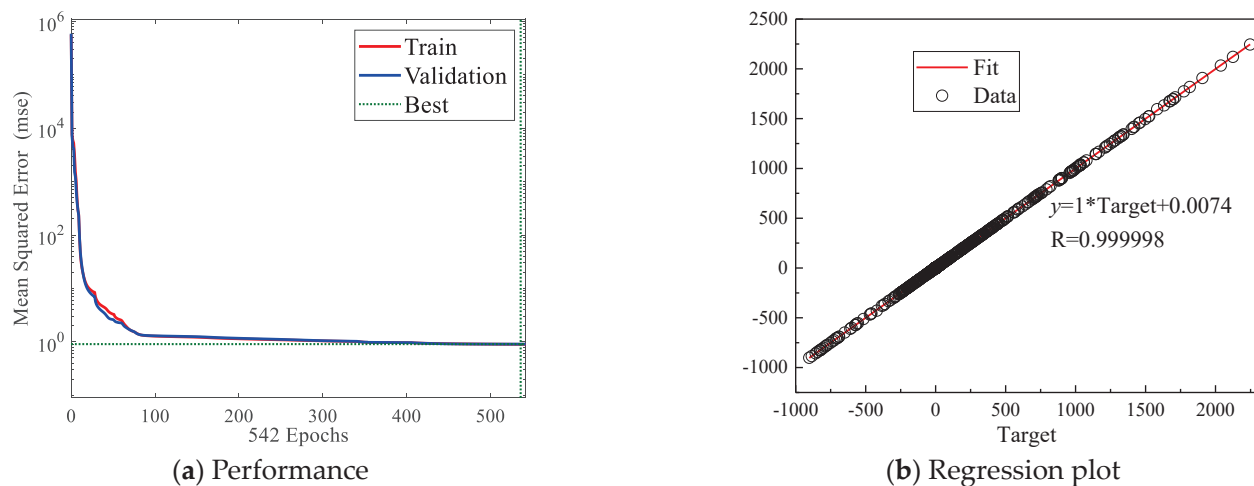


Figure 6. For the BP neural network of the steady situation, (a) evolution of mean squared error with epochs and (b) regression plot of the testing set.

The mean error and maximum error are shown in Table 6. Cases 1–4 have an error smaller than 2.599%, 2.247%, 0.406%, and 1.403%, respectively, but there is a relatively larger error for Case 5, which can reach 6.035%. This is because of the fact that Case 5 has both the boundary parameters (or property parameters) and geometry parameters outside the sampling range, making the temperature distribution significantly different from the samples.

Table 6. Mean and maximum errors of multiple cases in the steady situation.

Case No.	Case 1	Case 2	Case 3	Case 4	Case 5
$\bar{\epsilon}$	0.845%	0.748%	0.124%	0.390%	3.052%
$\epsilon_{\max}$	2.599%	2.247%	0.406%	1.403%	6.035%

On the whole, the POD-BP model has high accuracy in predicting the steady temperature field surrounding the hot oil pipe and, in particular, it can successfully capture the variation caused by geometry parameters.

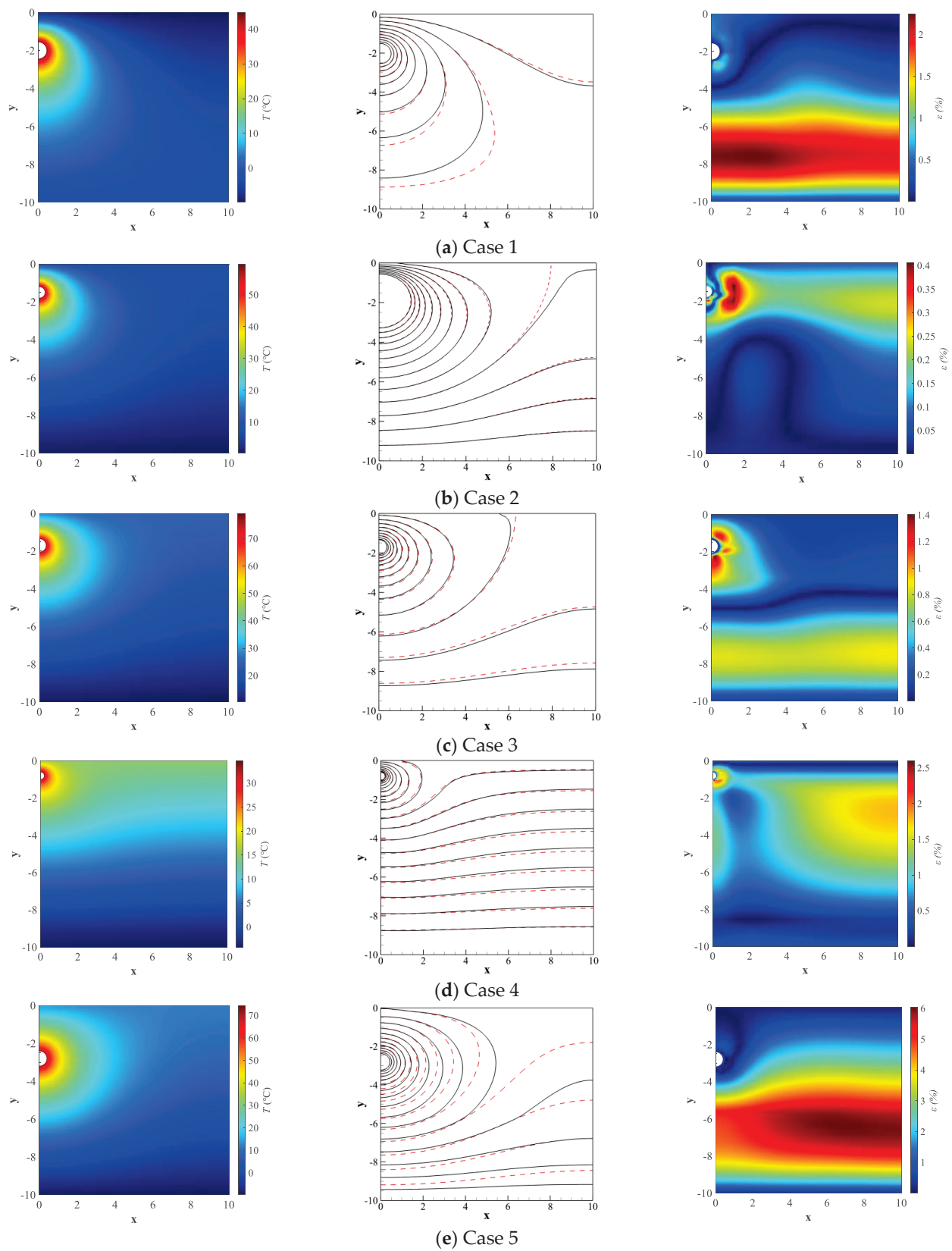


Figure 7. Prediction results of the POD-BP model in the steady situation. The left subgraphs are accurate temperature distributions obtained by the FVM, the middle subgraphs are comparisons of contours of POD-BP prediction (dashed line) and FVM solutions (solid line), and the right subgraphs are error distributions.

3.2. Unsteady Situation

For the unsteady situation, the initial temperature field is required for the simulation, and it is assumed that there is a linear distribution between T_a and T_c from the ground surface to the thermostatic layer. The calculation period is ten days and the discretized time step of the FVM is half an hour. However, the recorded time step used to establish the sample matrix is six hours, which ensures the computed size of the sample matrix is correct. Hence, each sampling condition has 40 temperature fields related to different moments, and the size of the sampling matrix is $3846 \times$.

According to the singular-value decomposition method, 25,920 basis functions are obtained for the unsteady situation. Table 7 presents the eigenvalues, energy contribution, and accumulative energy of the first eight basis functions. It is observed that the first six basis functions can account for 99.9% of the total energy. Similar to the steady situation, the first and third basis functions have continuous distributions and significant gradients around the pipe, while the fifteenth and twenty-fifth basis functions have heterogeneous distributions to capture the local information, as shown in Figure 8. The first thirty basis functions are employed in the POD-BP model to predict the unsteady temperature field.

Table 7. Eigenvalues of the first eight POD basis functions in the unsteady situation.

n	1	2	3	4	5	6	7	8
λ_n	1.53×10^{10}	8.84×10^9	1.10×10^9	4.08×10^8	5.51×10^7	3.83×10^7	6.81×10^6	2.82×10^6
ζ_n	59.381	34.345	4.282	1.584	0.214	0.149	0.0265	0.0109
ω_n	59.381	93.726	98.008	99.593	99.807	99.956	99.982	99.993

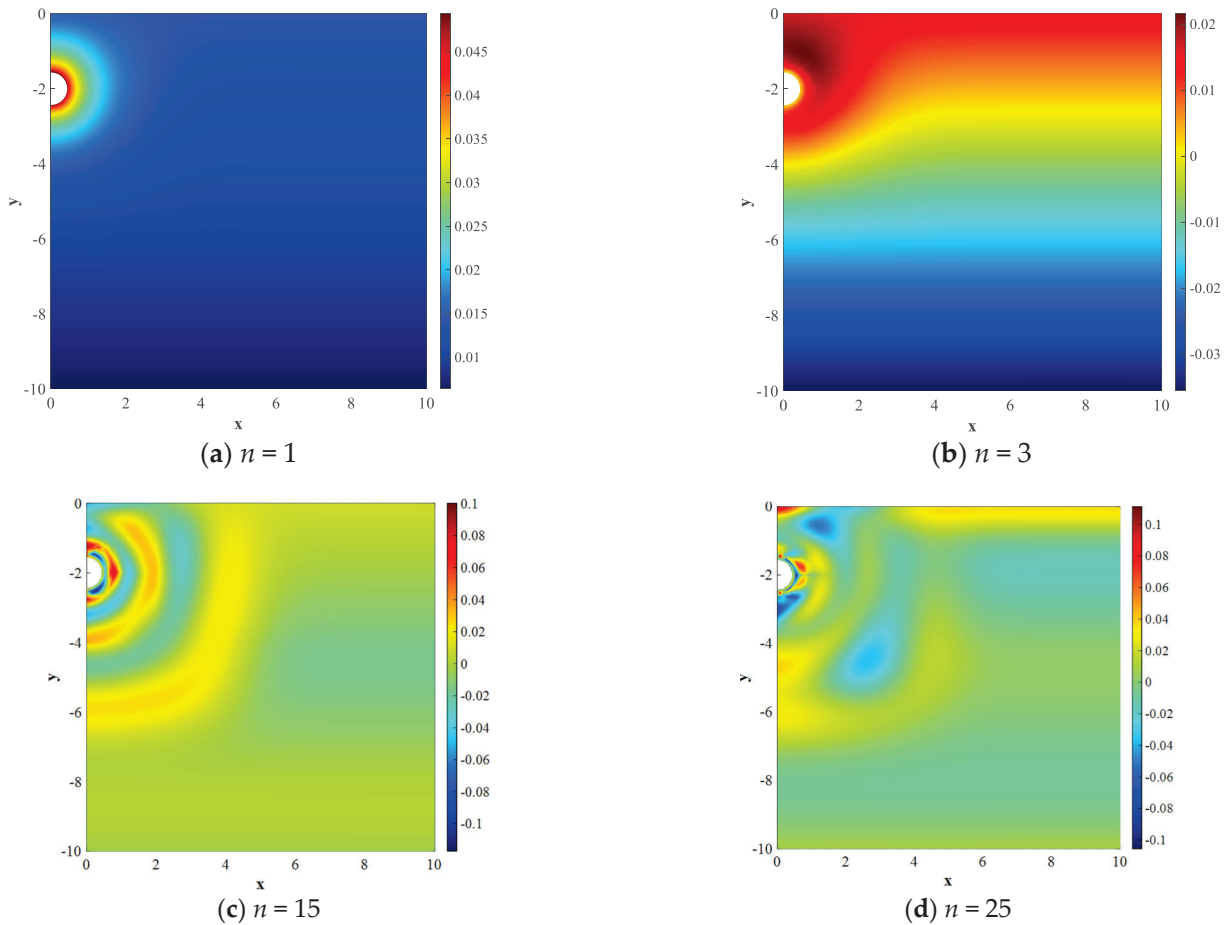


Figure 8. Distributions of the typical POD basis functions applied to the unsteady situation.

The BP neural network consists of fifteen hidden neurons and thirty output neurons, and its training process takes 2778 s. Figure 9 shows the performance with epochs and the regression plot of the testing set for the trained BP neural network. After that, the preset parameters of five validation cases corresponding to the second and tenth days are inputted into the BP neural network to obtain the predicted spectrum coefficients. Figures 10 and 11 present the comparison of predicted temperature fields and accurate results for the second and tenth days, respectively. It can be observed that our present model can effectively calculate the temperature evolution with time, in which the region having distinct temperature disturbance becomes larger. In general, the POD-BP model can obtain temperature fields and contours comparable to the accurate results in the unsteady situation.

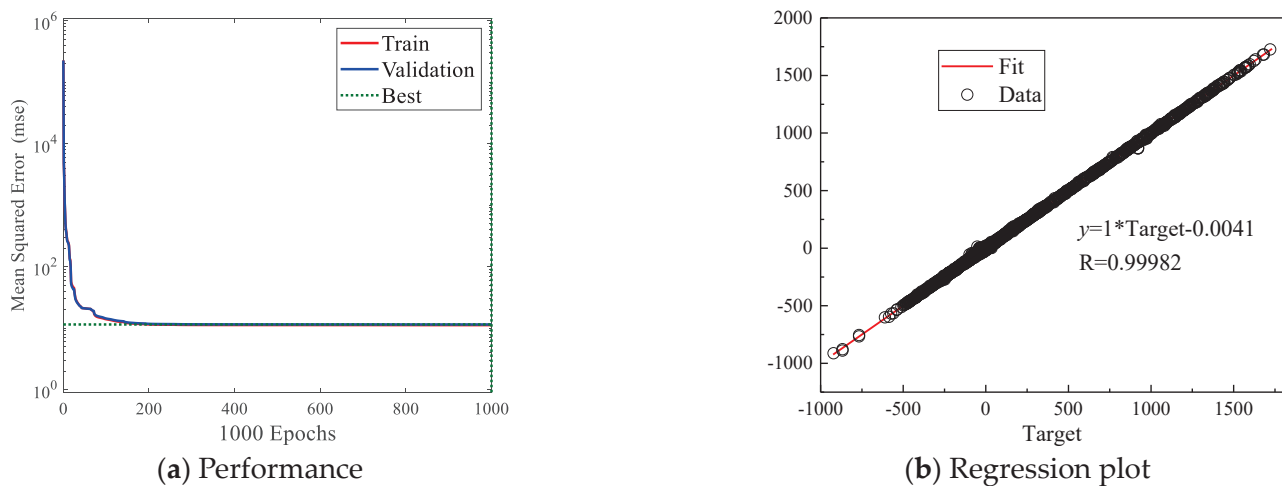


Figure 9. For the BP neural network of the unsteady situation, (a) evolution of mean squared error with epochs and (b) regression plot of the testing set.

Table 8 presents the quantitative errors of five cases at the moments of the second day and tenth day, where the mean error of the PO-BP model is 0.133~1.439% and the maximum error falls at 0.885~7.058%. Appealingly, the 10-day simulation of FVM needs around 70 s to compute, while the POD-BP model consumes a very short time that can be ignored. This is because the neural network is applied directly in the POD-BP model, and no discretization equations of spectrum coefficients are solved.

Table 8. Mean and maximum errors and computational time of multiple cases in the unsteady situation.

		Case No.	Case 1	Case 2	Case 3	Case 4	Case 5
Prediction moment	2nd day	$\bar{\varepsilon}$	0.260%	0.166%	0.310%	0.623%	1.359%
		$\varepsilon_{\max}$	3.956%	2.139%	1.471%	3.165%	2.906%
	10th day	$\bar{\varepsilon}$	0.133%	0.133%	0.424%	1.439%	1.316%
		$\varepsilon_{\max}$	0.885%	0.905%	2.180%	7.058%	2.739%
Computational time	FVM		67 s	74 s	68 s	70 s	71 s
	POD-BP		0.008 s	0.008 s	0.008 s	0.008 s	0.008 s

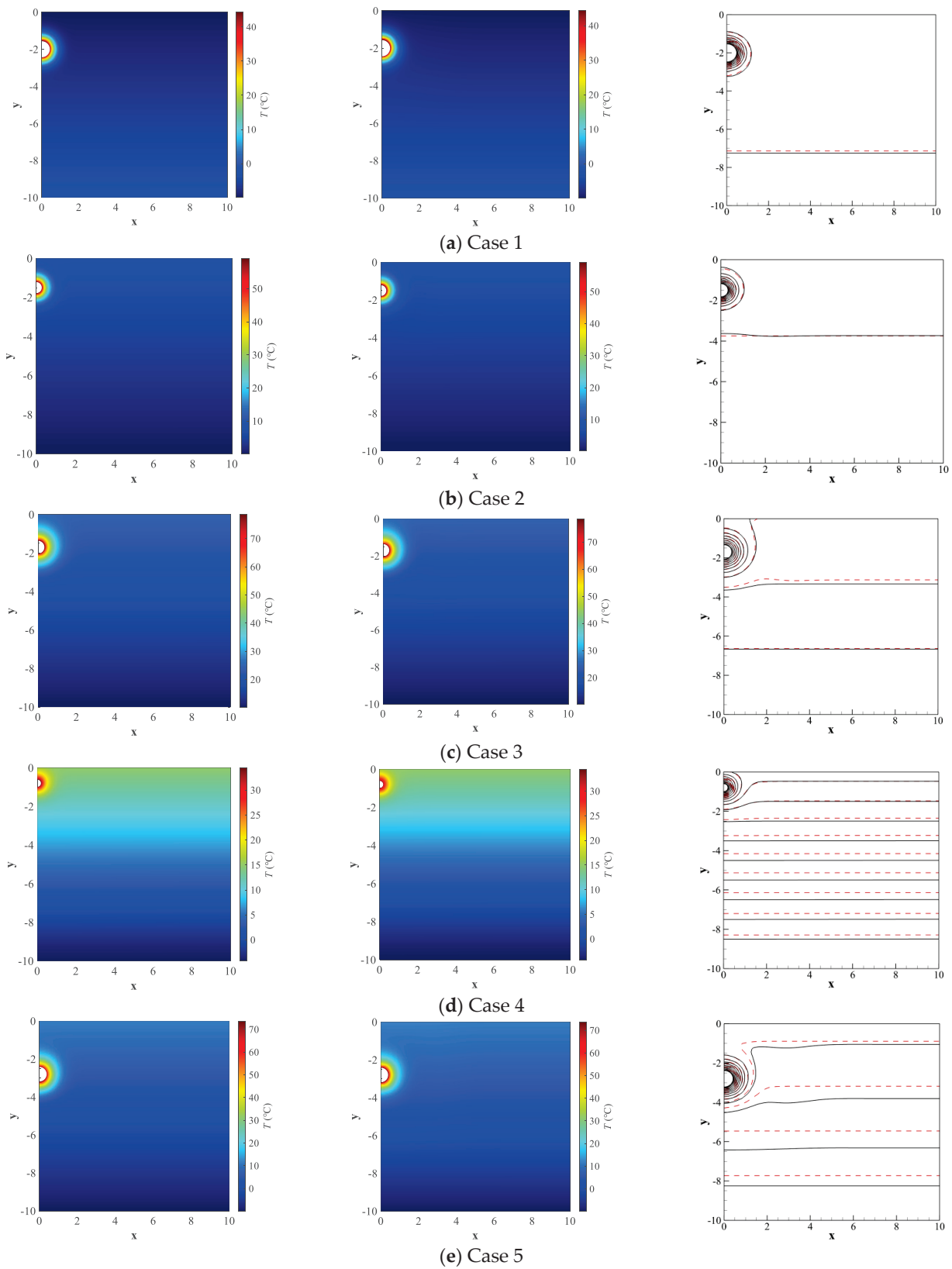


Figure 10. Prediction results of the POD-BP model in the unsteady situation on the second day. The left subgraphs are accurate temperature distributions obtained by the FVM, the middle subgraphs are POD-BP results, and the right subgraphs are comparisons of POD-BP predicted contours (dashed line) and FVM solutions (solid line).

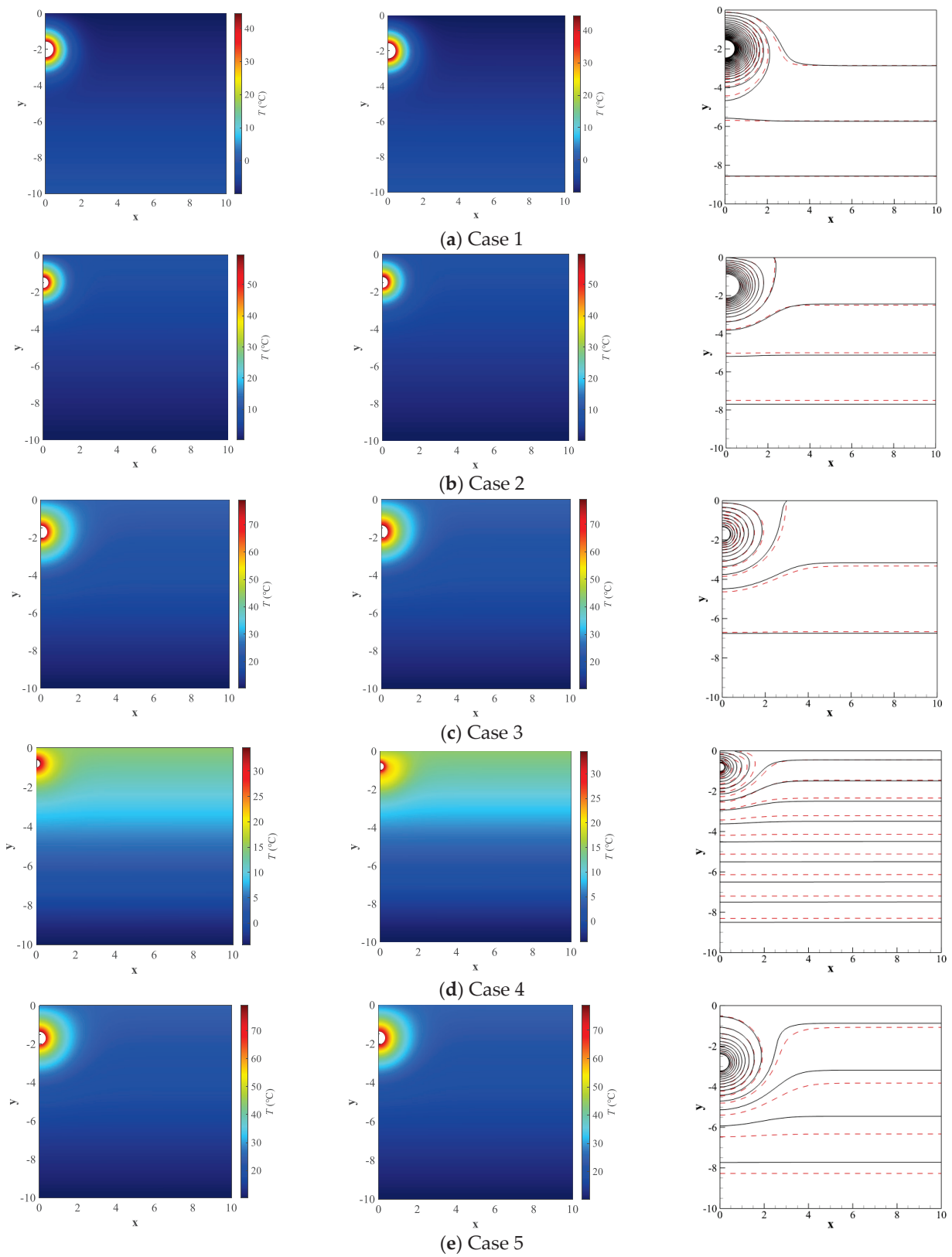


Figure 11. Prediction results of POD-BP in the unsteady situation on the tenth day. The left subgraphs are accurate temperature distributions obtained by the FVM, the middle subgraphs are POD-BP results, and the right subgraphs are comparisons of POD-BP predicted contours (dashed line) and FVM solutions (solid line).

4. Conclusions

The fast prediction of the temperature field surrounding a hot oil pipe is important for the optimal design and risk assessment of the pipeline system. This paper proposes a novel POD-BP model to predict the temperature field surrounding a hot oil pipe efficiently. Unlike the classical POD reduced-order model, the BP neural network is adopted here to directly output the spectrum coefficients of the predicted sample according to its preset parameters. Moreover, introducing the BP neural network can omit the complex mathematical derivation of reduced-order governing equations and the solving of the spectrum coefficients system.

Then, we use the presented model to predict the temperature field surrounding the hot oil pipe in both steady and unsteady situations. The sample matrix is constructed based on the numerical results of FVM with 3846 grid cells. Three boundary parameters, one thermal property, and eight geometry structures are selected as the preset parameters of samples, which are comprehensive and rigorous for verification. Five validation cases with completely different preset parameters, including geometry parameters of buried depth and pipe diameter, are tested. The results show that our model can predict the temperature fields comparable to the FVM; the mean errors are 0.845~3.052% and 0.133~1.439% for steady and unsteady situations, respectively; and the max errors are 0.406~6.035% and 0.885~7.058%, respectively. What is more important is that there is almost no computation time for unsteady prediction using our model.

Our future work will concentrate on improving the prediction accuracy of the POD-BP model. First, an advanced network framework, such as the Bayesian neural network, can replace the two-layered BP network to robustly capture the mapping relationship. Second, the preset parameters of samples and recorded time steps in the unsteady situation will be optimized to obtain a series of basis functions with more accuracy.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Roman Symbols

a_m	Spectrum coefficient
A	Matrix of spectrum coefficients
c_p	Specific heat capacity, $\text{J}\cdot\text{kg}^{-1}\cdot^\circ\text{C}^{-1}$
d	Inner diameter of the steel pipe, m
h_a	Heat transfer coefficient between the soil and air, $\text{W}\cdot\text{m}^{-2}\cdot^\circ\text{C}^{-1}$
h_{oil}	Heat transfer coefficient between the oil and the wax layer, $\text{W}\cdot\text{m}^{-2}\cdot^\circ\text{C}^{-1}$
H_0	Buried depth, m
K	Number of recorded moments
L	Number of sampling conditions
M	Number of selected basis functions
N	Number of grid cells
Q	Single sample matrix
S	Entire sample matrix
t	Time, s

T	Temperature, °C
T_a	Atmosphere temperature, °C
T_c	Temperature of the thermostatic layer, °C
T_{oil}	Hot oil temperature, °C
x, y	Cartesian coordinate, m
Greek Symbols	
δ_1	Thickness of the wax layer, m
ε_i	Error of the i th grid cell
φ	Single basis function
Φ	Matrix of basis functions
λ	Thermal conductivity, $W \cdot m^{-1} \cdot ^\circ C^{-1}$
λ_n	Eigenvalue of the n th basis function
ζ_n	Energy contribution of the n th basis function
ω_n	Accumulative energy of the first n basis functions
ρ	Density, $kg \cdot m^{-3}$
τ	Simulation time step
Subscripts	
1, 2, 3, s	Layers of wax, steel, corrosion protection, and soil

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Article

Optimal Scheduling Strategy of Wind Farm Active Power Based on Distributed Model Predictive Control

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Abstract: In recent years, the development and utilization of China's wind energy resources have been greatly developed, but the large-scale wind power grid connection has brought threats to the safe and stable operation of the power grid. In order to ensure the stability of the power grid, it is necessary to reduce wind power output fluctuation and improve the tracking accuracy of dispatch instructions. Therefore, based on the distributed model predictive control of wind farm active power distribution strategy, an ultra-short-term wind power hybrid deep learning predictive model is proposed. The prediction results of a wind farm in North China show that the hybrid neural network model can achieve high ultra-short-term wind power prediction accuracy and is suitable for active power control prediction models. A two-layer distributed model is proposed to predict the active power control architecture of wind farms by implementing the clustering process with the Crow Search Algorithm. The distributed model predictive control strategy is proposed in the upper layer, and the centralized model predictive control algorithm is adopted in the lower control structure and optimized. The results show that the dual-layer distributed model predictive control strategy can better track the active power distribution instructions, reduce output fluctuation and scheduling value changes, and enhance the robustness of active power regulation, which is suitable for active power online control in wind farms.

Keywords: GCN-LSTM; ultra-short-term wind power prediction; wind farms; distributed model predictive control; active power control

1. Introduction

Energy is the foundation of human survival and social development. Global climate change, environmental pollution, and rising energy costs are increasingly becoming urgent issues that need to be addressed by countries. The twentieth report also pointed out the need to actively and steadily promote carbon peaking and carbon neutrality, improve the control of total energy consumption and intensity, and promote the clean, low-carbon, and efficient utilization of energy [1]. The wind power installed capacity has been increasing year by year, and the scheduling and control strategies of wind power electricity systems are leading the development of energy into a new era. It is imperative to design effective and reliable strategies for controlling the active power of wind power.

The traditional active power control strategies of wind farms often adopt the feedback correction method and only use the power and load value to carry out active power control. The control strategies adopted, such as equal proportional distribution, variable proportional distribution, and sequential cutting machine, are based on a single and poor active power control precision and have lagged in time, lack flexibility, and effectiveness [2]. The output of the wind turbine always fluctuates randomly and the instructions issued by the dispatching department are constantly changing. Only a fixed single standard is used to

classify the units, resulting in a decrease in the coordination degree between active power scheduling and system instructions. The specific classification index of the cluster has poor adaptability to the adjustment and change of the dispatching instructions, and cannot meet the needs of accurate control of active power, and the active power loss is greatly increased. Therefore, it is necessary to establish a more accurate wind power prediction model, and at the same time consider the coupling and constraints between different cluster individuals to implement distributed control. Such an active power control strategy is more targeted, conducive to improving control accuracy, smoothing wind power fluctuations, and making full use of wind power consumption space.

Artificial Neural Network (ANN) [3] and support vector machine are representative machine learning methods. Zhou et al. combined pole symmetric mode decomposition, extreme learning machine, and particle swarm optimization algorithm to build a short-term wind power prediction model. The average absolute percentage error in the experiment was less than 5%, and this method achieved a more accurate prediction effect [4]. Support vector machine is often combined with the meta-heuristic intelligent optimization algorithm. Lu et al. used the gray wolf optimization algorithm to optimize the kernel function parameters of the multi-output support vector machine model, and predicted the wind power of 15 wind farms, outperforming other benchmark models in terms of multiple error indicators such as improvement percentage [5]. Li et al. combined the improved Dragonfly algorithm with a support vector machine, and its model effectiveness was verified on the real data set of French wind farms, which is suitable for short-term wind power prediction [6]. In recent years, the traditional machine learning method has developed slowly in improving the accuracy of wind power prediction. The deep learning method based on large-scale and multidimensional data has been increasingly applied in the field of wind power prediction because of its powerful mapping ability. Deep learning methods widely used in wind power prediction include recurrent neural networks [7,8], convolutional neural networks, deep belief networks [9,10], and generative adversarial networks [11,12]. Among them, a convolutional neural network generally does not predict wind power alone but is often combined with a recurrent neural network or other intelligent optimization algorithms to build prediction models [13]. Duan et al. used a variational mode decomposition (VMD) technique to extract the local characteristics of the original wind power sequence, using long short term memory (LSTM) and a deep belief network built based on particle swarm optimization sequence prediction model, multiple child sequence prediction model by the nonlinear weighted combination, the short-term wind power prediction sequence [14] is obtained. From the above analysis, it can be seen that the current research on wind power prediction has certain shortcomings, such as failing to make full use of the spatial characteristics of wind turbines, and not considering the changes in the non-European spatial layout of wind turbines and environmental factors [15]. Therefore, finding a suitable method to simultaneously apply spatial state timing features and wind power series to wind power prediction, improving the utilization of spatially relevant information, mining spatial-temporal data associations, and referencing to numerical weather prediction (NWP) data are the keys to improving the accuracy of wind power prediction.

With the continuous development of wind power generation technology, the installed capacity of wind power continues to rise, which will put forward higher requirements on the active power distribution and output curve smoothing of wind farms. Literature [16] carries out active power control for a wind farm composed of double-fed induction generators. The central control layer sends power reference signals to each wind turbine separately, and the local wind turbine control layer ensures that the single machine tracks active power instructions. Literature [17] classifies wind turbines according to the statistics of the actual operating conditions of fans and ultra-short-term power prediction results and adjusts the output of fans according to the ranking table of active power regulation ability. The essence of the above method is the static optimal scheduling control of multiple moments, and only the current optimization of the control point is considered. Different from traditional

open-loop scheduling control methods, model predictive control designs predictive models for concerned system variables and uses rolling optimization and closed-loop feedback correction to optimize control in the time domain, which is widely used in the field of new energy scheduling control [18]. The flexibility and fast dynamic performance of model predictive control (MPC) make it have obvious advantages in dealing with various practical complex problems, and formulate corresponding strategies to deal with various problems in the development process of wind power, so as to achieve multi-dimensional control goals. In order to reduce the fatigue load of wind turbines and take into account the high impedance ratio of the wind farm collector, Guo et al. proposed a distributed active power control strategy based on MPC to achieve optimal control of the pitch angle and generator torque of wind turbines and track the power reference value delivered by the system [19]. The main control objective of the literature [20] is that MPC controller can minimize the change of wind turbine axial force while solving the reference power. The effectiveness of the strategy is verified through a parallel large eddy simulation case study. Based on MPC, literature [21] designed prediction models in the time domain for optimization at different time scales, and set decision objectives according to different warning levels of new energy to ensure sufficient absorption space for wind power and improve the economy of system operation. Literature [22] proposes the application of finite control set model predictive control to power electronic devices of wind farms, aiming to improve the dynamic performance of static reactive compensators with the shortest execution time. This strategy has been verified in 10 MW wind farms.

In recent years, many scholars have carried out research on distributed model predictive control of wind farms. Literature [23] uses the distributed idea to coordinate the control actions among wind turbines affected by wake interaction and uses the iterative distributed control method to improve wind power utilization and reduce turbine load. Literature [24] established a piece-based static model based on input variables and state variables to represent the nonlinearity of wind turbines. After validity verification, it was applied to a distributed MPC prediction model to achieve optimal active power control objectives of scheduling instruction tracking and load minimization. From the above analysis, it can be seen that the current research on wind power prediction has certain shortcomings, such as failing to make full use of the spatial characteristics of wind turbines, and not considering the changes in the non-European spatial layout of wind turbines and environmental factors [15].

In previous studies, most researchers focused on the construction of state-space models, which largely relied on the linearization of nonlinear models and were not suitable for wind power changes with high noise and strong uncertainty. In addition, the above control methods do not directly consider the dynamic characteristics of wind power. Although the tracking accuracy of active power instructions has improved to a certain extent, the static control structure and method are not flexible and lag compared with the scheduling instructions of changes, and the power distribution lacks rationality and balance. When dispatching instructions are issued, the working state of the wind turbine should be considered first. The dynamic power characteristic parameters are used to cluster the fans and then carry out distributed active power control, which can adapt to different changes in dispatching instructions, improve the wind power absorption rate, and smooth the output curve.

2. Ultra-Short Term Wind Power Prediction Based on Graph Convolutional Networks-Long Short Term Memory (GCN-LSTM) Deep Neural Network

In order to improve the accuracy of ultra-short-term wind power forecasts, a neural network model has become a common method in recent years. Both short-term and long-term memory networks for time series prediction effect are good. The convolutional neural networks (CNN) are often combined with the LSTM model and are used to make up for the large amount of network computing and the defects of slow convergence speed. However, CNN can only process the data of the European space, which makes the

topological information such as the location information of the wind farm not utilized. To make full use of the time-series data of wind farm and space information, improve the wind power prediction accuracy, fine regulation of wind turbines, first of all, use map CNN processing, coupling information fusion associated with topological structure of the fan, then multi-dimensional local spatial features of wind turbines are extracted, and deep-seated representations are sent into LSTM network for power prediction. An ultra-short-term wind power prediction method based on GCN-LSTM deep neural network is proposed. Finally, a domestic wind farm is taken as an example for simulation verification.

2.1. Construction of Hybrid Deep Learning Prediction Model

At present, the deep learning prediction model of wind power mostly adopts a single time series analysis method, which only considers the power value and the change of NWP data in the time dimension. Whether it is the management of wind turbines or the prediction of wind power, it is often carried out in the basic unit of the station, rather than for a single wind turbine, and the biggest influencing factor of wind power—wind speed—always acts on all wind turbines in a space.

2.1.1. Graph Structure and Predictive Model Input Data

From the perspective of space, the geographical location, which is also one of the characteristics of wind turbines, represents the spatial correlation and dependence of each wind turbine [25], which plays a certain importance in wind power prediction. Based on this idea, the non-European spatial layout of the wind farm enables it to be constructed as a graph structure suitable for graph convolutional networks (GCN).

Using the wind turbine coordinates of the wind farm and the actual line connection, the diagram structure as shown in Figure 1 is generated. Each wind turbine is a node, and the connection line between two wind turbines is the edge. The characteristics of each wind turbine node include four dimensions, namely power, wind speed, wind direction, and temperature. The last three dimensions can be obtained from the NWP data of the wind farm. Thus, the structure, type, and scale of the graph are determined, and the basic input parameter matrix required by the GCN network is obtained.

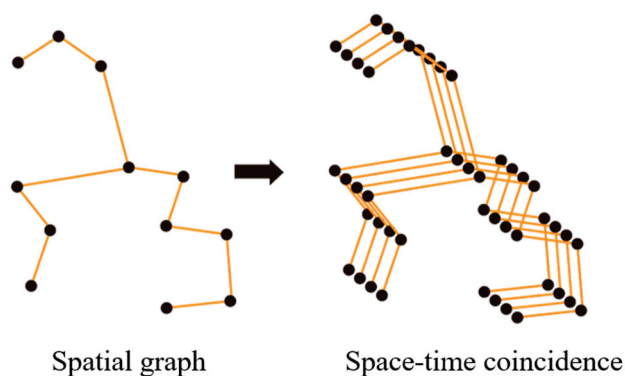


Figure 1. Generates a graph structure for predicting model inputs.

2.1.2. Construction of Wind Power Prediction Model in GCN-LSTM Network

NWP data and historical wind power data are used as the input of the GCN-LSTM prediction model, and the predicted wind power value is used as the output.

As the number of network layers increases, the receptive field becomes larger and larger, that is, the characteristics of the wind turbine node integrate the historical data of the local machine and more units. All the information in the graph is aggregated by graph convolution, and the first-order embedded representation of each wind turbine node is obtained after updating. The intuitive convolution diagram of the graph is shown in Figure 2. Multi-order neighbor information is obtained after multi-layer GCN. After obtaining the feature matrix $H(i)$ of each node after multi-layer GCN, it is taken as the

final node representation and fed into the downstream LSTM network. Finally, the parallel LSTM unit of GCN-LSTM obtains the time dependence from each node and obtains the prediction result sequence.

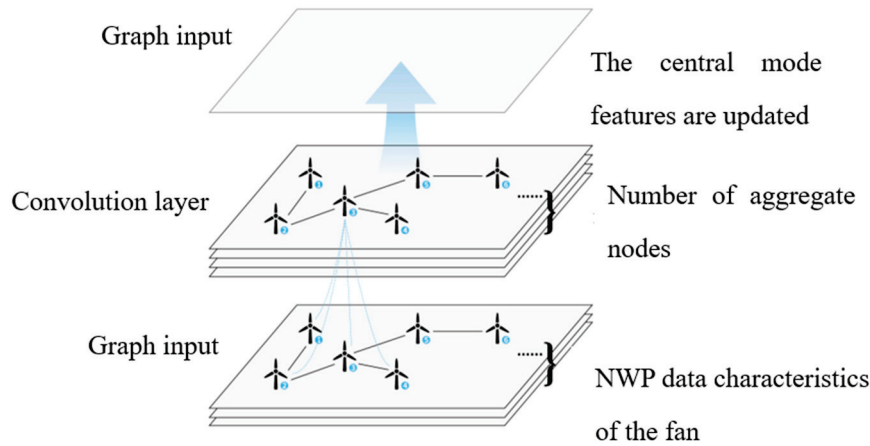


Figure 2. Schematic diagram of the convolution process.

At present, GCN is more suitable for shallow network structures. Due to the simple structure of a one-layer GCN network, the feature extraction power of the wind power data set is insufficient, while gradient disappearance and overfitting problems are easy to occur in a three-layer convolutional network structure, so two-layer GCN is used in the experiment.

GCN and LSTM are used to jointly build deep-learning models. The constructed prediction model consists of two layers of GCN, three layers of LSTM, one layer of Dropout, and one layer of fully connected layer. The ultra-short-term wind power prediction model based on GCN-LSTM is shown in Figure 3.

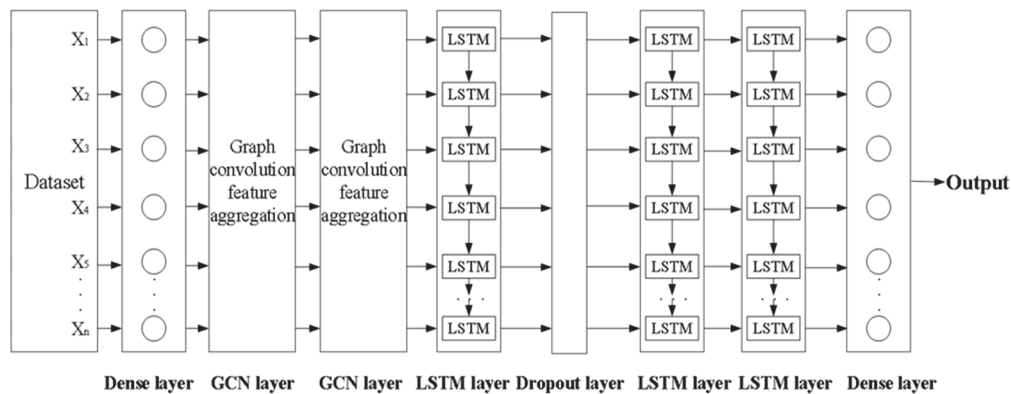


Figure 3. GCN-LSTM prediction model network structure.

The operation process of the GCN-LSTM deep learning ultra-short-term wind power prediction model is described as follows:

- (1) The input layer data set uniformly passes the input data to the next layer of the neural network.
- (2) Excavation and dimensionality reduction in deep features by two GCN layers.
- (3) The first LSTM layer learns the autocorrelation between the NWP data and the deep information of the spatial dimension of the wind turbine and the wind power in time and passes it to the next layer.
- (4) The operation performed by the Dropout layer is to randomly delete a portion of hidden neurons, preventing deep learning from overfitting.

- (5) The second and third LSTM layers further conduct neural network self-learning on the information coming from the front to improve the accuracy of nonlinear fitting of the power prediction model.
- (6) The network outputs wind power sequence through the final fully connected layer, rolling prediction for each cycle.

2.2. Analysis of Experiments and Examples

The data used to establish the study came from the measured data of a wind farm in North China in 2021, and the data used included four-time series of wind speed, wind direction, temperature, and wind power. The learning samples of the power prediction model may contain unreasonable data, and there are often missing data or data anomalies. The data anomaly of the learning sample weakens the correlation between the data and the wind power and affects the convergence speed and accuracy of the training algorithm. Therefore, in order to obtain accurate prediction results, it is necessary to preprocess the data.

2.2.1. Data Preprocessing and Experimental Design

The historical data of each sample of wind turbines include several dimensional characteristics of wind speed, wind direction, and temperature. The max-minimum normalization of the data of the characteristic dimension of each sample of wind turbines is carried out, respectively, as shown in Formula (1), and the original data is converted into a unified order of magnitude.

$$\tilde{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}, i = 1, 2, \dots, n \quad (1)$$

where: x_i is the original meteorological data of samples such as measured wind speed and temperature, $\tilde{x}_i$ is the normalized data, $x_{\max}$ and $x_{\min}$ represents the maximum and minimum values of the data set, respectively, and n is the number of samples.

In order to obtain the best LSTM parameter values, a model optimization algorithm is designed. The results show that the RMS error of the model is the smallest when the LSTM of three layers and the number of neurons in each layer are 32, 64, and 32, respectively. Therefore, the number of hidden layers of LSTM is finally selected as 3, and the number of neurons in each layer is 32, 64, 32. The GCN-LSTM prediction model can obtain the best prediction effect when the time sliding window size is 7 and the batch size is 16.

Finally, the experimental parameter settings of GCN-LSTM wind power prediction are obtained, which are described as follows. The weight matrix of GCN is randomly initialized in $[0, 1]$, and the adjacency matrix size of GCN is 3×3 , which is equivalent to the convolution kernel size of traditional convolutional neural networks. To achieve a single-step prediction of wind power, each read starts from the next row next to each other. The LSTM network time step is 7. The training parameter Settings of the LSTM network are shown in Table 1. lr is the learning rate, which controls the rate of weight updating; shuffle is true, and its representation randomly sorts the training data set before each training.

Table 1. LSTM network training parameter Settings.

Parameter Name	Parameter Value
Number of iterations	100
Batch_size	16
Learning rate	0.001
Dropout Layer weight	0.1
Activation function	sigmoid

Root mean square error (RMSE) and mean absolute error (MAE) are selected as statistical indicators of wind power prediction error. MAPE, mean absolute percentage error

(MAPE) [26,27]. The specific expressions of RMSE, MAE, and MAPE are as follows: (2) to (4):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (x'(i) - x(i))^2} \quad (2)$$

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |x'(i) - x(i)| \quad (3)$$

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^N \left| \frac{x'(i) - x(i)}{x(i)} \right| \times 100\% \quad (4)$$

where: $x(i)$ is the actual value, $x'(i)$ is the predicted value, and N is the number.

2.2.2. Analysis of Example Results

After the pre-processing of abnormal and missing data, the wind power sequence of 12 wind turbines in the wind farm is shown in Figure 4.

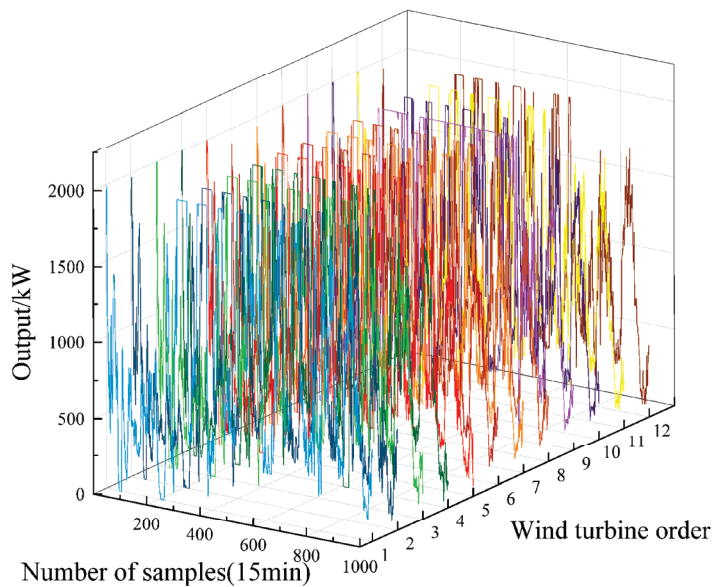


Figure 4. Ultra-short-term wind power forecast data set of wind turbines.

LSTM model, CNN-LSTM model, and GCN-LSTM model are used to compare and analyze the actual power curves and predicted power values of different wind turbines, as shown in Figure 5a,c. These show that the power predicted by the LSTM model with small fluctuations in a short time always tends to change linearly with time. It is because the ReLU function adopted by the LSTM layer is a piecewise linear function, and the filling of missing test data is also linear, resulting in an approximately horizontal line. However, the phenomenon that the forecast trend of LSTM is completely opposite to the actual value at some points is because LSTM focuses on the analysis of historical wind power, and can not make good use of the relationship between data when the power fluctuation is small.

The average prediction error and prediction time of different models are shown in Table 2. The prediction errors of the GCN-LSTM network for different wind turbine sizes are shown in Table 3, and the evaluation indexes of prediction errors for different wind turbine sizes are shown in Figure 6. The RMSE value of the GCN-LSTM network model is the smallest. Compared with GCN-LSTM, the CNN-LSTM model is slightly slower, because the training process of CNN takes a long time. After the sample is fused and dimensionality reduction through the GCN network, the total prediction time is shortened by the LSTM layer.

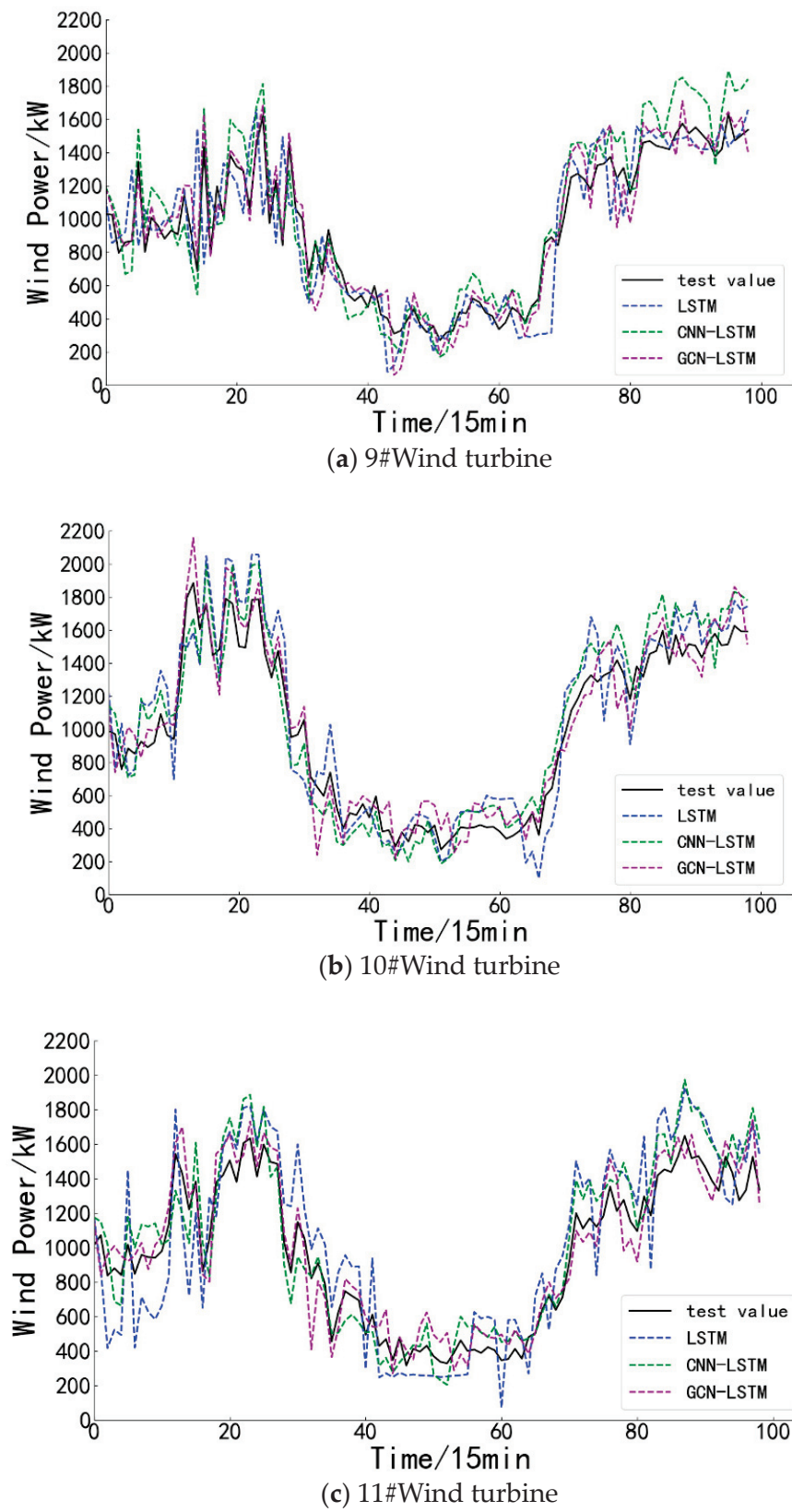


Figure 5. Cont.

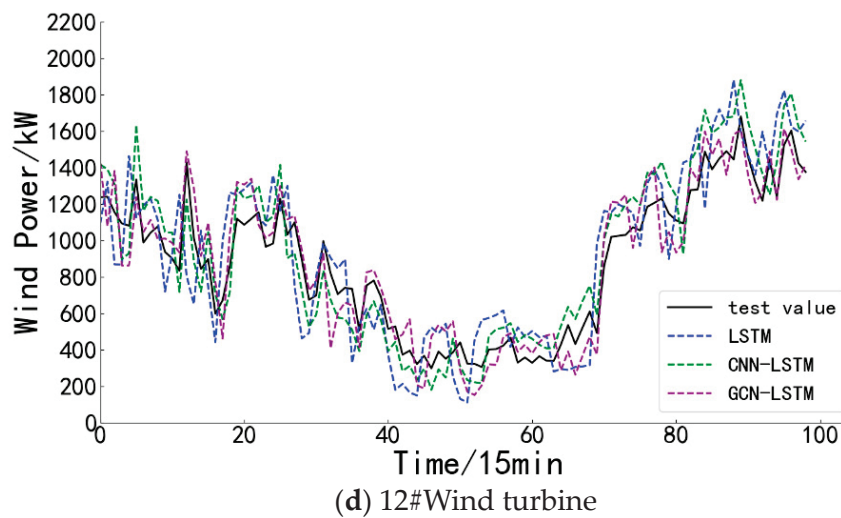


Figure 5. Wind power prediction curves of different models.

Table 2. Average prediction error and prediction time of different models.

Prediction Model	RMSE	MAE	MAPE (%)	Forecast Time/s
LSTM	240.75	199.98	27.12	61.2
CNN-LSTM	158.13	142.62	18.17	72.8
GCN-LSTM	137.88	115.66	16.05	68.5

Table 3. GCN-LSTM network prediction errors for different wind turbine sizes.

Wind Turbine Size	RMSE	MAE	MAPE (%)
Wind turbine group 1	133.16	106.80	15.67
Wind turbine group 2	138.24	110.36	14.68
Wind turbine group 3	138.85	122.44	17.83
Wind turbine group 4	141.62	125.40	16.87
Wind power plant	137.88	115.66	16.05

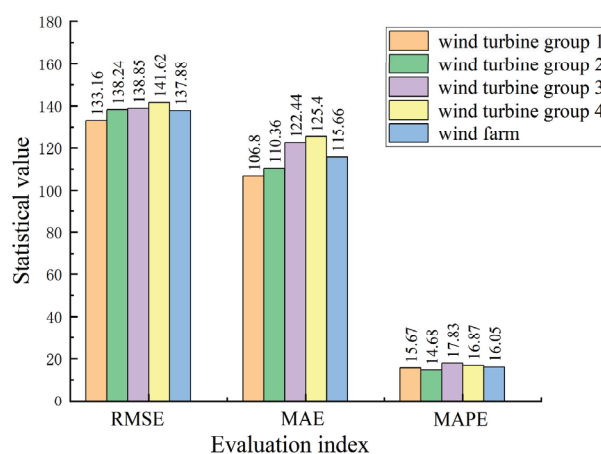


Figure 6. Prediction error evaluation index values of different wind turbine sizes.

As can be seen from Table 3, the three error evaluation indexes of wind farms are smaller than those corresponding to most wind turbine clusters, which indicates that the larger the wind turbine scale, the smaller the fluctuation of wind power value, and the smaller the prediction error of wind power by the proposed GCN-LSTM model. The GCN-LSTM deep learning model has achieved a more ideal effect for the power prediction

of multiple wind turbines. The proposed model is not only suitable for the ultra-short-term wind power prediction of a single wind turbine but also suitable for the ultra-short-term wind power prediction of wind turbine groups and the whole field.

3. Cluster Strategy for Wind Turbines Based on Improved K-Means Clustering Algorithm

When optimizing active power control of wind farms, a centralized strategy or single-machine fine modeling strategy can be selected. However, the active power generation capacity of each fan is different, and the centralized strategy often reduces the reliability of the control, and cannot ensure that the control signal is calculated within a fixed time interval. However, the single-machine refined strategy requires solving multiple parameters in the wind farm during the simulation process, which leads to the increase in data storage and the excessive calculation burden of the controller, which greatly improves the simulation performance. On the other hand, wind turbines frequently track scheduling instructions and significantly change output, which is not conducive to reducing the climb rate and mechanical losses of fans. In order to take into account the fine control of the active power of the wind farm, optimize the computational efficiency of the control model, smooth the output of the wind farm, and solve the problem that the K-means clustering results are sensitive to the initial centroid, a K-means clustering method based on Crow Search Algorithm is proposed in the optimal scheduling of the active power of the wind farm by adopting the distributed control strategy of machine cluster division. It mainly studies the fan clustering method that is friendly to wind farm scheduling, designs four clustering indexes that can characterize the active power characteristics of fans from multiple angles, optimizes the optimal initial clustering center through the Crow Search Algorithm, and finally groups fans based on the K-means clustering method.

3.1. K-Means Clustering Algorithm Principle

K-means cluster analysis is a cluster analysis algorithm for iteratively solving sample objects, which is widely used in many fields. The important steps of complete cluster analysis include choosing the distance function, running the clustering algorithm, and evaluating clustering validity. The K-means clustering algorithm divides the feature matrix X of a group of N samples into K clusters without intersection and considers that the data in a cluster belong to the same class. Clustering is the result of clustering. The mean of all the data in a cluster is often called the Centroids of the cluster. In a two-dimensional plane, the horizontal coordinate of the center of mass of a data sample is the mean of the horizontal coordinate of the data cluster, and the vertical coordinate of the center of mass is the mean of the vertical coordinate of the data cluster. The same can be generalized to higher dimensions. The implementation of the clustering algorithm is described below. First, input N P -dimensional sample vectors, specify the maximum number of iterations as t_{max} and the number of clusters as K , and then randomly select K samples as the initial centroid. For each of the remaining sample points, the Euclidean distance or some other distance function from K centroids is traversed and assigned to the cluster with the smallest centroid distance. Based on the total sample data assigned to each previous centroid, the mean of all objects in each cluster is recalculated to obtain the new centroid. Repeat the steps to calculate the distance and determine the cluster where the center of mass is located. The difference between the old centroid and the new centroid is calculated. When the difference is less than the threshold value, the centroid does not move significantly, the samples in the cluster do not change, or the maximum number of iterations is reached, and the clustering results are divided.

3.2. Wind Turbine Cluster Index Design

Based on the wind speed and power characteristics of wind turbines, the smooth coefficient, active power trend index, generation potential coefficient, and anomaly coefficient are proposed as clustering indexes of wind turbines.

In order to quantify and distinguish the difference of active power output in the volatility of the time dimension, the index smoothness coefficient reflects the smoothness of the power curve of each wind turbine [28], and the fluctuation degree of active power of the wind turbine becomes one of the clustering considerations.

The adjacent active power points are fitted linearly by the least square method. The slope of the obtained line represents the trend of active power change of the unit, and the fitting slope is defined as the active power trend index.

In order to make full use of the available power of the wind farm and ensure the safety of the transmission channel, the proper dispatching command is sent to the less-than-full load unit, and the generation potential of the wind turbine is quantified and characterized.

Using the anomaly data identification method in literature [29], scattered points with substandard tightness are identified as anomalies. In this paper, the anomaly coefficient is used to characterize the numerical characteristics of abnormal data points.

3.3. Improved K-Means Clustering Algorithm for Wind Turbine Clustering

To solve the problem that the classical K-means clustering algorithm cannot achieve the global optimal clustering result because of its strong dependence on the initial clustering center, the Crow Search Algorithm is used to improve the clustering accuracy and clustering stability, so that several wind turbines with multidimensional similarity are clustered into a cluster to achieve the best clustering effect.

The change of the measured wind speed and power of the wind turbine and the predicted value of the active power limit the search space of the crow within a certain range, so the feasibility of the new position should be judged after each update of the position. As the result of CSA optimization is the clustering center of the K-means algorithm, the final value should be within the upper and lower limits of the characteristic indicators calculated by each wind turbine. The mathematical model to check the feasibility of crow position is expressed as the following Formula (5):

$$\mathbf{X}^{i,iter+1} = \begin{cases} \mathbf{X}^{i,iter+1}, & \min([r_s \ r_a \ r_p \ r_{P-V}]) \leq \mathbf{X}^{i,iter+1} \leq \max([r_s \ r_a \ r_p \ r_{P-V}]) \\ \mathbf{X}^{i,iter}, & \text{o.w.} \end{cases} \quad (5)$$

where: For the D-dimensional search space, the position vector of the i th crow at the $iter$ iteration is $\mathbf{X}^{i,iter} = [x_1^{i,iter}, x_2^{i,iter}, \dots, x_d^{i,iter}]$, where, $iter = 1, 2, \dots, iter_max$, $i, j = 1, 2, \dots, N_c$.

4. Active Power Control Strategy of Wind Farm Based on Distributed MPC

While the global wind power installed capacity continues to increase, the amount of abandoned wind is still high, and the active power regulation ability of wind farms still needs to be improved. The traditional centralized control method has high requirements on the central controller and poor parallel computing ability. In order to optimize the utilization of wind energy resources and fine-tune the on-site wind turbines, it is necessary to study how to actively control the active power output of the wind farm effectively, and how to coordinate the changes of wind power and superior scheduling instructions, so that the issued scheduling instructions can maintain the local optimal within each control time and adapt to the uncertain environment. Therefore, a two-layer active power control method for wind farms is proposed, which is divided into different scales in time and space to control the active power of wind farms.

4.1. Hierarchical Active Power Scheduling Strategy for Wind Farms

The static scheme adopted by the traditional active dispatching control has high efficiency but a relatively simple structure, which does not consider the objective factors such as the difference in wind conditions and power generation status of each fan, ignores the uncertainty of wind power generation, and has a low degree of intelligence. In order to achieve the safe and stable operation of the system we must improve the active power control accuracy of wind farms, improve the tracking accuracy of wind farm active power

dispatching instructions, carry out active adjustments according to the deep power characteristics of wind turbines, smooth wind power output curve and make full use of wind power consumption space, etc., create an operation control scheme from the perspective of multi-time scale active control management strategy of wind farm, and formulate a double-layer distributed active power dispatching.

4.1.1. Multi-Time Scale Active Power Control Management Strategy

In order to smooth the wind power output curve and improve the wind power consumption rate, active power control strategies are developed for different time scales. Based on the idea of “multi-level coordination and step-by-step refinement”, a multi-time scale active power control management strategy is constructed based on the time scale of intra-day rolling scheduling and real-time online rolling scheduling plans, as shown in Figure 7. Based on the measured active power output value, the deviation of the daily plan is corrected in real-time to reduce the unbalance of power caused by uncertainty. With the shortening of the time scale, the precision of the active power control plan increases, and the active power tracking becomes more accurate.

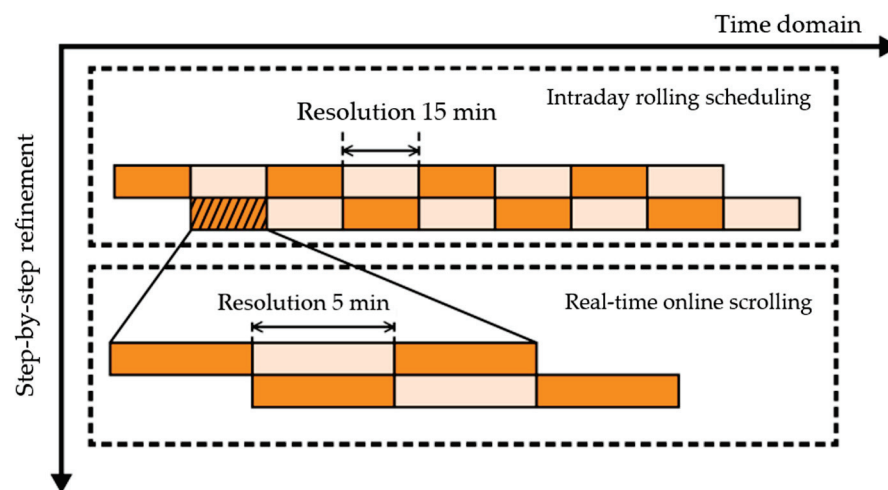


Figure 7. Schematic diagram of multi-time scale active power control management for wind farms.

4.1.2. Hierarchical Control Framework for Active Power of Wind Farm

The hierarchical control strategy for the active power of wind farms based on distributed MPC can be expressed in the following Figure 8. In this paper, GCN-LSTM deep neural network model is used to forecast ultra-short-term wind power. Four clustering criteria are formulated by combining the measured power values, predicted power values, and dynamic temporal correlation of power over a period of time. The improved K-means clustering algorithm proposed based on CSA aggregates wind turbines into several clusters, and makes effectiveness evaluation according to evaluation indicators.

4.2. Design and Solution of Dual-Layer Distributed Active Power Prediction Controller for Wind Farms

The key to a two-layer distributed active predictive control strategy for wind farms lies in the realization of distributed model predictive control.

The wind farm is divided into multiple wind turbine clusters by using the improved K-means clustering algorithm. The DMPC controller corresponding to each cluster calculates the optimal active power command sequence according to the measured value of the past state, the predicted value of the future state, and information shared by the neighbor subsystem. The first of these values is sent to the MPC controller in the lower wind turbine balancing layer. The DMPC of each subsystem shares information through the communication network. In addition, the DMPC controller needs to take into account the synergies and constraints between the various clusters. The DMPC controller is optimized

to realize the optimal control and stable operation of wind power active power. The design and solving methods of each layer model predictive controller are introduced below.

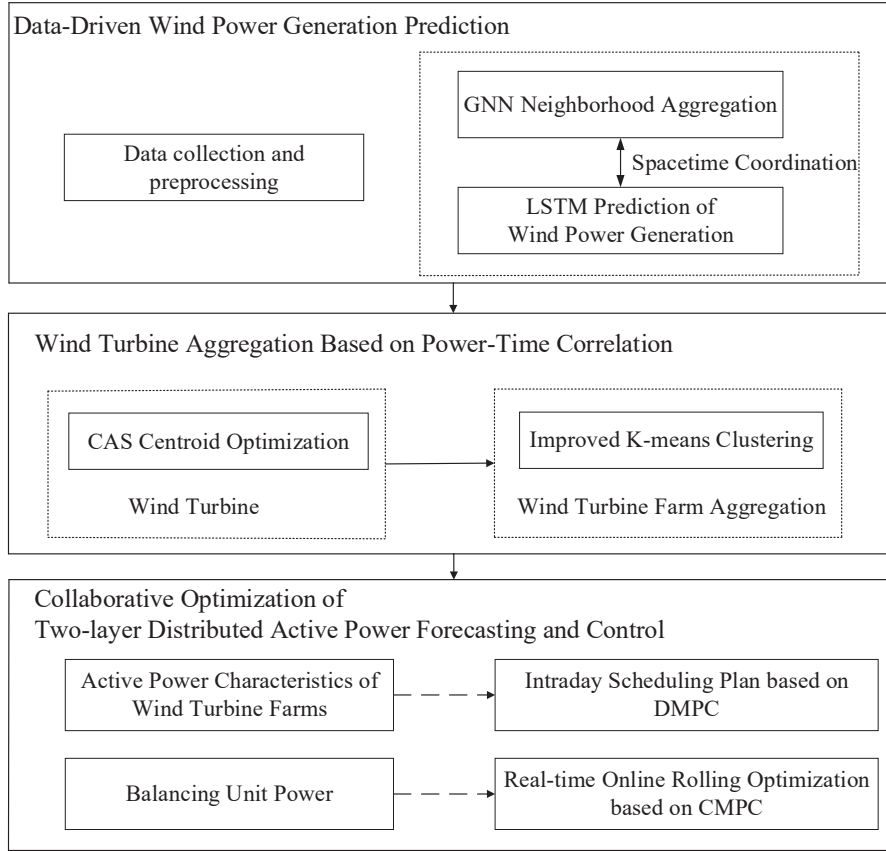


Figure 8. Optimal control strategy for active power of wind farm based on distributed model predictive control.

4.2.1. Design of Upper Layer DMPC Controller Based on Scheduling Coordination Dynamic Index Optimization Method

In this paper, the scheduling coordination dynamic index active power optimization strategy is applied to the distributed active power predictive control layer, and the relationship between the clustered index and the upper control is established. The ultra-short-term wind power prediction model of GCN-LSTM based on a deep neural network is adopted in the upper layer DMPC of a two-layer distributed active power control architecture. The optimization time domain of the intraday rolling scheduling plan is 2 h, the sampling point resolution and the prediction time step are both 15 min, and the output power prediction model can be expressed as the following Formula (6):

$$\begin{aligned} P_i^{for} &= [P_i^{for}(t + \Delta t_1), P_i^{for}(t + 2\Delta t_1), \dots, P_i^{for}(t + T_1 \cdot \Delta t_1)] \\ i &= 1, 2, \dots, Cl \end{aligned} \quad (6)$$

where: P_i^{for} is the predicted output power sequence of the i cluster, Cl is the cluster number of wind turbines, and the prediction time domain $T_1 = 8$.

In order to ensure the maximum number of wind turbines in the wind farm, the optimal scheduling of the cluster coordination layer takes maximizing wind power output as the control goal and requires the active power regulation to be as small as possible. The objective function is expressed as follows (7):

$$\min J_{WTC} = \sum_{k=1}^{T_1} \sum_{i=1}^{Cl} \left([P_i^{dis}(t + k\Delta t_1) - P_i^{for}(t + k\Delta t_1)]^2 + [P_i^{dis}(t + k\Delta t_1) - P_i^{real}(t)]^2 \right) \quad (7)$$

The constraint conditions mainly include absolute power limit and incremental limit [30], which should meet the following Equations (8) to (11):

- (1) Scheduling plan tracking constraints, as follows (8):

$$\sum_{i=1}^{Cl} P_i^{dis}(t + \Delta t_1) = P_{sys}^{dis} \quad (8)$$

- (2) The sum of the active power output of the wind farm is less than or equal to the total installed capacity of the wind farm, as follows (9):

$$\sum_{i=1}^{Cl} P_i^{dis}(t + \Delta t_1) \leq P_{WF}^N \quad (9)$$

- (3) The sum of active power output of each cluster is less than the installed capacity of the cluster, as follows (10):

$$0 \leq P_i^{dis}(t + \Delta t_1) \leq P_{WTCi}^N, i = 1, 2, \dots, Cl \quad (10)$$

- (4) The change rate of active power output of the fleet is within a reasonable range, as shown in Equation (11):

$$\left| \frac{P_i^{dis}(t + \Delta t_1) - P_i^{real}(t)}{P_i^{real}(t)} \right| \leq C_{WF}, i = 1, 2, \dots, Cl \quad (11)$$

where: $P_i^{dis}(t + \Delta t_1)$ is the scheduling value of the i cluster after 15 min; $P_i^{real}(t)$ is the measured power value of the i cluster measurement system at time t ; P_{sys}^{dis} is the wind farm intra-day rolling plan scheduling instruction issued by the scheduling department; P_{WF}^N is the total installed capacity of the wind farm; P_{WTCi}^N is the installed capacity of cluster i ; C_{WF} is the limit of active power climb rate of the wind farm. The intra-day rolling plan resolution is $\Delta t_1 = 15$ min, T_1 is the optimization period, and the cluster coordination layer optimizes the planned value for the next 2 h each time, then the optimized time domain $T_1 = 8$. The control time domain of the upper DMPC is $T_{c1} = 4$, and the control instructions of 4 time points are obtained after each solution of the penalty function, and only the first active command is sent to each wind turbine group.

In the feedback correction link of the upper layer of distributed active power scheduling, the deviation between the actual output power of the wind power cluster and the control instruction is compared, and the current actual active power value of the wind power cluster is taken as the initial value of a new round of rolling optimization scheduling. The ultra-short-term wind power prediction error is corrected, so that the output active power value of the wind power cluster at the next moment is more realistic, and a closed-loop control is formed. The feedback correction is calculated as follows (12):

$$P_{i,0}(t + \Delta t_1) = P_i^{real}(t + \Delta t_1) \quad (12)$$

where: $P_{i,0}(t + \Delta t_1)$ is the initial active power optimization value of wind turbine group i at time $t + \Delta t_1$, and $P_i^{real}(t + \Delta t_1)$ is the measured active power output value of wind turbine group i at time $t + \Delta t_1$.

4.2.2. Lower Layer CMPC Controller Design

The prediction model of the wind turbine in the lower centralized MPC adopts the linearized state space model established in the literature [31], and the matrix form is expressed as the following Equation (13):

$$\begin{cases} \dot{\tilde{x}} = A\tilde{x} + B\tilde{u} + E\tilde{v} \\ \tilde{y} = C\tilde{x} + D\tilde{u} \end{cases} \quad (13)$$

where: $x = [\omega_m \ \omega_r \ \theta]^T$ is the state variable, and $\tilde{x}$ is the offset between the state variable and the nominal system state; $y = [\omega_m \ P_g]^T$ is the output variable, $\tilde{y}$ is the offset between the output and the steady-state value; $u = [\beta \ T_m]^T$ is the control variable, $\tilde{u}$ is the offset between the input and the operating point. v is the wind speed, $\tilde{v}$ is the offset value between the wind speed and the steady state value, and is the uncertainty.

As the actual engineering stroke mechanism is limited by mechanical strength and safety, the constraint conditions mainly include the upper and lower threshold constraints of the control variables, which should meet the following Equations (14) to (19):

- (1) The sum of the active power change of the wind turbine is equal to the active power reference change value of the cluster, as follows (14):

$$\sum_{j=1}^{m_i} [P_{g,j}(t + \Delta t_2) - P_{g,j}^{real}(t)] = P_i(t + \Delta t_1) - P_i^{real}(t + s \cdot \Delta t_2) \quad (14)$$

$s = 0, 1, 2$

- (2) Generator angular velocity threshold constraints, as shown in Equation (15):

$$\omega_{m \min} \leq \omega_{m,j}(t + \Delta t_2) \leq \omega_{m \text{ rated}}, j = 1, 2, \dots, m_i \quad (15)$$

- (3) Generator torque threshold constraint and change rate constraint, as follows (16):

$$\begin{cases} T_{m \min} \leq T_{m,j}(t + \Delta t_2) \leq T_{m \max} \\ -\Delta T_{m \max} \leq T_{m,j}(t + \Delta t_2) - T_{m,j}^{real}(t) \leq \Delta T_{m \max} \end{cases}, j = 1, 2, \dots, m_i \quad (16)$$

- (4) Wind turbine blade pitch Angle physical structure constraints and change rate security constraints, as shown in Equation (17):

$$\begin{cases} \beta_{\min} \leq \beta_j(t + \Delta t_2) \leq \beta_{\max} \\ -\Delta \beta_{\max} \leq \beta_j(t + \Delta t_2) - \beta_j^{real}(t) \leq \Delta \beta_{\max} \end{cases}, j = 1, 2, \dots, m_i \quad (17)$$

- (5) The output power of the unit is within a reasonable range, as follows (18):

$$0 \leq P_{g,j}(t + \Delta t_2) \leq P_{g \text{ rated}}, j = 1, 2, \dots, m_i \quad (18)$$

- (6) The wind turbine climb rate is within the permitted range, as follows (19):

$$\left| \frac{P_{g,j}(t + \Delta t_2) - P_{g,j}^{real}(t)}{P_{g,j}^{real}(t)} \right| \leq C_{WTN}, j = 1, 2, \dots, m_i \quad (19)$$

where: m_i is the number of wind turbines contained in the i -th cluster; $P_{g,j}(t + \Delta t_2)$ and $P_{g,j}(t)$ are, respectively, the dispatching value of the j wind turbine after 5 min and the measured power at time t ; $\omega_{m,j}(t + \Delta t_2)$ and $\omega_{m,j}^{real}(t)$ are the generator speed after 5 min of the j wind turbine and the measured speed at time t , respectively. $\omega_{r,j}^{real}(t + \Delta t_2)$ and $\omega_{r,j}^{real}(t)$ are, respectively, the wind turbine angular velocity after 5 min of the j wind turbine and the measured wind turbine angular velocity at time t . $\omega_{m \min}$ and $\omega_{m \text{ rated}}$ are the minimum and rated speed of the generator; $\omega_{r \min}$ and $\omega_{r \text{ rated}}$ are the minimum speed and rated speed of the turbine; $P_{g \text{ rated}}$ is rated active power of wind motor; C_{WTN} is the limit

of single-machine climb rate. T2 represents the optimization period. The wind turbine balance layer optimizes the active power reference value of the future 15 min each time, and the intra-day rolling plan resolution $\Delta t_2 = 15$ min, then the time domain T2 = 3 is optimized. The control time domain of the lower CMPC is Tc2 = 3, and the reference value of single output at 3 time points is obtained after each solution of the penalty function, and only the first item is sent to each wind turbine. At this point, the two-layer model predicts that the lower layer of active power control completes an online rolling optimization.

In the feedback correction section of the lower layer of distributed active power control, the error weighting method is used to correct the output value of the forecast model at other times in the future. Due to model mismatch, external interference, and uncertainty factors, the actual output value at time $t + \Delta t_2$ is different from the predicted output at time t to time $t + \Delta t_2$, so for unit j , the prediction error at time $t + \Delta t_2$ is as follows (20):

$$\Delta y_j(t + \Delta t_2) = y_j(t + \Delta t_2 | t) + y_j^{real}(t + \Delta t_2) \quad (20)$$

where: $\Delta y_j(t + \Delta t_2)$ is the output variable error of unit j at the $t + \Delta t_2$ moment; $y_j(t + \Delta t_2 | t)$ is the time-to-time $t + \Delta t_2$ forecast output of unit j at time t ; $y_j^{real}(t + \Delta t_2)$ is the measured output value of unit j at the $t + \Delta t_2$ moment.

After the error is weighted, the output value of the predicted output sequence of unit j at other times except time $t + \Delta t_2$ is corrected, as shown in Equation (21):

$$\hat{Y}_j = Y_j + h \cdot \Delta y_j(t + \Delta t_2) \quad (21)$$

where: $Y_j = [y(t + \Delta t_2 | t), y(t + 2\Delta t_2 | t), y(t + 3\Delta t_2 | t)]$ is the predicted output of T2 moments in the future of the system under the action of control variables $u(t + \Delta t_2 | t)$ at time t ; $\hat{Y}_j = [\hat{y}(t + \Delta t_2 | t), \hat{y}(t + 2\Delta t_2 | t), \hat{y}(t + 3\Delta t_2 | t)]$ is the predicted output value taking into account the error correction at time $t + \Delta t_2$; $h = [h_1, h_2, \dots, h_{T_2}]$ is the error correction vector, and $h_1 = 1$.

4.2.3. Optimal Solution of Active Power Predictive Control Problem

Combined with the proposed scheduling coordination dynamic index optimization strategy, the paper adopts the sequential method to solve the problem [32].

When MPC is applied to wind power control, the active power control problem of each time step is transformed into a quadratic optimization solution problem, with the purpose of finding a control strategy that can satisfy the constraint conditions while minimizing the penalty function [33]. Firstly, vectorization transformation is performed on the control objective function of the upper cluster, and the following Equation (22) is obtained:

$$\min J_{WTC}(t) = q \left[P_i^{dis}(t) - P_{WF}^{for}(t) \right]^2 + \left\| P_i^{dis}(t + \Delta t_1) - P_i^{real}(t) \right\|_R^2 \quad (22)$$

where: $P_{WF}^{for}(t)$ is the ultra-short-term wind power predicted value of wind farm at time t ; q is the error weight; control weight matrix $R = \text{block-diag}[r_1, r_2, \dots, r_8]$.

Applying the same method, the objective function of the i -th wind turbine group in the lower layer is expressed in vector form as Equation (23):

$$\begin{aligned} \min J_{WTi}(t) = & \left\| \omega_{m,j}(t + \Delta t_2) - \omega_{m,j}^{real}(t) \right\|_G^2 + \left\| P_{g,j}(t + \Delta t_2) - P_{g,j}^{real}(t) \right\|_L^2 \\ & + \left\| T_{m,j}(t + \Delta t_2) - T_{m,j}^{real}(t) \right\|_W^2 + \left\| \beta_j(t + \Delta t_2) - \beta_j^{real}(t) \right\|_Z^2 \end{aligned} \quad (23)$$

where G , L , W , and Z are the penalty weighting matrices of generator rotor angular speed, output power, pitch angle, and motor torque, respectively, and they are all three-dimensional diagonal matrices. The elements in R , G , L , W , and Z are assigned according to the principle that the greater the time distance, the smaller the weight.

In order to save computing time and improve control efficiency, the penalty function is transformed into a quadratic programming problem (QP). The form of quadratic programming is as follows (24):

$$\min f(x) = \frac{1}{2}x^T Hx + g^T x \quad (24)$$

Based on the constraints of Equations (8) to (11) and (14) to (19), the quadratic programming is solved, and the dual-layer distributed model is obtained to predict the active power commands of each cluster of active power control daily rolling planning and each unit of online rolling scheduling. The rationality and precision of active power distribution of wind farms are improved, so as to achieve multi-objective active power coordination optimization.

5. Control Effect Comparison and Performance Analysis of Dual-Layer Distributed Active Power Predictive Control Strategy

(1) Control performance of the upper DMPC

As can be seen from Figure 9, the dispatch command of 11:45–12:30 is greater than the predicted wind power value. On the premise of ensuring the safety of the unit and the transmission channel, the actual output of the wind farm using the DMPC control strategy is closer to the active power dispatch command, while the control methods are relatively conservative for the wind farm dispatch. This indicates that DMPC's active power control strategy can improve the utilization rate of wind power and better coordinate the scheduling index.

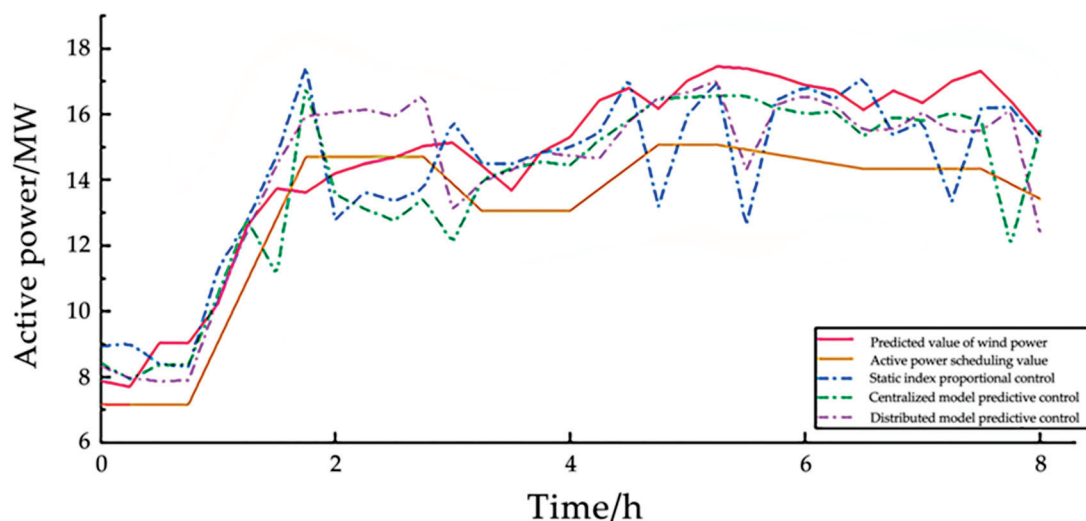


Figure 9. Active power control results of wind farms under different strategies.

Figures 10–12 show that the dynamic index DMPC cluster active power control strategy based on scheduling instruction coordination ADAPTS to various scheduling instruction changes. Specifically, when the active power command rises, the power generation space of each cluster can be fully utilized. When the active power command drops, it can limit the change of the scheduling value of adjacent control steps within a certain range, and balance the output of each group. When the active command is stable, the DMPC reduces the fluctuation of the group of instructions and reduces the mechanical loss as much as possible.

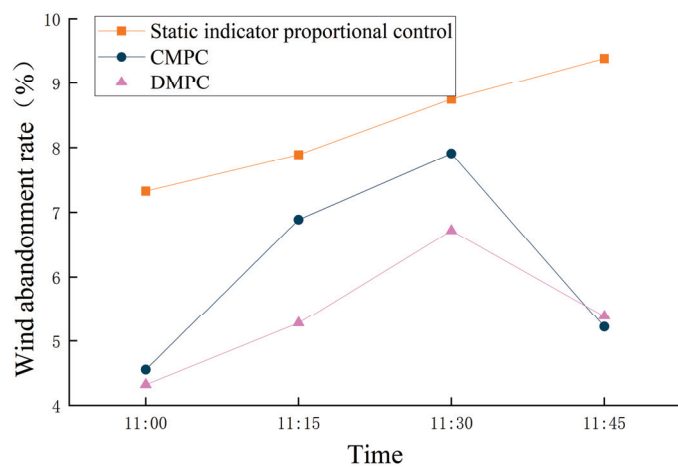


Figure 10. Cluster control results from different strategies during the rise period of wind farm dispatching instruction.

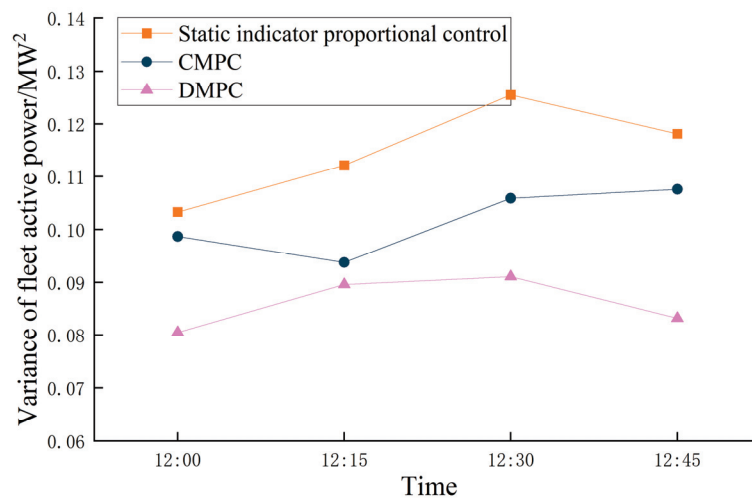


Figure 11. Cluster control results from different strategies during the stationary period of wind farm dispatching instruction.

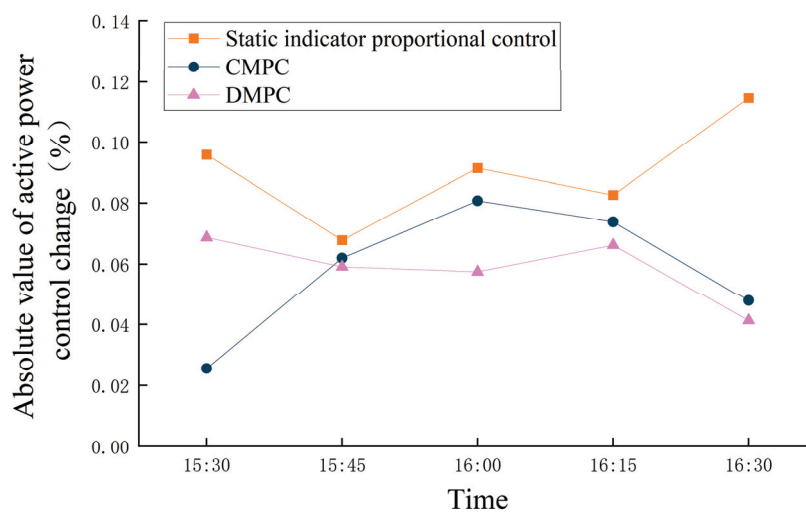


Figure 12. Cluster control results of wind farm dispatching instruction decline period with different strategies.

(2) Control performance of the lower CMPC

As can be seen from Figures 13 and 14, the output curve of the centralized model predictive control method is smoother. Since the scheduling instructions of proportional distribution largely depend on the predicted power value of the wind turbine, the power prediction sequence is highly volatile, and the feedback link of active power output is ignored in traditional proportional distribution. Therefore, the scheduling result of the low-level centralized MPC is superior to the proportional active scheduling strategy.

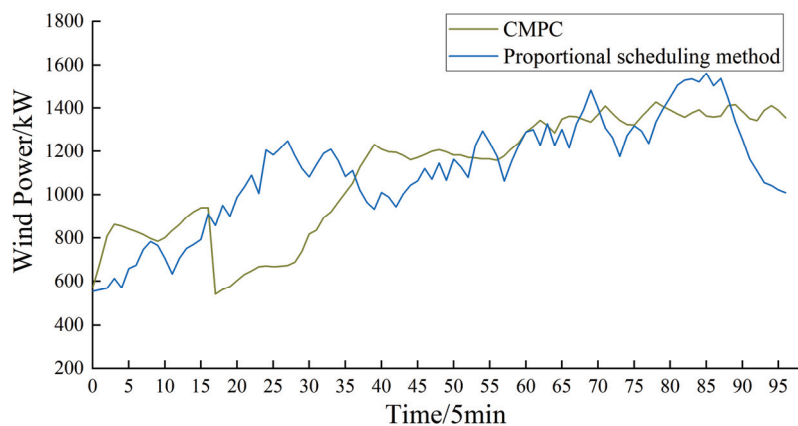


Figure 13. Active power control results of wind turbine 10# under different strategies.

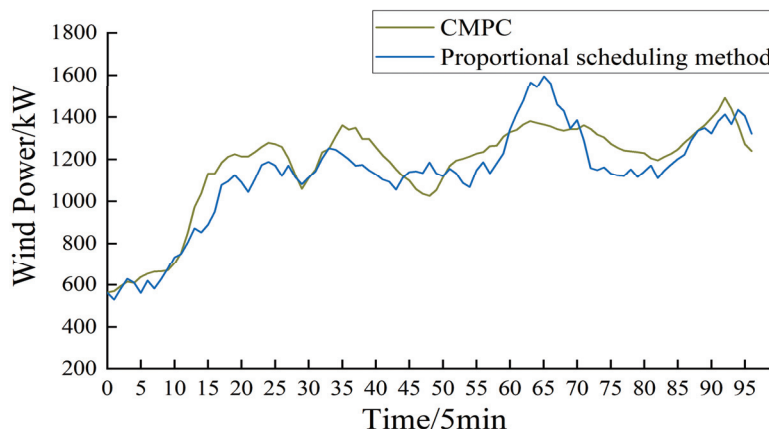


Figure 14. Active power control results of wind turbine 11# under different strategies.

For most of the time of fan 11#, the output value of active power control using the lower centralized MPC is higher than the active power output of proportional scheduling, and the average active power of the former is 8.61% higher than that of the latter. The average active power optimization of the centralized MPC for fan 10# is smaller than that of the proportional scheduling mode. The average active power optimization of the two strategies is 1099.11 kW and 1108.50 kW, respectively, mainly because the dispatching output of the centralized MPC for fan 10# is smaller than that of the proportional scheduling mode during the period of 11:25 to 12:55. The specific reasons are analyzed as follows. The wind farm received the dispatch instruction from TSO during this period and was in a stable state and transitioned to a declining state. At 11:25, the output of other units in the same group as fan 10# was at a higher level, resulting in a smaller dispatch instruction from the centralized MPC controller to fan 10#. After the subsequent optimization of the time domain of the fleet division and the update of the online rolling plan, the power of fan 10# changes steadily and gradually increases.

6. Conclusions

China's wind power technology is developing rapidly. In order to help the process of carbon neutralization and carbon peaking, we must improve the utilization rate of wind energy and the regulation performance of wind power control systems, and promote the development and consumption of clean energy. It is urgent to solve the problem that the randomness of wind energy brings as an impact to the power grid, and it is necessary to study the wind power prediction and optimization controls. The main research work of this paper is as follows:

- (1) The proposed GCN-LSTM ultra-short-term wind power prediction model is used to construct a neural network input data set, aggregate neighbor node information at each sampling moment by using graph convolutional network, and input deep features into a long and short-term memory neural network for deterministic wind power prediction after feature fusion and dimensionality reduction. The time-sliding window size and batch size of the LSTM network can obtain the optimal combination settings through experiments. The model makes full use of the information fusion of neighboring nodes and reduces the amount of data input to the LSTM network, which improves prediction efficiency and accuracy.
- (2) An improved K-means clustering method for wind turbines based on a Crow Search Algorithm is proposed. Based on the smooth degree, changing trend, shape characteristics, and abnormal data of fan power, four time-varying fan clustering indexes are designed to reflect wind power characteristics from multiple angles. The Crow Search Algorithm is used to optimize the initial centroid of K-means clustering. Experimental results show that the contour values of the proposed clustering method under different clustering indexes are superior to classical K-means clustering. The improved K-means algorithm based on CSA centroid optimization can achieve accurate and effective wind turbine clustering, providing solid conditions for active power refining control of wind farms.
- (3) The proposed dual-layer distributed wind farm active power model predictive control strategy. The simulation results of a wind farm with 12 fans show that the upper-layer control strategy can make full use of the power generation space of each cluster during up-up power scheduling, effectively reducing the fluctuation degree of optimization instructions during balanced power scheduling, and reducing the change of cluster scheduling values during power reduction scheduling. The lower layer control strategy effectively smooths the wind power output curve, improves the tracking accuracy of active power to instructions, improves the optimization efficiency, enhances the robustness and scalability of active power control, and improves the overall active power control performance compared with other control algorithms.

In this paper, research work has been carried out on ultra-short-term prediction of wind power and optimal control of active power of wind farms, and some progress has been made. There are still some problems and shortcomings in this paper, which can be further improved and discussed in future work:

- (1) Considering the efficiency of unit grouping, this paper designs an improved K-means clustering algorithm and a variety of clustering indicators. For randomly fluctuating wind turbine power sequences, clustering methods that are more suitable for the overall time series data, such as feature space transformation clustering method or multi-resolution analytical clustering method, can be designed to obtain higher quality cluster analysis results and further improve the refined regulation and control ability of active power of wind farms.
- (2) The distributed model prediction control of dynamic indicators carries out a unit clustering in each control step, the group results change dynamically according to the active characteristics, and the group regulated by each distributed controller is not fixed, so the communication structure requires each distributed controller to be connected to all fans, which increases the scheduling cost at a certain level. At

the same time, on this basis, a more rigorous comparative analysis is required to determine the location of the distributed controller.

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Article

A Multi-Period Model of Compressor Scheme Optimization for the Shale Gas Gathering and Transportation System

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Abstract: In the process of shale gas production, with the change in gas productive parameters, the pressurization demand for the shale gas gathering and transportation system (SGGTS) also changes, which affects the choice of pressurizing location and timing. Our purpose is to effectively respond to the impact of parameter changes during shale gas production and to better select the pressurization schemes. Therefore, we considered the modularization of the compressors and established a mixed-integer nonlinear programming (MINLP) model to minimize the total cost of the SGGTS. Taking an actual shale gas field as an example, by discretizing the time during a given production period to solve the model under multi-period and single-period conditions, the optimal pressurization scheme for the SGGTS in the specified production period is obtained. It indicates that the results obtained under a multi-period condition are more conducive to actual production. Compared with the results obtained under the single-period condition, the cumulative cost obtained in the multi-period condition is reduced by 17.19%. By deploying the MINLP model in the specified production period, the pressurization demand is met in each time period. This greatly improves the utilization rate of modular compressors, reduces the total cost, and improves the economic benefits of the SGGTS.

Keywords: shale gas; modular compressor; pressurization; MINLP; optimization model

1. Introduction

1.1. Background

In a contemporary energy landscape, natural gas has emerged as a competitive and predominant energy vector (Zhou et al., 2021) [1]. Yet, as disparities between supply and demand in the natural gas sector continue to escalate, conventional gas resources have consistently fallen short of satisfying prolonged market requirements (Wei et al., 2021) [2]. Shale gas, recognized as a significant unconventional reservoir of natural gas, is progressively gaining heightened attention. Encapsulated within shale formations, this gas can be extracted. Notably, China boasts considerable reserves of this exploitable resource. The formation and accumulation of shale gas have unique characteristics, such as the thick and widely distributed shale source rocks found in basins. Compared with conventional natural gas resources, shale gas resources have the advantages of a longer exploitation lifetime and production period, as well as a higher economic worth.

Shale gas production typically exhibits cyclical and seasonal fluctuations, with initial output and pressure significantly higher than other production stages. This might lead to the need for compressor solutions to adapt to continuously changing gas flow. As the production rate decreases, the compressor may need to adjust its operating mode or be reconfigured to accommodate a lower output, while a higher operational capacity is

required during high production. This production characteristic also impacts the efficiency of the compressor operation. Under different production conditions, while a single compressor can meet the production needs, its power or energy consumption might not be in the most optimal state. Therefore, we need different types of compressors and operating parameters to ensure the best efficiency. Additionally, in shale gas production, there may be peak demand periods, requiring extra boosting to meet instantaneous high requirements. Compressor solutions must consider how to fulfill these additional demands during peak periods while avoiding excessive operation.

Hence, within the ambit of shale gas development, there exists a pronounced decline in the production capacity of shale gas, leading to continual alterations in equipment load rates and assorted operational states. Such dynamics critically influence decisions concerning compressor typology, the location of pressurization, and its timing. For the efficacious extraction of shale gas, an optimized operational strategy and a dynamic blueprint for the shale gas gathering and transportation system (SGGTS) are imperative. Modular compressors present a solution adept at countering these evolving productive parameter shifts. Distinct from their conventional counterparts, modular compressors are compact, highly mobile units fabricated as independent modules, allowing swift on-site assembly. As pressurization venues transition, these units can be promptly disassembled and re-located, thereby circumventing compressor resource waste and augmenting utilization efficiency. This approach not only fosters sustained and stable shale gas production but also curtails production expenditures, enhancing the economic viability of shale gas fields. Consequently, delving into optimal pressurization strategies within the SGGTS that employ modular compressors is of paramount significance.

Integrating modular facilities into traditional compressor optimization schemes requires considering the diversity of compressors, management, control, and coordination with existing systems. By knowing the pressure, flow rate, network structure, pipeline length, pipeline diameter, shale gas molar composition, adiabatic compression efficiency, and compressor mechanical efficiency, we can determine the installation location, quantity, and rearrangement of the compressors and obtain the optimal combination of boosting methods, boosting locations, SGGTS compressor operating power, and compressor type. Representing these complex operational dynamics through mathematical models is a long-term and intricate task.

1.2. Related Work

As shale gas gains prominence within the global energy matrix, scholarly interest in its development has surged. International academic circles have embarked on multifaceted investigations into shale gas production nuances, registering noteworthy findings. A salient distinction between the extraction methodologies of shale gas and its conventional counterpart lies in the deployment of horizontal drilling coupled with high-volume hydraulic fracturing (Vengosh et al., 2013) [3]. Advancements in horizontal drilling techniques have catalyzed the economically viable recovery of shale gas. In this realm, Yuan et al. (2013) [4] introduced an innovative predictive technique for ascertaining geostress within shale strata, geared towards bolstering drilling stability during horizontal well construction in shale gas repositories. Similarly, Lin et al. (2021) [5] advanced an optimal schematic for shale gas volumetric fracturing, predicated upon a robust assessment of fracturing outcomes. Real-Miranda et al. (2022) [6] employed stochastic dynamic programming techniques to determine the equivalent insurance premium for extraction personnel during the gas well extraction process. On another front, Cafaro et al. (2018) [7] put forth a continuous-time optimization paradigm tailored for orchestrating multiple re-fracture interventions across a shale gas well's lifecycle. Complementarily, Drouven et al. (2017) [8] elucidated an optimization matrix, aiming to discern the feasibility of a well undergoing re-fracturing within its operational tenure. Meanwhile, Grossmann et al. (2014) [9] propounded a cutting-edge mixed-integer optimization framework dedicated to the strategic design of shale gas infrastructure, targeting the meticulous calibration of well counts, gas compressor

capacities, and judicious planning of freshwater requisites for both drilling and fracturing processes. The aforementioned research primarily focuses on the optimization studies of underground processes and techniques, with relatively less consideration given to surface gathering and transportation systems. To achieve more comprehensive optimization and resource utilization, there is a need to systematically analyze and model the entire shale gas extraction process, including the surface operations.

The trajectory of protracted shale gas development has been an increasingly focal subject in contemporary academic literature. The intricate design and execution of long-term shale gas field development present substantial challenges, attributed to multifaceted developmental operations and an extensive gamut of potential deployment sites. In this context, Tavallali et al. (2013) [10] developed a mixed-integer nonlinear model by integrating sub-surface, surface, and oil wells, it provides the optimal number of new producers, their locations, and optimal production plan over a given planning horizon. Cafaro and Grossmann (2014) [11] introduced a mixed-integer non-linear programming (MINLP) framework tailored for the sustainable, long-term strategic planning of the shale gas supply chain. This model adeptly determines optimal parameters, such as well counts per site, natural gas processing plant capacity, compressor potency, and freshwater requisitions for hydraulic fracturing and drilling processes, with an overarching objective to amplify the net present value. Subsequently, Yang et al. (2015) [12] proffered a novel mixed-integer linear programming (MILP) framework devised to fine-tune capital allocation decisions concerning water resources for shale gas extraction, leveraging a discrete-time rendition of a state tasks network. Further enriching the discourse, Drouven and Grossmann (2016) [13] delineated a large-scale, non-convex MINLP framework accentuating quality-centric, enduring shale gas ventures. Adding another dimension, Cafaro et al. (2016) [14] promulgated a discrete-time, multi-temporal MILP model, meticulously outlining the prospects of successive re-fracture interventions throughout a well's operational lifespan. In a complementary study, Mahmoud et al. (2020) [15] embarked on a holistic assessment of both prolonged and short-term outputs, pivoting on specific shale gas reservoir and completion parameters. Their findings underscored that, while completion parameters influence both temporal output dimensions, it is the reservoir parameters that predominantly steer the long-term production dynamics. Rounding off this cascade of contributions, Peng et al. (2021) [16] proposed an innovative MILP framework for the strategic design and roll-out of enduring shale gas field projects. In tandem, they also presented a solution pool-centric, dual-layer decomposition algorithm to effectively navigate this model. The aforementioned studies focus on the entire process of shale gas extraction and transportation. They utilize various types of mathematical planning methods to address issues related to shale gas development and production, covering areas such as supply chain planning, water resource allocation, and production optimization. These studies have provided essential insights for the long-term development of the shale gas field. However, they have not considered the factor of modular facilities. Modular facilities are gradually playing a pivotal role in modern shale gas development. Through modular facilities, production flexibility can be enhanced, adaptability to production parameter fluctuations can be ensured, and resource waste can be reduced.

Modular facilities, characterized by their technical and economic merits alongside adaptive operability, are increasingly permeating diverse sectors. Delving into this theme, Gao and You (2017) [17] advanced a novel mixed-integer nonlinear fractional programming model to ascertain if modular manufacturing might serve as a pivotal disruptor in designing and operationalizing the shale gas supply chain, with a vision of achieving both economic and ecological sustainability. Similarly, Yang and You [18] conducted a comparative techno-economic and environmental analysis of different shale gas monetization scenarios and showed that modular generation is more advantageous. Tackling capacity planning within a modular infrastructure for shale gas endeavors, Allen et al. (2018) [19] constructed a multi-stage stochastic model that factored in ambiguous production projections. Conversely, the MILP framework conceived by Hong et al. (2020) [20] seamlessly

amalgamated decisions spanning shale gas extraction, conveyance, and processing with modular infrastructure deliberations. Their empirical evaluations revealed that the dynamic schema of modular infrastructure adeptly counterbalances productivity oscillations. Furthermore, in 2021, Hong et al. [21] crafted an MILP optimization paradigm, aiming to optimize the spatial arrangement of modular amenities within shale gas domains, thereby enhancing operational efficiency and financial feasibility. Yang and You's study in 2017 honed in on modular methanol production as a potential strategy for plant repositioning, concluding its superior economic competitiveness vis-à-vis traditional shale gas methodologies. Baldea et al. (2017) [22] proffered a comprehensive synthesis of the various catalysts spurring modular production, subsequently assessing modular production blueprints predicated on a unique metric: the value density of raw material resources coupled with product market dynamics. Pakizer et al. (2020) [23] championed the integration of modular water frameworks with existing centralized infrastructures, thereby sculpting hybrid systems. Lier and Grünewald (2011) [24] undertook a financial juxtaposition of modular and conventional large-scale chemical plants by evaluating their respective net present values. Meanwhile, Palys et al. (2018) [25] introduced modular methodologies into ammonia synthesis, which, as per their findings, engendered diminished supply chain expenditures and augmented utilization of renewable assets relative to continuous operations. Lastly, Tan and Barton (2015) [26] proposed a layered optimization construct tailored to guide optimal temporal allocation and operational resolutions, empowering decision-makers to monetize associated or confined gas through mobile installations. Subsequently, Tan and Barton (2016) [27] further improved the optimization framework to further illustrate the advantages of mobile devices in coping with uncertainty by taking into account the uncertainty of future parameters.

The aforementioned studies have incorporated modular facilities into their respective optimization systems and explored the economic and ecological sustainability of modular facilities in various fields. These studies offer insights into how modular facilities can enhance various industrial processes and supply chains. Traditional fixed facilities are difficult to disassemble once they are installed, which makes it difficult to flexibly adapt to changes in production capacity and to work continuously in high-efficiency work areas (Zhou et al., 2019) [28]. In contrast, modular facilities are better able to adapt to changing production capacities due to their compact structure, ease of disassembly, ease of movement, and low development risk. The academic and engineering communities have recognized the importance of modular infrastructure for shale gas production. However, modular compressors are usually ignored in related research on SGGTS pressurization. The compressor is crucial in the shale gas production process, as it plays an essential role in boosting and transporting the shale gas. Therefore, we establish a MINLP model in this paper, considering the modularity of compressors. and take an actual field as an example to verify the model.

1.3. Contributions

The main contributions of this work include:

1. Establishing a MINLP model to solve the pressurization optimization problem in the shale gas field
2. Considering the compressor modularization to deal with the influence of the pressurizing location changing with the fluctuation in the productive parameters
3. Verifying the model through a practical case

1.4. Paper Organization

The paper proceeds as follows: Section 2 describes the problem; Section 3 introduces the mathematical model; Section 4 introduces the algorithm; Section 5 provides a case study to prove the validity of the model; and Section 6 summarizes the conclusions.

2. Problem Description

The schematic diagram of the optimal pressurization scheme and the rearrangement of modular compressors in the shale gas production process is shown in Figure 1. The rearrangement here is the movement of modular compressors from one location to another over different time periods. In this example, three different shale gas production periods are included. The first period is in the early stage of shale gas production, and there is no need to pressurize the SGGTS. The second period is in the early stage of pressurization, and it is necessary to purchase modular compressors to pressurize some of the platforms. In the third period, the mid-to-late stage, when the pressurizing positions of the SGGTS change, it is not only necessary to purchase more modular compressors but also to rearrange modular compressors. All decisions at each time period are aimed at minimizing the total cost of modular compressors over the entire production period.

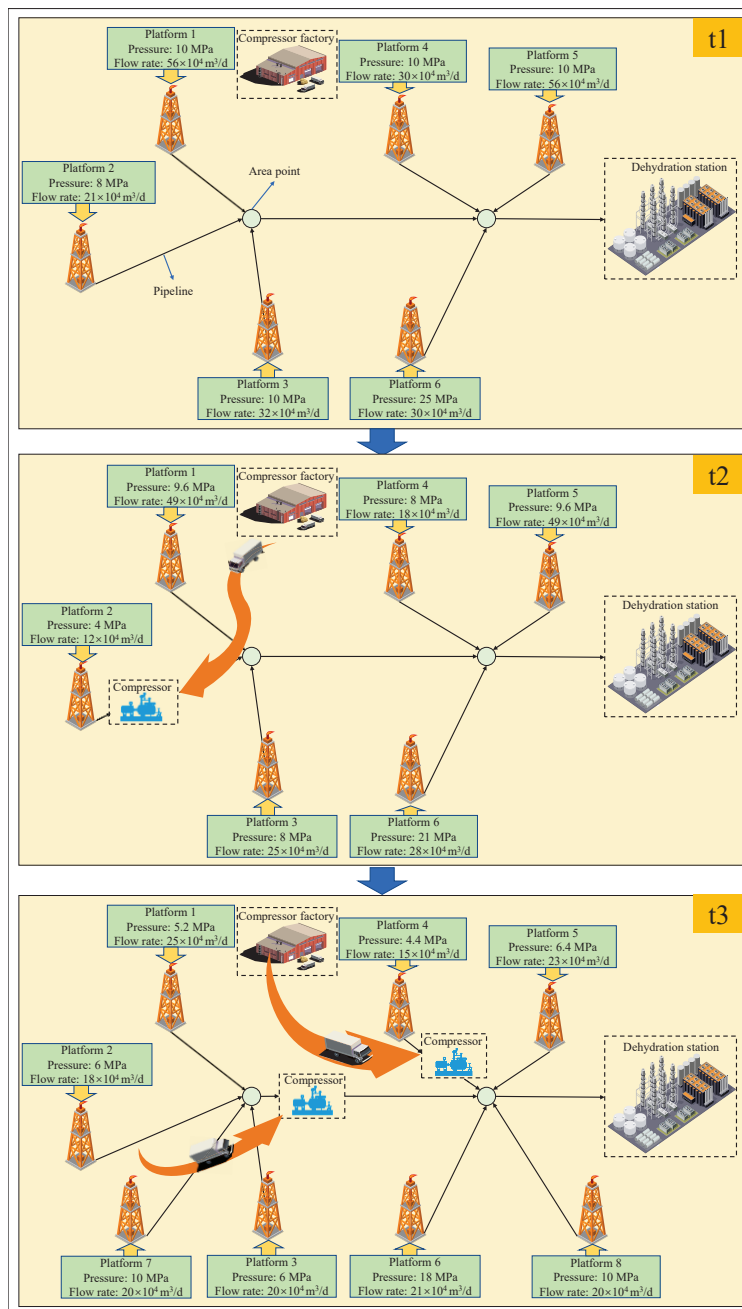


Figure 1. Optimization problem description of a pressurization scheme. t1: early stage of shale gas production; t2: early stage of shale gas pressurization; t3: mid-late stage of shale gas pressurization.

The optimization problem of pressurization and rearrangement based on modular compressors is that we have to already know the pressure, flow rate, network structure, pipeline length, internal diameter of the pipeline, molar composition of the shale gas, adiabatic compression efficiency, and compressor mechanical efficiency in order to determine the installation location, quantity, and rearrangement of compressors and then obtain the optimal combined pressurization mode, pressurizing position, compressor operating power, and compressor type of the SGGTS. As shown in Figure 2, there are four types of pressurization modes.

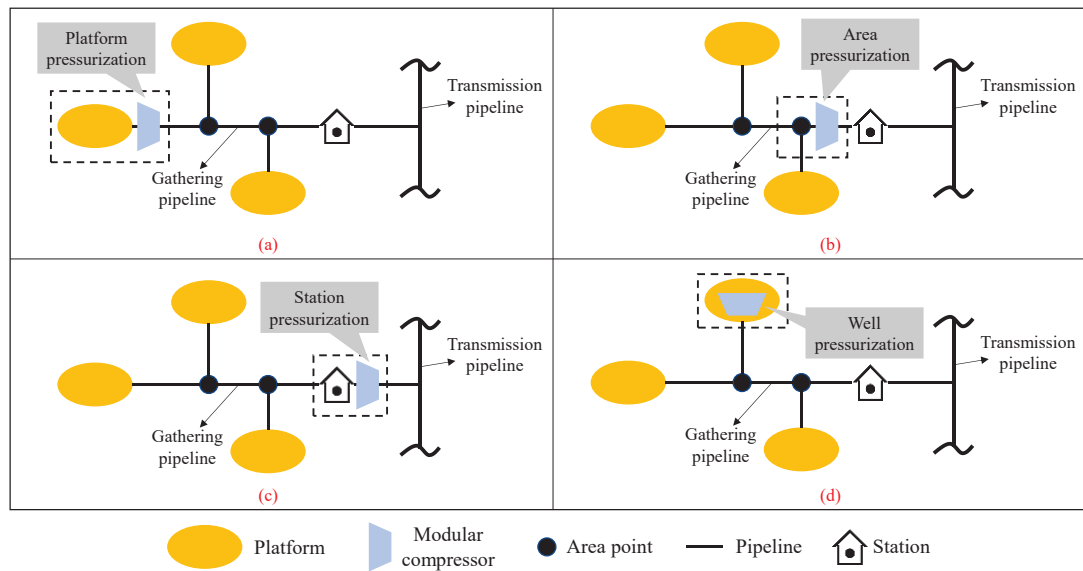


Figure 2. Pressurization modes: (a) platform pressurization; (b) area pressurization; (c) station pressurization; (d) well pressurization.

1. Platform pressurization is to arrange the compressor at the platform, as shown in Figure 2a.
2. Area pressurization is to arrange the compressor at the point of the region to pressurize the low-pressure area, as shown in Figure 2b.
3. Station pressurization is to arrange the compressor at the station, as shown in Figure 2c.
4. Well pressurization is to arrange the compressor to pressurize the single well or the same half-branch well inside the platform, as shown in Figure 2d.

The objective is to provide the pressurization scheme and modular compressor rearrangement for a shale gas production cycle. To facilitate modeling and improve model-solving efficiency, the shale gas production cycle is typically discretized into a series of short time intervals, and within each interval, the system's operating and production conditions are considered constant to better understand and manage the system's operation. The following assumptions are made:

1. The shale gas production time can be divided into a series of short, discrete periods (Allen et al., 2018) [19].
2. The shale gas production parameters do not change within a unit time period.
3. During the specified shale gas production period, the modular compressors will not be damaged or require additional maintenance costs.
4. The lead time for purchasing modular compressors is not taken into consideration.

3. Mathematical Formulation

3.1. Objective Function

The objective function is the minimum total compressor cost, as shown in Equation (1). The purchase cost (F_{cc}), operation cost (F_{oc}), and rearrangement cost (F_{mc}) are shown in Equations (2)–(4), respectively.

$$\min F = F_{cc} + F_{oc} + F_{mc} \quad (1)$$

$$F_{cc} = \sum_{t \in T} \sum_{y \in Y} \sum_{i \in I} b_{i,y,t} z_{i,y,t} \alpha_{i,y,t} \quad (2)$$

$$F_{oc} = \sum_{t \in T} \sum_{i \in I} N_{i,t} r_{i,t} \quad (3)$$

$$F_{mc} = \sum_{t \in T} \sum_{y \in Y} \sum_{i \in I} u_{i,y,t} \varphi_{i,y,t} \quad (4)$$

In the formula, $r_{i,t}$ is the operating price, 10^4 Yuan/kW; $b_{i,y,t}$ is the location variable; $z_{i,y,t}$ is the type y compressor number installed, set; $N_{i,t}$ is the operating power, kW; $u_{i,y,t}$ is the type y compressor number rearranged, set; $\varphi_{i,y,t}$ is the rearrangement price, 10^4 Yuan/set; and $\alpha_{i,y,t}$ is the compressor price, 10^4 Yuan/set.

3.2. Constraint

3.2.1. Pipeline Pressure and Flowrate Constraints

The pipeline pressure and flowrate constraints include pressure drop constraints, maximum pressure constraints, minimum pressure constraints, and flow constraints, as shown in Equations (5)–(8), respectively. The pipeline starting pressure ($p_{i|(i,j),t}$) cannot exceed the maximum pressure ($p_{\max}$). The pipeline end pressure ($p_{j|(i,j),t}$) cannot be less than the minimum pressure ($p_{\min}$). The node flow rate ($q_{i|(i,j),t}$, $q_{j|(i,j),t}$) of the pipeline (i, j) is equal to the pipeline flow rate ($Q_{i,j,t}$).

$$Q_{i,j,t} = 5033.11 d_{i,j}^{8/3} \left[\frac{(p_{i|(i,j),t})^2 - (p_{j|(i,j),t})^2}{Z \Delta T_{i,j,t} L_{i,j}} \right]^{0.5} \quad \forall (i, j) \in A, i \neq j, \forall t \in T \quad (5)$$

$$p_{i|(i,j),t} \leq p_{\max} \quad \forall (i, j) \in A, i \neq j, \forall t \in T \quad (6)$$

$$p_{j|(i,j),t} \geq p_{\min} \quad \forall (i, j) \in A, i \neq j, \forall t \in T \quad (7)$$

$$q_{i|(i,j),t} = Q_{i,j,t} = q_{j|(i,j),t} \quad \forall (i, j) \in A, i \neq j, \forall t \in T \quad (8)$$

In the formula, $d_{i,j}$ is the pipeline diameter, cm; Z is the compressibility factor; Δ is the relative density; $T_{i,j,t}$ is the temperature in the pipeline (i, j), K; and $L_{i,j}$ is the pipeline length, km.

3.2.2. Compressor Constraints

The compressor constraints contain suction pressure ($p_{i,t}^{in}$) constraints, discharge pressure ($p_{i,t}^{out}$) constraints, compression ratio ($\varepsilon_{i,t}$) constraints, compressor power ($N_{i,t}$) constraints, and compressor number ($z_{i,y,t}$) constraints, as shown in Equations (9)–(13), respectively.

$$p_{i,t} = p_{i,t}^{in} \quad \forall i \in I, \forall t \in T \quad (9)$$

$$p_{i,t}^{out} = p_{i|(i,j),t} \quad \forall (i, j) \in A, i \neq j, \forall t \in T \quad (10)$$

$$\varepsilon_{i,t} = \frac{p_{i,t}^{out}}{p_{i,t}^{in}} \quad \forall i \in I, \forall t \in T \quad (11)$$

$$N_{i,t} = 16.745 p_{i,t}^{in} q_{i,t} \frac{k}{k-1} (\varepsilon_{i,t}^{\frac{k-1}{k}} - 1) \frac{Z_{i,t}^{in} + Z_{i,t}^{out}}{2Z_{i,t}^{in}} \frac{1}{\eta} \quad (12)$$

$$z_{i,y,t} = \frac{N_{i,t}}{N_y} \quad \forall i \in I, \forall y \in Y, \forall t \in T \quad (13)$$

In the formula, $p_{i,t}$ is the node i pressure, MPa; $q_{i,t}$ is the node i flow rate, m³/min; k is the gas-specific heat ratio; η is the compression efficiency; and N_y is the maximum operating power, kW/set.

3.2.3. Well or Platform Throttling Constraints

The throttling at the well is to control well pressure ($p_{w,t}$), as shown in Equation (14). $p_{w|(w,g),t}$ is the pressure before throttling at the well. Similarly, platform throttling is to control the platform pressure ($p_{g,t}$) to a certain value, as shown in Equation (15). $p_{g|(g,j),t}$ is the pressure before throttling at the platform.

$$\delta_{w,t} = \frac{p_{w|(w,g),t}}{p_{w,t}} \quad \forall w \in W, \forall (w,g) \in WGA, \forall t \in T \quad (14)$$

$$\delta_{g,t} = \frac{p_{g|(g,j),t}}{p_{g,t}} \quad \forall g \in G, \forall (g,j) \in GIA, \forall t \in T \quad (15)$$

In the formula, $\delta_{w,t}$ is the well w throttle ratio and $\delta_{g,t}$ is the platform g throttle ratio.

3.2.4. Pressure Balance Constraints

The pressure balance constraints need to be considered at platforms, area points, and stations, as shown in Equations (16)–(18), respectively. $\tau(g)^+$ is the set of wells at the platform g . The smallest well pressure is denoted by $p_{\tau(g)^+,t}^{\min}$. The pressure balance constraint is used to construct the relationship between the starting pressure ($p_{s|(i,s),t}$) and ending pressure ($p_{n|(i,n),t}$) of the pipeline and the facility point pressure ($p_{s,t}$).

$$p_{\tau(g)^+,t}^{\min} = p_{g,t} \quad \forall g \in G, \forall t \in T \quad (16)$$

$$p_{n|(i,n),t} = p_{n,t} \quad \forall n \in N, \forall (i,n) \in INA, \forall t \in T \quad (17)$$

$$p_{s|(i,s),t} = p_{s,t} \quad \forall s \in S, \forall (i,s) \in ISA, \forall t \in T \quad (18)$$

3.2.5. Well Flow Rate Constraints

Well throttling has some effects on gas productivity. The relationship between flow rate and throttling is shown in Equation (19). The flow rate after well throttling needs to be controlled, as shown in Equation (20), and the maximum flow rate of the nozzle flow $q_{sc,t}^{\max}$ is shown in Equation (21). If wells do not need throttling or pressurizing, the flow rate is the initial flow rate $q_{w,t}^0$, as shown in Equation (22).

$$q_{sc,t} = \frac{0.408 p_{1,t} d^2}{\sqrt{\Delta T_{1,t} Z_{1,t}}} \sqrt{\frac{\omega}{\omega-1} \left[\left(\frac{p_{2,t}}{p_{1,t}} \right)^{\frac{2}{\omega}} - \left(\frac{p_{2,t}}{p_{1,t}} \right)^{\frac{\omega+1}{\omega}} \right]} \quad (19)$$

$$q_{w,t}^1 = \begin{cases} q_{sc,t} & q_{sc,t} \leq q_{sc,t}^{\max} \\ q_{sc,t}^{\max} & q_{sc,t} > q_{sc,t}^{\max} \end{cases} \quad \forall w \in W, \forall t \in T \quad (20)$$

$$q_{sc,t}^{\max} = \frac{0.408 p_{1,t} d^2}{\sqrt{\Delta T_{1,t} Z_{1,t}}} \sqrt{\frac{\omega}{\omega-1} \left[\left(\frac{2}{\omega+1} \right)^{\frac{2}{\omega-1}} - \left(\frac{2}{\omega+1} \right)^{\frac{\omega+1}{\omega-1}} \right]} \quad (21)$$

$$q_{w,t} = \begin{cases} q_{w,t}^0 & \delta_{w,t} \geq 1 \\ q_{w,t}^1 & \delta_{w,t} < 1 \end{cases} \quad \forall w \in W, \forall t \in T \quad (22)$$

In the formula, $q_{sc,t}$ is the flow rate through the nozzle in standard condition, m^3/d ; $p_{1,t}$ is the pressure in front of the nozzle, MPa; $p_{2,t}$ is the pressure behind the nozzle, MPa; d is the nozzle hole diameter, mm; $T_{1,t}$ is the temperature in front of the nozzle, K; $Z_{1,t}$ is the compressibility factor under temperature T_1 and pressure p_1 ; and ω is the gas adiabatic index (take $\omega = 1.3$ for calculation).

Where $q_{sc,t}^{\max}$ is the maximum flow rate through the nozzle, m^3/d .

3.2.6. Compressor Rearrangement Constraints

The decision-making difference between time t and time $t - 1$, where 0 represents no need to rearrange the compressor, 1 represents the need to install the compressor, and -1 represents the need to rearrange the compressor, is shown in Equation (23). The number of identical elements in the set is shown in Equations (24)–(26). The expressions of compressor installation and rearrangement number at time t are shown in Equations (27) and (28), respectively.

$$B_{i,t,y} = b_{i,t,y} - b_{i,t-1,y} \quad \forall i \in I, \forall t \in T, \forall y \in Y \quad (23)$$

$$PoslNum_t = \sum_{t \in T} \sum_{i \in I} (B_{i,t,y} = 1) \quad \forall i \in I, \forall t \in T, \forall y \in Y \quad (24)$$

$$NeglNum_t = \sum_{t \in T} \sum_{i \in I} (B_{i,t,y} = -1) \quad \forall i \in I, \forall t \in T, \forall y \in Y \quad (25)$$

$$Num_t^{P-N} = PoslNum_t - NeglNum_t \quad (26)$$

$$o_{i,t}^c = \begin{cases} Num_t^{P-N} & Num_t^{P-N} \geq 1 \\ 0 & Num_t^{P-N} < 1 \end{cases} \quad \forall i \in I, \forall t \in T \quad (27)$$

$$o_{i,t}^u = \begin{cases} NeglNum_t & Num_t^{P-N} \geq 1 \\ PoslNum_t & Num_t^{P-N} < 1 \end{cases} \quad \forall i \in I, \forall t \in T \quad (28)$$

In the formula, $B_{i,t,y}$ is the decision difference between the compressor location at time t and time $t - 1$; $PoslNum_t$ is the number of 1 defined in the set; $NeglNum_t$ is the number of -1 defined in the set; and Num_t^{P-N} is the difference value.

4. Solution Approach

The optimization framework for the SGGTS is characterized as an MINLP model, encompassing both 0–1 integer variables and non-linear constraints. The realm of MINLP problem solvers is vast, boasting tools like COUENNE (Belotti, 2009) [29], DICOPT (Duran and Grossmann, 1987) [30], CONOPT (Drud, 1985) [31], and SCIP (Kronqvist et al., 2018) [32], among others. Notably, SCIP stands out as one of the premier high-speed solvers for mixed-integer programs and MINLPs. Furthermore, it serves as an architectural scaffold for constrained integer programs, employing the branch-and-bound methodology. SCIP's inherent mechanism employs linear programming relaxations paired with cutting planes to delineate a robust dual boundary. Simultaneously, it integrates constraint programming to manage diverse (non-linear) constraints and propagation mechanisms to refine the variable domain. This solver's design grants comprehensive oversight over the solution trajectory and facilitates access to granular information, delving deep into the solution's core. Given its capabilities, this research harnesses SCIP to resolve the designated MINLP challenges. A visual representation of the optimization model's solution process is depicted in Figure 3. First, determine the pressurization location of the SGGTS and establish the optimization model. Then obtain the known data of the SGGTS, including the network structure, number of wells, production time, pipeline parameters, etc. Program the collections, variables, parameters, equations, etc., in GAMS, and finally solve it using SCIP.

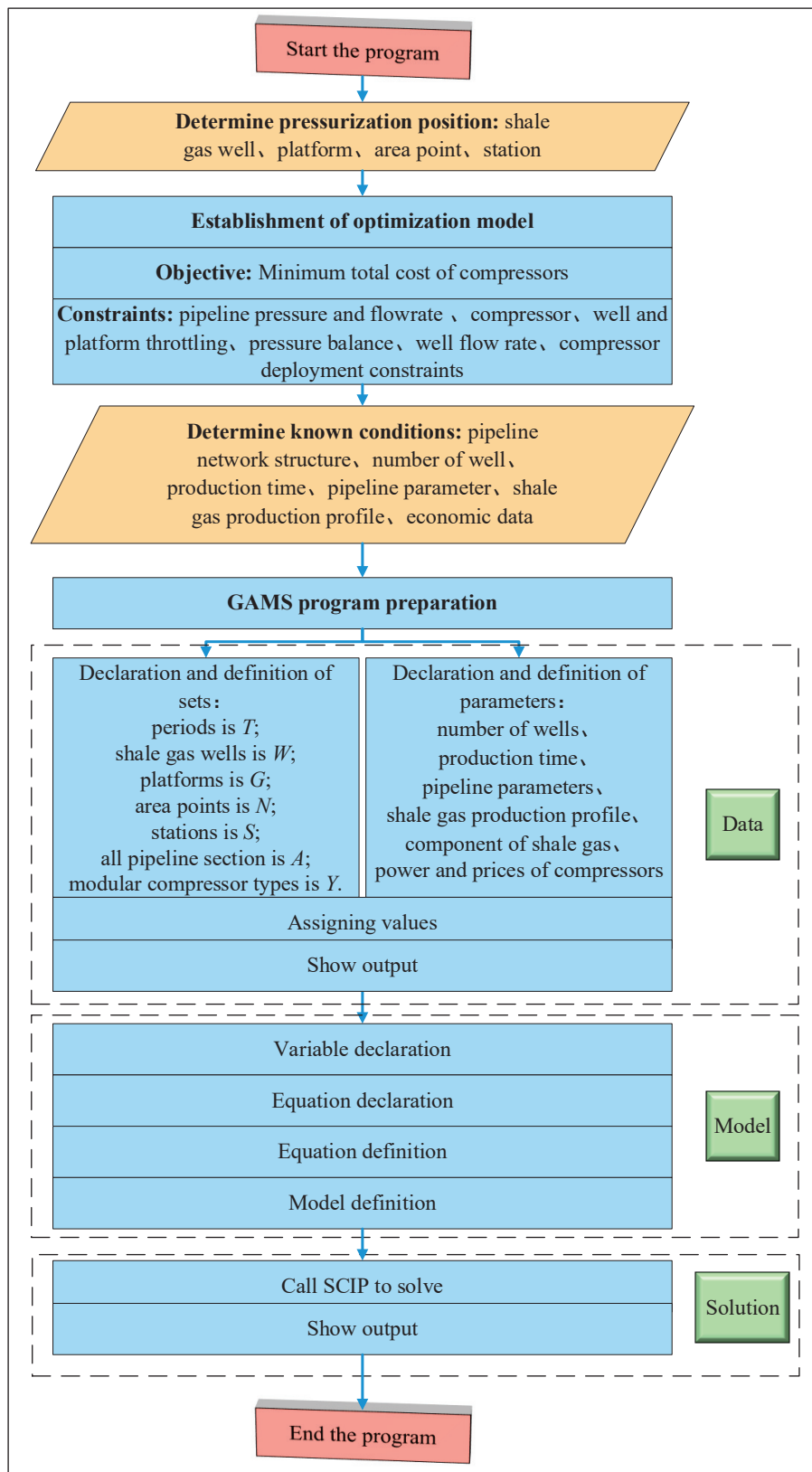


Figure 3. Optimization model solution procedure.

5. Case Study

5.1. Basic Parameters

The pipeline network in the shale gas field is a branch system, as shown in Figure 4. The pipeline network includes a total of 51 wells, 13 platforms, 8 area points, and 1 station. The gas collected from the wellheads is gathered at the platforms and then transported to the station through the gathering pipeline. After processing, it is exported. The production parameters in the 4-year production period are selected for research. The specified production period is discretely divided into 48 periods of monthly units, which are named M1, M2, ..., and M48. The number and production time of wells at each platform are shown in Table 1. Pipeline parameters are represented in Table 2. The well production data is shown in Figure 5. The station pressure is 6.3 MPa. The gas composition is shown in Table 3. The purchase and rearrangement costs of modular compressors of different powers are shown in Table 4. The electricity cost is 0.67 Yuan/(kW·h).

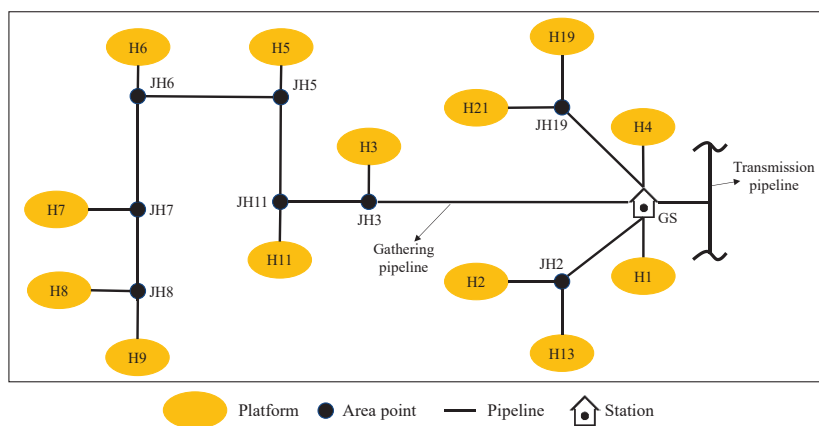


Figure 4. Pipeline network structure.

Table 1. Production parameters.

Number	Platform	Well Number	Production Time	Number	Platform	Well Number	Production Time
1	H1	8	M1	8	H8	3	M19
2	H2	4	M1	9	H9	6	M19
3	H3	3	M15	10	H11	3	M10
4	H4	3	M16	11	H19	3	M16
5	H5	4	M21	12	H21	3	M1
6	H6	8	M1	13	H13	4	M1
7	H7	1	M24	-	-	-	-

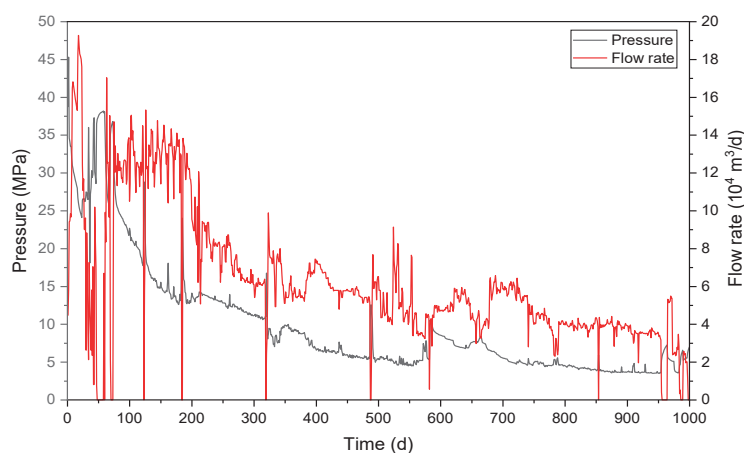


Figure 5. Production data of a single well in the shale gas field.

Table 2. Pipeline parameters.

Pipeline	Starting	End	Diameter (mm)	Length (km)
1	H1	GS	200	0.2
2	H2	GS	200	1.4
3	H3	GS	200	1.5
4	H4	GS	200	4.4
5	H5	H11	200	2.7
6	H6	H5	200	3.2
7	H7	H6	200	2.8
8	H8	H7	200	2.1
9	H9	H8	200	1.3
10	H11	H3	200	2.6
11	H13	H2	200	6.2
12	H19	GS	200	8.2
13	H21	H19	200	5.5

Table 3. Shale gas composition.

Composition	CH ₄	C ₂ H ₆	C ₃₊	CO ₂	H ₂ S	He	H ₂	N ₂
Mol (%)	99.09	0.44	0.02	0.27	0.00	0.02	0.00	0.16

Table 4. Compressor price.

Number	Compressor Power	Purchase Price (10 ⁴ Yuan/Set)	Rearrangement Price (10 ⁴ Yuan/Set)
1	315 kW	63	5
2	500 kW	96	5
3	710 kW	136	5
4	900 kW	170	5
5	1000 kW	190	5
6	1250 kW	240	5
7	1400 kW	270	5

5.2. Result Analysis

5.2.1. Iterative Solution

The model is solved under multi-period and single-period conditions, respectively, and the solution parameters under a single-period condition are shown in Table 5. Under single-cycle conditions, the system was solved the fastest in the 17th month, taking 0.09 s and 944 iterations to complete, and the slowest in the 18th month, taking 0.75 s and 1239 iterations to complete. Due to the different number of constraints and variables in different cycles, the complexity of problem-solving varies, resulting in different solution times and numbers of iterations.

The iterative solution process of the model under a multi-period condition is shown in Figure 6. The original problem has 11,053 variables, 12,827 constraints, and 32,628 non-zero elements. The total computation time is 1039.63 s, with a total of 4.255 million iterations. It takes 2.1 s to preprocess the original problem, which reduces the original variables to 4872 and constraints to 6945. After preprocessing, the iteration starts, and the whole solution process is carried out under two boundary conditions: the dual bound and the primal bound. Initially, an initial value is found under the dual bound conditions after 2.8 s, and then the initial value gradually decreases. In the 57.5th second, the initial value of the feasible solution is found under the primal bound conditions, and the value gradually

increases. As the values under the two bound conditions get closer to each other, the relative error of the two values reaches 9.91% in the 1039.63rd second (the SCIP error is limited to 10%), and the program stops iterating and outputs the result.

Table 5. Iterative of a single-period condition.

Time Period (Month)	CPU Time (s)	Iteration Count	Time Period (Month)	CPU Time (s)	Iteration Count
14	0.20	696	32	0.15	1140
15	0.10	737	33	0.17	1050
16	0.09	900	34	0.60	1164
17	0.09	944	35	0.20	1062
18	0.11	1021	36	0.66	864
19	0.48	819	37	0.53	1179
20	0.38	1091	38	0.75	1239
21	0.44	864	39	0.58	1304
22	0.72	1100	40	0.17	1451
23	0.41	1044	41	0.11	1317
24	0.52	1118	42	0.15	715
25	0.22	1039	43	0.14	1197
26	0.11	1236	44	0.18	1227
27	0.13	1107	45	0.18	1274
28	0.32	1189	46	0.17	1285
29	0.48	763	47	0.11	1147
30	0.14	1496	48	0.16	1051
31	0.18	1076	-	-	-

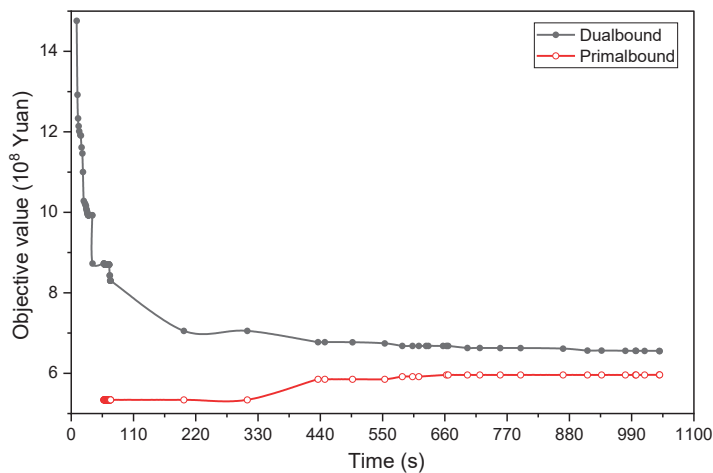


Figure 6. Convergence curve.

5.2.2. Type and Quantity of Modular Compressors

The change in the number of modular compressors over time is shown in Figure 7. Different compressor power levels are represented by different shapes. To ensure stable production in the shale gas field within the specified production period, a total of 13 modular compressors, including 5 power types, are required under a multi-period condition, and a total of 26 modular compressors, including 7 power types, are required under a single-period condition. It is evident that a multi-period condition requires fewer compressors and fewer power types. However, as production progresses, the requirement for compressor power becomes larger and larger, and the number of compressors also increases. Not only are the required power types of modular compressors different in various pressurizing

periods, but the number of modular compressors with the same power also changes. This requires managers to reasonably rearrange modular compressors according to the changes in pressurization demand to avoid idle facilities.

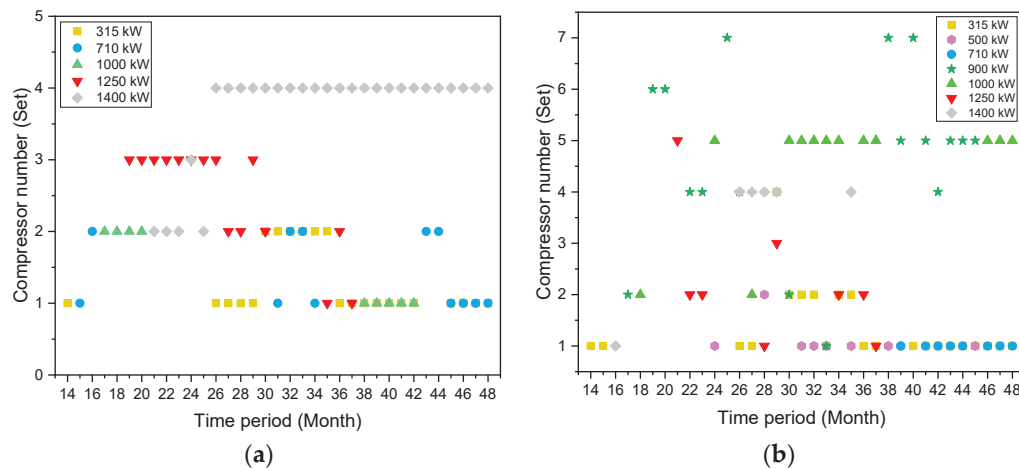


Figure 7. Number of modular compressors over time: (a) multi-period and (b) single-period.

5.2.3. Pressurization Scheme

The pressurization scheme of modular compressors for the SGGTS during the specified production period is shown in Figure 8. The colors of different cells represent modular compressors of different powers, and the numbers inside the cells represent the number of modular compressors. This shale gas field enters the pressurization stage at M14. Due to the constant changes in pressurization demand, the purchase and rearrangement of modular compressors are needed continuously. Figure 8a shows the pressurization scheme for each period under the multi-period condition, with a total of 18 rearrangements for the modular compressor during the specified production period. Figure 8b shows the pressurization scheme for each period under the single-period condition, with a total of 33 rearrangements for the modular compressor during the specified production period. It indicates that the results obtained under a multi-period condition are more stable than under a single-period condition, both in terms of the change in the pressurizing position and the rearrangement frequency of the modular compressor.

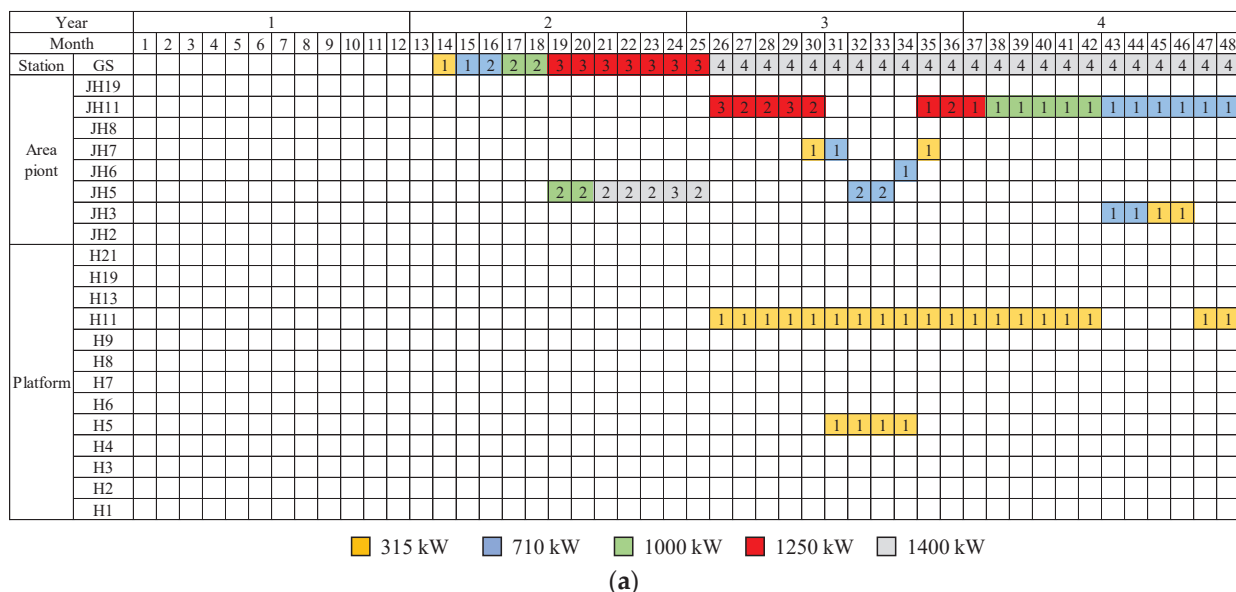


Figure 8. Cont.

As production progresses, the economic advantages under the multi-period condition become more and more pronounced. The cumulative cost under single-period and multi-period conditions within four years is $13,920.778 \times 10^4$ Yuan and $11,527.532 \times 10^4$ Yuan, respectively. The cumulative cost under multi-period conditions is reduced by 17.19%. Therefore, it can be concluded that the solution under multi-period conditions can lead to a more economical modular compressor pressurization scheme, which can help reduce the investment cost of shale gas field production.

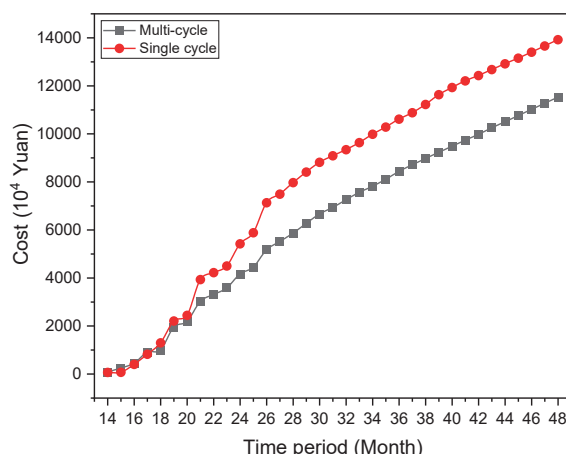


Figure 10. Cost comparison of a modular compressor.

6. Conclusions

1. Concentrating on the changing characteristics of the pressurization process of shale gas production and considering the compressor modularization, this study established an MINLP model for the pressurization and rearrangement optimization of the SGGTS. The reliability of the model was verified by studying a practical example.
2. By deploying the modular compressor, the idleness and waste of the modular compressor are avoided, the utilization rate of the modular compressor is greatly improved, and the production investment cost is also reduced to a certain extent, improving the economic benefits of the shale gas field.
3. Under a multi-period condition, it requires fewer compressors and types, and the change in pressurizing position and rearrangement frequency of modular compressors are more stable, as is the change in compressor operating power. In addition, the investment cost of shale gas field production can be reduced. After solving under multi-period conditions, the cumulative cost is reduced by 17.19%.
4. Compared with the previous work, our model has made great progress. In future work, we will consider the related uncertainty factors to establish an optimization model for the pressurization and rearrangement of the SGGTS to produce a pressurization scheme with more application values.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

$b_{i,y,t}$	Location variable, 0 or 1
$B_{i,t,y}$	Decision difference between the compressor location at time t and time $t - 1$
d	Nozzle hole diameter, mm
$d_{i,j}$	Pipeline diameter, cm
$N_{i,t}$	Operating power, kW
F	Total cost, 10^4 Yuan
F_{cc}	Purchase cost, 10^4 Yuan
F_{oc}	Operation cost, 10^4 Yuan
F_{mc}	Rearrangement cost, 10^4 Yuan
k	Gas-specific heat ratio
$L_{i,j}$	Pipeline length, km
N_y	Maximum operating power, kW/set
$o_{i,t}^c$	Installation compressor number
$o_{i,t}^u$	Rearrangement compressor number
$p_{\max}$	Maximum operation pressure, MPa
$p_{\min}$	Minimum operation pressure of the pipeline, MPa
$p_{1,t}$	Pressure in front of the nozzle, MPa
$p_{2,t}$	Pressure behind the nozzle, MPa
$p_{i,t}$	Node i pressure, MPa
$p_{w,t}$	Well w pressure, MPa
$p_{g,t}$	Platform g pressure, MPa
$p_{n,t}$	Area point n pressure, MPa
$p_{s,t}$	Station s pressure, MPa
$p_{i,t}^{in}$	Suction pressure, MPa
$p_{i,t}^{out}$	Discharge pressure, MPa
$p_{i (i,j),t}$	Pipeline starting pressure, MPa
$p_{j (i,j),t}$	Pipeline end pressure, MPa
$p_{\tau(g)^+,t}^{\min}$	Smallest well pressure, MPa
$q_{i,t}$	Node i flow rate, $m^3/\min$
$q_{w,t}^0$	Well w initial flow rate, m^3/d
$q_{w,t}$	Well w flow rate, m^3/d
$q_{sc,t}$	Flow rate through the nozzle in standard condition, m^3/d
$q_{i (i,j),t}$	Node i flow rate of the pipeline (i, j) , m^3/d
$q_{sc,t}^{\max}$	Maximum flow rate through the nozzle, m^3/d
$Q_{i,j,t}$	Pipeline flow rate, m^3/d
$r_{i,t}$	Operating price, 10^4 Yuan/kW
$T_{1,t}$	Temperature in front of the nozzle, K
$T_{i,j,t}$	Temperature in the pipeline (i, j) , K
$u_{i,y,t}$	Type y compressor number rearranged, set
$z_{i,y,t}$	Type y compressor number installed, set
Z	Compressibility factor
$Z_{1,t}$	Compressibility factor under temperature T_1 and pressure p_1
$Z_{i,t}^{in}$	Compressibility factor under the inlet condition
$Z_{i,t}^{out}$	Compressibility factor under the outlet condition
ϕ	Conversion factor
η	Compression efficiency
Δ	Relative density
ω	Gas adiabatic index, take $\omega = 1.3$ for calculation example 1
$\alpha_{i,y,t}$	Compressor price of type y , 10^4 Yuan/set
$\varphi_{i,y,t}$	Rearrangement price, 10^4 Yuan/set
$\varepsilon_{i,t}$	Compression ratio
$\delta_{w,t}$	Well w throttle ratio
$\delta_{g,t}$	Platform g throttle ratio
$\tau(g)^+$	Set of wells at platform g
$PoslNum_t$	Number of 1 defined in the set

$NegNum_i$	Number of -1 defined in the set
Num_i^{P-N}	Difference value

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Article

Optimization of Energy Storage Allocation in Wind Energy Storage Combined System Based on Improved Sand Cat Swarm Optimization Algorithm

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Abstract: In order to improve the operation reliability and new energy consumption rate of the combined wind–solar storage system, an optimal allocation method for the capacity of the energy storage system (ESS) based on the improved sand cat swarm optimization algorithm is proposed. First, based on the structural analysis of the combined system, an optimization model of energy storage configuration is established with the objectives of the lowest total investment cost of the ESS, the lowest load loss rate and the lowest new energy abandonment rate, which not only takes into account the economy of energy storage construction for investors and builders, but also reduces the probability of blackout for users to protect their interests and improves the utilization rate of the natural resources of wind and light, which can achieve a multi-win–win situation. The model can realize the win–win situation in many aspects. Secondly, an improved k-means clustering algorithm is used to cluster the renewable energy power and load data to realize the typical day data extraction. Then, for the proposed multi-objective optimization model, an SCSO is proposed based on the triangular wandering strategy, Lévy flight strategy and lens imaging reverse learning improvement, which can help the algorithm to jump out of the local optimum while improving its global optimization ability, and these improvements can significantly improve the optimization effect of the SCSO. Finally, simulation analysis is carried out in combination with typical daily extraction data, and the results verify the advantages and effectiveness of the proposed model and algorithm.

Keywords: new energy; energy storage system; sand cat swarm algorithm; optimal allocation; multi-objective optimization

1. Introduction

Climate change is a major issue shared by people around the world, and greenhouse gases are soaring year after year as countries increase their carbon dioxide emissions, threatening ecosystems. Against this backdrop, countries are reducing greenhouse gas emissions by means of a global pact, and China has proposed a low-carbon development goal of carbon peaking and carbon neutrality [1–3]. Therefore, wind power and photovoltaic, as clean energy sources, have been developing rapidly in recent years, and in China, a large number of wind power and PV are integrated into the power grid. However, the instability of wind power generation brings about a decrease in the reliability of the system as well as a higher rate of wind and light abandonment, both of which are problems that need to be solved urgently [4,5]. By configuring energy storage, the wind–power and photovoltaic power output volatility can be effectively suppressed by the wind–power and photovoltaic joint power generation system, which can be flexibly adjusted and can send out excess power when the system output is larger than the load, as well as make up the difference

through the grid when the system output cannot meet the load demand. However, the construction, operation and maintenance costs of energy storage devices are high, and an excessive configuration of the storage capacity will greatly increase the investment cost and therefore reduce the economy of the combined generation system [6]. On the other hand, if the capacity is too small, it will lead to a high wind and light abandonment rate and, subsequently, system reliability deterioration, so we need to comprehensively consider the economy, reliability and wind and light dissipation of the storage system capacity's configuration, all of which promote the dissipation of renewable energy and improve the stability of the combined system, which are of great significance [7].

The authors of [8] use particle swarm algorithm to solve the capacity of ESS by considering the construction and maintenance cost of ESS as well as the cost of wind abandonment and carbon treatment. The paper [9] establishes an economic model of wind power-photovoltaic-diesel power-ESS microgrid system with the introduction of outage penalties and the cost of pollution control, and then solves the capacity allocation of the microgrid via genetic algorithm. The study [10] uses system voltage deviation, the daily active network loss and the allocation of ESS capacity as the optimal configuration model of energy storage, while introducing the Tennessee whisker search and Logistic chaotic mapping to improve the multi-objective particle swarm algorithm, which improves its convergence speed and optimization ability. Ref. [11] investigates the optimal configuration of the storage system capacity in the independent photovoltaic system with the objectives of the system load shortage rate and the energy spillover ratio, which can effectively alleviate the energy spillover of the renewable energy sources and increase the renewable energy utilization rate. The authors of [12] studied the impact of the grid-connected location of an ESS on its configuration, and also analyzed and investigated the impact of wind-scenery combinations with different correlations, different sampling time intervals and different numbers of power stations on the configuration of the energy storage as well as on the wind-scenery complementarity. The authors of [13] established a two-layer optimization model for a multi-type energy storage integrated energy system (IES). The first layer optimization model takes the lowest total investment cost of the ESS as the optimization objective, and the second layer optimization model takes the lowest operation and maintenance cost of the ESS as the optimization objective. The study [14] proposes a distributed optimization framework for solving the cost minimization problem in energy storage and power generation planning, which takes into account the initial investment cost and the latter operation and maintenance costs, while at the same time solves the problem posed by large-scale optimization problems. Ref. [15] developed a two-tier optimization model combining PSO and DLOPF, where PSO adjusts and identifies the location of the battery storage system, and DLOPF uses the levelized cost of energy and storage to locate and size the RES in a spatiotemporal framework, which is used to minimize cost while limiting carbon emissions.

It can be seen that most scholars choose some form of a meta-heuristic optimization algorithm (stochastic optimization algorithms) when solving the energy storage allocation problem on the generation side of the power system, and these algorithms have obvious advantages over the traditional linear programming solvers and nonlinear programming solvers in solving the multi-objective optimization problems under multiple constraints, i.e., fast solution speed and good optimization results. The more mature meta-heuristic optimization algorithms include PSO, GA, WOA, BBO and SNO. PSO is an optimization algorithm developed according to the foraging behavior of bird flocks [16], which has the advantages of fast convergence speed, few parameters, simple algorithm and is easy to implement, but there is also the problem of falling into the local optimal solution because of the algorithm's simple structure. The GA algorithm simulates the phenomena of replication, crossover and mutation that occur in natural selection and heredity, and it also simulates the phenomena of natural selection and heredity [17]. In addition, the GA algorithm simulates the behaviors and phenomena, such as replication, crossover and mutation, that occur in the population and chromosome inheritance of species, and relies on the random selection, crossover and mutation operations of the initial population to produce a generation of

individuals that are more adaptive and more conducive to survival, i.e., to produce a more optimal set of solutions, which will make the individual particles progressively close to the optimal solution to produce the optimal individual, that is, to generate the optimal solution. The GA algorithm is highly scalable, and it is easy to be combined with other algorithms to create optimization algorithms with a better optimization capacity, and its strong global search ability will not fall into the local optimum. WOA is an optimization algorithm generated by simulating the hunting behavior of humpback whales [18], and the whole process of the algorithm includes three stages: searching for food, contracting the encirclement and updating the position of the spiral. The WOA algorithm has the advantages of fast convergence speed, strong global searching ability and simple algorithm, but it is more sensitive to the parameter settings and needs to be adjusted to achieve a better solution. However, it is more sensitive to parameter setting and needs to be adjusted to achieve better results, and its efficiency will be greatly reduced when dealing with high-latitude problems. BBO is an efficient swarm intelligence optimization algorithm proposed in 2008 [19], which achieves optimization by simulating the migration process of species between multiple habitats in nature and has a better performance in global search, as well as a fast iteration speed in the early stage of the algorithm and a strong ability to process information. However, the algorithm has the disadvantages of precocity and slow convergence in the later stage when dealing with high-complexity high-dimensional multi-objective problems. SNO is a new type of intelligent optimization algorithm proposed in 2018 [20], which mainly simulates the behavior of human beings communicating with each other and sharing their current situation to search for the optimal solution. The algorithm has strong optimal solution searching ability and fast convergence speed, which has the advantages of strong global searching ability, fast convergence speed and effective use of the current population information, but the local optimization ability is weak because it does not incorporate the mechanism of individual guided population.

The sand cat swarm optimization (SCSO) algorithm is a meta-heuristic optimization algorithm designed to simulate the behavior of sand cats [21]. It is implemented to find an optimal solution by simulating the two behaviors of a sand cat searching for prey and attacking the prey. Since it was proposed by Amir Seyyedabbasi and Farzad Kiani in April 2022, it has been applied in optimization problems in many fields. The SCSO pair achieves the transition between the two phases by introducing the parameter R . Therefore, it can perform a local search in the global search, and may also jump out of the local optimum to reperform the global search during the local search. It has a better performance in the global search compared to the algorithms presented in the above section. The algorithms presented perform better in high dimensions and multi-objectives. Energy storage capacity optimization is a high-dimensional and multi-objective optimization problem, and SCSO will have an advantage over other algorithms in solving this problem.

In view of this, based on the flexible regulation capability of the ESS, and considering the economy and reliability of the ESS, in this paper, an energy storage capacity optimization method based on an improved SCSO is proposed [22,23]. The method first uses k-means algorithm to cluster wind power, PV and load data to extract typical days [24], and then inputs the extracted typical day data into the ESS optimization model and performs multi-objective optimization search by using the improved SCSO in order to find several energy storage allocation schemes [25].

The main contributions made by this study are listed below:

- Established an optimal allocation model of the ESS that comprehensively considers the economy of the ESS, the reliability of system power supply and the utilization rate of new energy, and we verified its feasibility;
- Improved the k-means algorithm using the clustering effectiveness index BWP to improve its clustering ability;
- Enhanced the SCSO to improve its local optimization and global optimization ability, and added Pareto optimization to make it applicable to multi-objective optimization problems.

The following sections of this paper are as follows. Section II mainly introduces the mathematical formulation and boundary conditions of the energy storage optimization model. Section III details the fundamentals of SCSO and the improvement of the algorithm, which contains the involved formulas. Section IV focuses on the basic principles and improvements of the k-means algorithm, and a flowchart of the typical day extraction performed by the clustering algorithm is displayed. Section V focuses on an example analysis. First, we select the data of a wind farm, a photovoltaic (PV) farm and an area load in China for a whole year in terms of hours, and then use the improved k-means algorithm to cluster these data and extract the typical day data. Subsequently, the typical day data are input into the energy storage allocation optimization model and then solved using the improved SCSO as well as some other optimization algorithms, and their results are compared to verify the advantages of the improved SCSO. Section VI summarizes the entire article, discusses the results achieved and provides an outlook for future work. In addition, a roadmap of the content is shown in Figure 1.

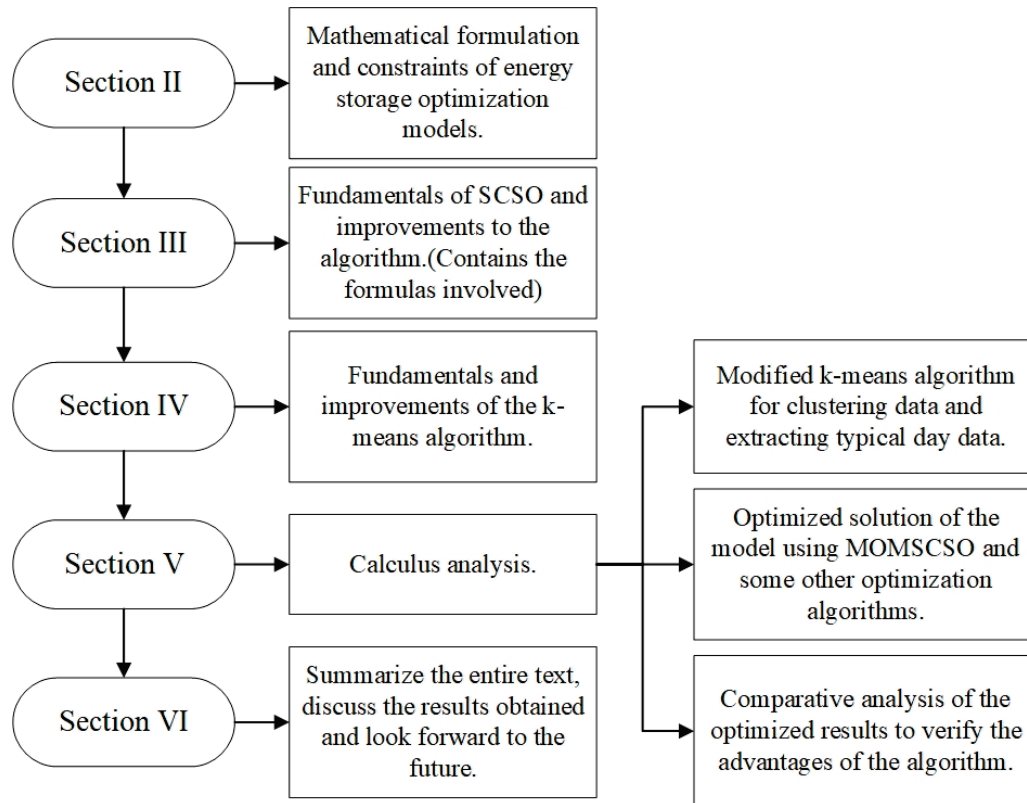


Figure 1. Article Structure Chart.

2. Optimization Model for Energy Storage Capacity Allocation

When designing an ESS, the construction cost of the storage system, the reliability and the consumption of wind and solar resources must be considered at the same time [26]. Therefore, this paper establishes an optimization model of the ESS with the objectives of minimizing the overall cost of the system, the load shortage rate and the new energy abandonment rate, the expression of which is shown in Equation (1):

$$\min F = \min \sum_{t=1}^T (C_A, \eta_{LPSP}, \eta_{EWR}) \quad (1)$$

In the formula: C_A is the total system investment cost; η_{LPSP} is the load shortage rate; η_{EWR} is the wind and light rejection rate.

2.1. Total System Investment Cost

The total expense of the ESS mainly includes the initial investment of the ESS built at one time, and the cost during operation and maintenance of the ESS after it is built [27]. In addition to this, the system will purchase shortfall power from the distribution grid when the output cannot meet the load, so the power purchase cost of the system should also be considered. In order to establishing the total investment cost of the system, the formula is:

$$C_A = C_0 + C_m + C_{np} \quad (2)$$

In the formula: C_0 is the initial investment of ESS; C_m is the cost of operation and maintenance of ESS; C_{np} is the joint system power purchase cost.

The initial investment of the ESS is proportional to the capacity size of the ESS, which is discounted to the average annual cost of the completed project, Eq:

$$C_0 = \frac{r(1+r)^n}{(1+r)^n - 1} \lambda_{BESS} S_{BESS} \quad (3)$$

In the formula: λ_{BESS} is the initial investment of the energy storage battery and the built-in inherent cost coefficient; S_{BESS} is the capacity of the ESS; n is the service life of the ESS; r is the discount rate, which is taken as 5%.

The ESS will cause damage to the equipment when running for a long time, so it requires regular maintenance and management, the cost of which is related to the initial investment in the ESS. The formula is:

$$C_m = aC_0 \quad (4)$$

In the formula: a is the parameter of the ratio of the operation and maintenance cost of the ESS to its initial investment cost; C_m is the annual maintenance cost of the ESS.

When both wind and solar output and storage output cannot fulfill the load requirement, the system would then have to purchase a portion of the power to fill the shortfall, thus incurring a power purchase cost, for which, the formula is:

$$C_{np} = p_{buy} \left[\sum_{t=1}^T P_{load}(t) - P_{PV}(t) - P_{WT}(t) + P_{BESS}(t) \right] \Delta t \quad (5)$$

In the formula: P_{BESS} is the power of storage batteries (positive value when charging, negative value when discharging); P_{PV} and P_{WT} are the output power of photovoltaic and wind power, respectively; P_{load} is the power of system power demand; p_{buy} is the purchase price of electricity.

2.2. System Power Supply Reliability

The load deficit rate characterizes the reliability of the system's power supply, and the load deficit rate is related to the combined output of the load and the system [28,29]. The formula is:

$$\eta_{LPSP} = \frac{\sum_{t=1}^T [P_{load}(t) - P_{out}(t)] \Delta t}{P_{load}(t)} \quad (6)$$

In the formula: $P_{out}(t) = P_{PV}(t) + P_{WT}(t) - P_{BESS}(t)$; the smaller η_{LPSP} is, the higher the reliability of the system power supply.

2.3. Total System Investment Cost

When supply exceeds demand, neither the load nor the energy storage system can fully consume the power generation, which will result in a waste of resources, so the new energy abandonment rate is also introduced as one of the optimization objectives [30,31]. Its formula is:

$$\eta_{EWR} = \frac{\sum_{t=1}^T [P_{out}(t) - P_{load}(t)] \Delta t}{\sum_{t=1}^T [P_{PV}(t) + P_{WT}(t)] \Delta t} \quad (7)$$

In the formula: η_{EWR} is the rate of wind and light abandonment, the smaller η_{EWR} is, the higher the energy utilization rate.

2.4. Constraint

The state of charge (SOC) of a battery represents the ratio of the battery's current remaining charge to its charge when fully charged [32,33]. The formula is:

$$S_{OC}(t) = S_{OC}(t-1) + \frac{\eta P_{BESS}}{C_{BESS}} \Delta t \quad (8)$$

In the formula: $S_{OC}(t)$ is the SOC value of Li-ion battery at time t ; P_{BESS} is the charging and discharging power of the Li-ion battery (positive value when charging, negative value when discharging); C_{BESS} is the rated capacity of Li-ion battery; η is the charging and discharging efficiency (0.65~0.85 when charging, 1.00 when discharging [34,35]); Δt is the sampling time period.

In order to prolong the life of the battery and prevent it from being overcharged and discharged to cause harm to the battery, the SOC of the lithium battery is set with upper and lower limits:

$$S_{OC,min} \leq S_{OC}(t) \leq S_{OC,max} \quad (9)$$

In the formula: $S_{OC,min}$ and $S_{OC,max}$ are the upper and lower limits of the SOC of the lithium battery, respectively, $S_{OC,min} = 0.1$, $S_{OC,max} = 0.9$ [36,37].

The capacity of the ESS will be limited by preset upper and lower limits during optimization.

$$S_{BESS,min} \leq S_{BESS} \leq S_{BESS,max} \quad (10)$$

In the formula: $S_{BESS,min}$ and $S_{BESS,max}$ are the min and max capacities of the ESS, respectively.

Constraining the charging and discharging power of the ESS and controlling it within a specified range can effectively extend the service life of the battery:

$$P_{ch,min} \leq P_{BESS}(t) \leq P_{ch,max} \quad (11)$$

$$P_{disch,min} \leq P_{BESS}(t) \leq P_{disch,max} \quad (12)$$

In the formula: $P_{ch,min}$ and $P_{ch,max}$ are the min and max values of the charging power of the ESS, respectively; $P_{disch,min}$ and $P_{disch,max}$ are the min and max values of the discharging power of the ESS, respectively.

3. Improvement of SCSO

The algorithm (SCSO) used in this paper then focuses on the merit-seeking process by simulating the sand cat's searching-for-prey and attacking-prey behaviors, and also proposes a mechanism to achieve a balance between the searching and exploiting phases.

3.1. Search Stage

Sand cats in the search for prey mainly rely on emitting a low-frequency noise, where the low-frequency noise will be reflected when it touches the object and then the sand cats that receive these low-frequency noises will determine the location of the prey. Therefore, the sensitivity of the cat to low-frequency sound determines the scope of the cat's search for prey: the higher the sensitivity, the larger the search range. According to this characteristic principle of the sand cat, the mathematical formula to define the range of the general auditory sensitivity of a sand cat is as follows:

$$r_G = S_M - \left(\frac{2 \times S_M \times iter_c}{iter_{Max}} \right) \quad (13)$$

In the formula: S_M is the hearing ability of sand cats; $iter_c$ is the number of current iterations; $iter_{Max}$ is the max number of iterations; and r_G is the general auditory sensitivity range of the sand cat.

Generally the range of auditory sensitivity affects the search range of the entire sand cat population, but to avoid falling into a local optimum, each sand dune cat has a different range of sensitivity, so the equation for individual sensitivity is:

$$r = r_G \times rand(0, 1) \quad (14)$$

In the search phase, the sand cat updates its next position based on the global optimal solution and the current position of the individual, thus moving to other positions that may be easier to find prey, and then obtains the latest local optimum from the new search area. The above search process is mathematically modeled by the following equation:

$$P(t+1) = r \times (P_{bc}(t) - rand(0, 1) \times P_c(t)) \quad (15)$$

In the formula: P_{bc} is the optimal position; P_c is the present position.; r is the personal sensitivity range.

3.2. Attack Phase

The attack behavior of the sand cat also relies on its sense of hearing, and the second phase of the SCSO algorithm is mathematically modeled based on the attack behavior of the sand cat. The formula is:

$$P(t+1) = P_{bc}(t) - r \times P_{rand}(t) \times \cos \theta \quad (16)$$

$$P_{rand}(t) = |rand(0, 1) \times P_{bc}(t+1) - P_c(t)| \quad (17)$$

In the formula: P_{bc} is the optimal position; P_c is the present position; P_{rand} is the random position.

The flow of the attack phase is as follows. P_b and P_c are used to generate a random position P_{rand} . In addition, a roulette wheel is introduced to provide each sand cat with a randomly selected angle, increasing the randomness in turn to ensure population diversity; and finally, the attack on the prey is realized by using the equation. Among them, the random position can ensure that the sand cat is close to the prey, and the random angle can avoid the algorithm from falling into local optimization.

3.3. Transition between Search Phase and Attack Phase

Setting the parameter R determines whether the sand cat is in the search or hunt phase. The formula is:

$$R = 2 \times r_G \times rand(0, 1) - r_G \quad (18)$$

When $|R| > 1$, the sand cat will be in the search phase, at which point the position is updated according to the search phase formula. When $|R| < 1$, the sand cat will be in the attack phase, at which point the position is updated according to the attack phase formula. It is easy to see that R is a random value in the interval $[-r_G, r_G]$, where r_G gradually decreases from 2 to 0 during the iteration process, while in $r_G > 1$, $|R|$ may be greater than 1 or less than 1, so the sand cat may be in any stage of the search or the attack. This transformation method facilitates the ability of individuals to extricate themselves from a local optimum when they are trapped in it, in order to expand the global search capability.

3.4. Algorithmic Improvements

The inclusion of the triangular wandering strategy in the search phase makes it possible to improve the search range by not approaching the prey directly and quickly while the sand cat searches for the prey, but rather by randomly wandering around the prey [38]. The formula is:

$$L_1 = P_{bc}(t) - P_c(t) \quad (19)$$

$$L_2 = rand(0, 1) \times L_1 \quad (20)$$

$$\beta = 2 \times \pi \times rand(0, 1) \quad (21)$$

$$P_t(t) = L_1^2 + L_2^2 - 2 \times L_1 \times L_2 \times \cos \beta \quad (22)$$

$$P_{new}(t+1) = P_{bc}(t) + r \times P_t(t) \quad (23)$$

In the formula, P_{new} is the position obtained through the triangular random wandering strategy.

Lévy flight is an improved method that can add randomness to the algorithm. Lévy flight can provide a random wandering method with a step length conforming to the Lévy distribution. However, the Lévy flight sometimes has too long a step length. In order to be more consistent with the sand cat's behavior of attacking its prey, the Lévy flight is multiplied by a constant, thus reducing the step length and allowing the sand cat to wander as close as possible to its prey; the formula is as follows:

$$P_{new}(t+1) = P_{bc}(t) + (P_{bc}(t) - P_c(t)) \times C \times Levy \quad (24)$$

In addition, the lens imaging direction learning strategy is introduced, which extends the search by using an individual's current position to generate another position opposite to it, so that arithmetic can jump out of the current position and expand the search range, improving the diversity of the population. Its main formula is as follows:

$$k = \frac{\frac{a+b}{2} - x}{x^* - \frac{a+b}{2}} \quad (25)$$

$$x_j^* = \frac{a_j + b_j}{2} + \frac{a_j + b_j}{2k} - \frac{x_j}{k} \quad (26)$$

In the formula, a and b are the upper and lower bounds of x ; x^* is the point where x is image-reversed through the convex lens; x_j is the position of the individual in the j th dimension and x_j^* is the inverse solution of x_j . a_j and b_j are the maximal and minimal bounds, respectively, in the j th dimension of the search space.

Finally, Pareto is introduced to make it applicable to the multi-objective optimization problem.

3.5. Application of Improved Algorithms and Processes

The optimization model of the energy storage capacity allocation of the combined wind ESS developed in the paper takes the capacity of the ESS as the decision variable, which is the position information of an individual sand cat in the improved multi-objective SCSO. The optimization algorithm to solve the energy storage capacity allocation problem requires coding the model:

$$\left\{ \begin{array}{l} X = [x \ P] \\ x = S_{BESS} \\ P = [P_{BESS} \ P_{PV} \ P_{WT} \ P_{load}] \\ F = [f_1 \ f_2 \ f_3] \\ f_1 = C_A \\ f_2 = \eta_{LPSP} \\ f_3 = \eta_{EWR} \end{array} \right. \quad (27)$$

When using the algorithm to solve the model, the charging and discharging power, capacity constraints and SOC constraints of the storage system as described above are used to limit the wandering range of the sand cat, and then the capacity of the storage system can be calculated based on the wind and PV power and load demand of the combined system at each time node.

Based on the improved multi-objective SCSO to solve the ESS capacity problem, the flow chart is shown in Figure 2.

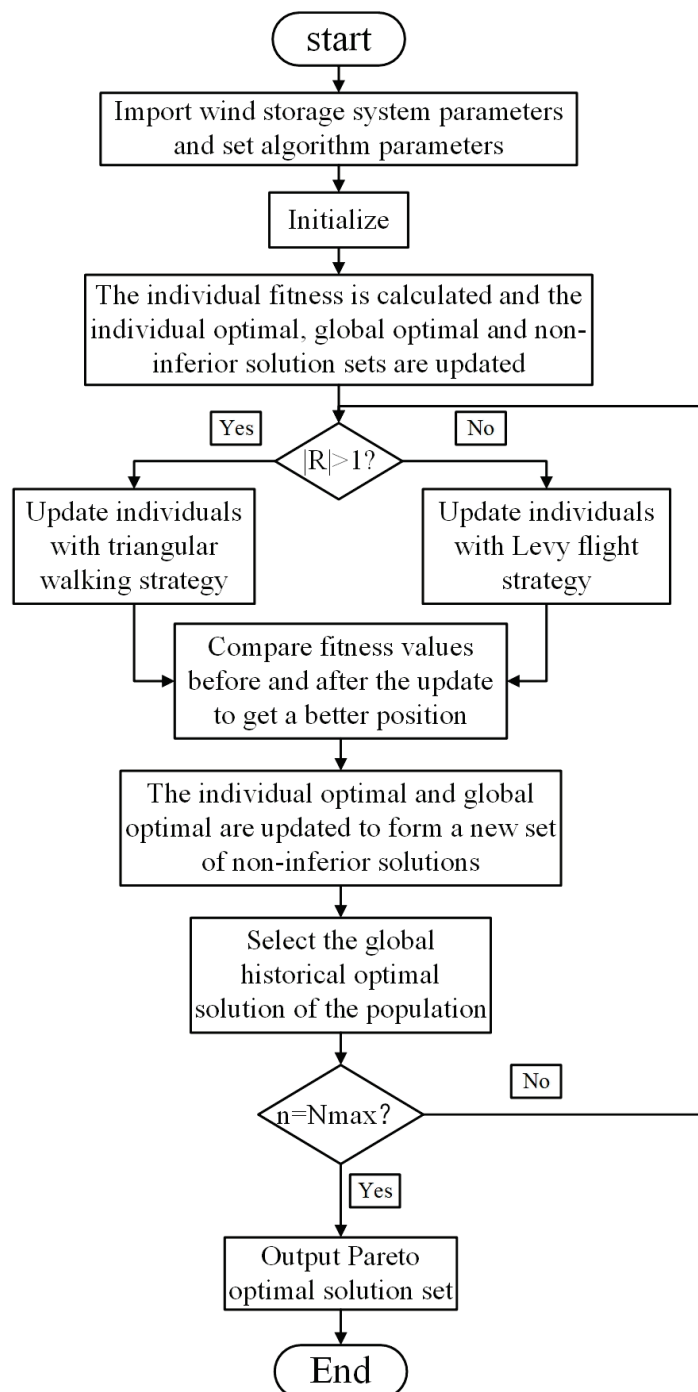


Figure 2. Flowchart of the improved algorithm.

4. Improved k-Means Clustering Algorithm

The k-means algorithm is one of several most widely used and frequently used clustering algorithms [39,40]. Its main principle and working method is: When given a value of K and K initial class cluster centroids, classify each point (data) into the class cluster represented by the nearest class cluster center point. After all the points have been assigned, take the average of all the points in a cluster as the centroid of that cluster, and then iteratively assign the points and update the center of the clusters until either the

centroid of the class clusters, which is calculated multiple times, changes slightly, or to achieve a specified number of iterations [41].

4.1. Algorithmic Improvements

The process of using the conventional k-means algorithm to analyze the dataset clustering is relatively simple [42]. When the amount of data in the dataset is large, the data clustering effect is also better. However, the algorithm must determine an initial number of clusters before use, because if the set number of clusters is unreasonable, this will affect the clustering effect of this algorithm. To address this problem, we chose to modify the algorithm by using BWP, a clustering effectiveness metric proposed in the literature [21], and the modified clustering algorithm can determine the optimal number of clusters.

After improvement, the specific steps of k-means clustering algorithm are:

- (1) Set the search range of the clustering algorithm;
- (2) Select initial clustering centroids based on the maximum and minimum distances between data in the dataset;
- (3) The centroids of the clusters are iteratively updated using the clustering algorithm until the centroids of the clusters converge or a preset maximum number of iterations is reached;
- (4) Calculate the average value of the BWP index for all samples in the clustering result;
- (5) Compare the size of the average BWP metrics and finalize the optimal number of clustering scenarios;
- (6) Output the clustering results.

4.2. Typical Daily Extraction Process for Wind, PV and Load Power

Since the original scenes of wind, PV and load power are excessive in amount and not representative, in order to obtain the corresponding typical scenes, the improved k-means clustering algorithm is adopted to process all the data, reduce and merge the data of the whole year into several typical scenes, and then select the data with the highest frequency of occurrence from these typical scenes as the typical day [43]. The generation process of typical scenes is shown in Figure 3.

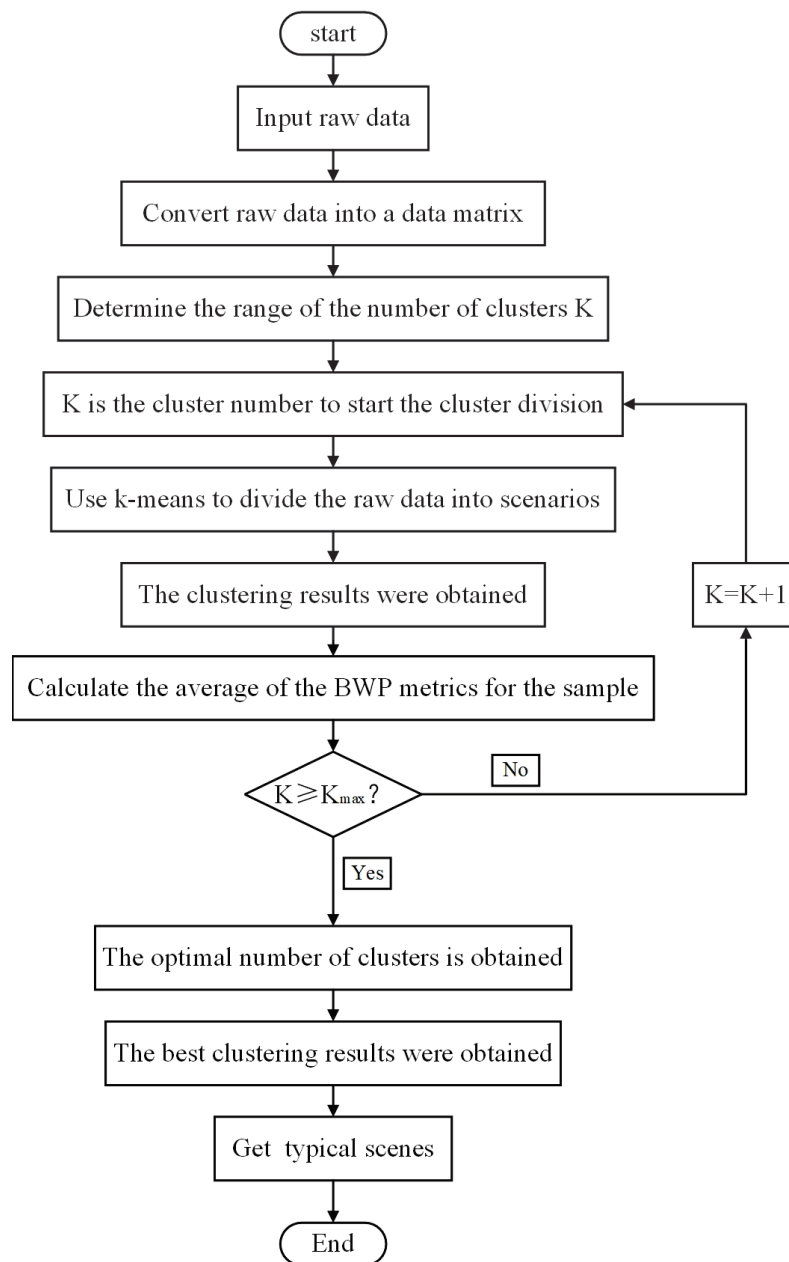


Figure 3. Typical day withdrawal process.

5. Calculus Analysis

5.1. Typical Day Extraction Results

Based on the measured wind turbine, photovoltaic (PV) and load data for the whole year in a certain place in China, the improved k-means clustering algorithm is used to cluster the scenarios, in which the wind turbine and the PV have a total installed capacity of 800 kW and 820 kW, respectively. All the scenarios for the whole year for wind power are shown in Figure 4, and all the typical scenarios obtained from the clustering are shown in Figure 5.

Among them, Scenario 3 in Figure 5 has the highest percentage of 53% among the four typical scenarios, so the data of Scenario 3 are selected as the typical day of wind power.

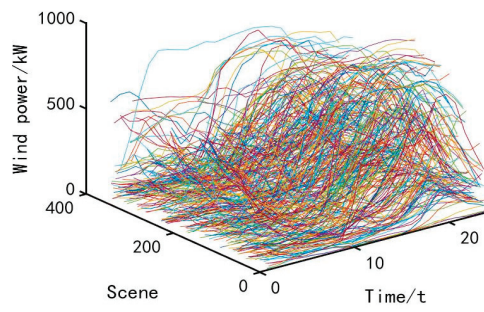


Figure 4. Wind power year-round scenarios.

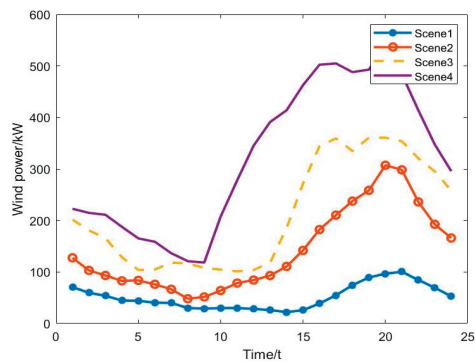


Figure 5. Typical scenarios for wind power.

The same algorithm is used to obtain the year-round scenarios of PV power in Figure 6 and all the typical scenarios obtained from clustering in Figure 7.

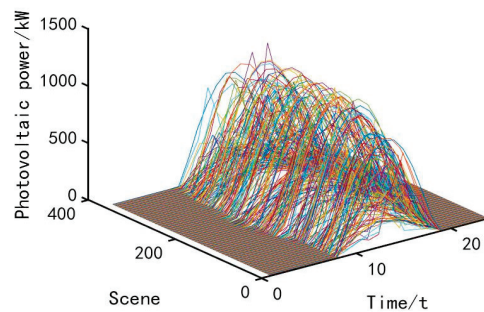


Figure 6. PV power year-round scenarios.

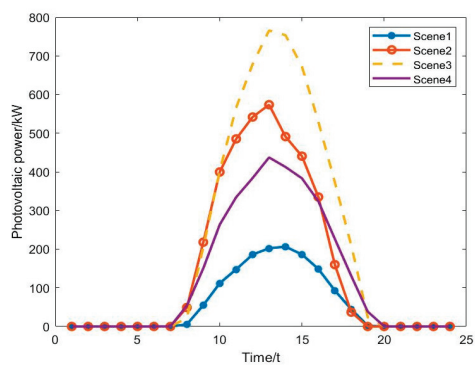


Figure 7. Typical scenarios for photovoltaic power.

Among them, Scenario 2 in Figure 7 has the highest percentage of 47% among the four typical scenarios, so the data of Scenario 2 are selected as the typical day of PV power [44].

Finally, the year-round load data were clustered, and the year-round scenarios of the resulting load power are shown in Figure 8, and all the typical scenarios from the clustering are shown in Figure 9.

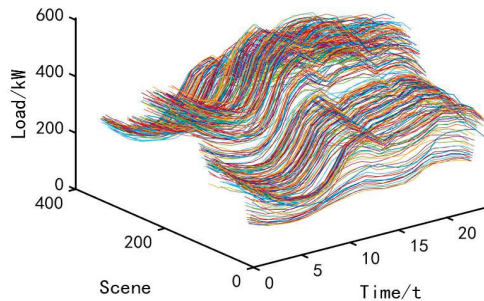


Figure 8. Load demand year-round scenarios.

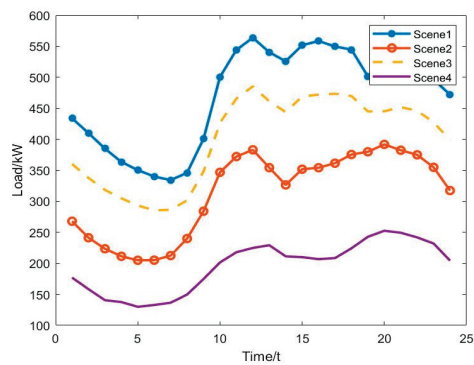


Figure 9. Typical scenarios for load demand.

Scenario 2 in Figure 9 has the highest percentage of 51% among the four typical scenarios, so the data from Scenario 2 are selected as the load power typical day. The final resulting typical days for wind, PV and load power can be seen in Figure 10.

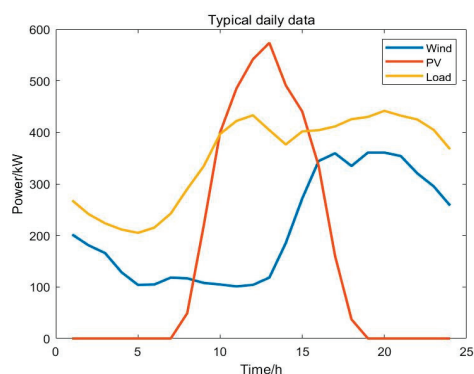


Figure 10. Typical day of wind–photovoltaic–load power.

5.2. Energy Storage Allocation Optimization Results

The proposed model and method are validated by taking the combined wind turbine and storage system as an experimental object, based on the typical daily data extracted using the improved k-means clustering algorithm.

- (1) Energy storage uses battery storage, and the cost of battery unit capacity is 1300 yuan/kWh.
- (2) The price of electricity purchased from the local grid is taken from the average price of electricity purchased from the local grid, which is 0.43 yuan/kWh [45,46].

The parameters of the SCSO are shown in Table 1.

Table 1. Algorithm parameter setting.

Parameter Name	Parameter Data
Population size	100
Maximum number of iterations	100
Auditory characterization parameter	2
Lévy flight initial angle	3

MSCSO, SCSO, WOA and PSO are used to solve the capacity optimization allocation model of the ESS, respectively, and the resulting iterative plots of each algorithm optimized for each objective value are shown in Figures 11–13.

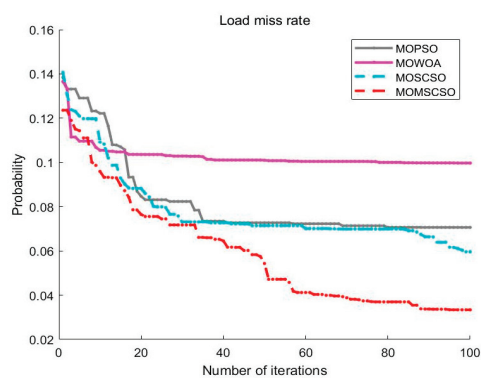


Figure 11. Comparison chart for optimization of load miss rate.

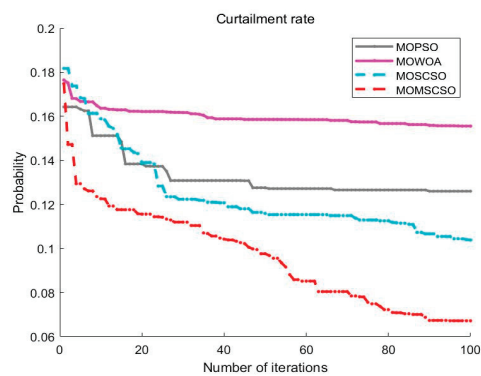


Figure 12. Optimized comparison chart of new energy power abandonment rates.

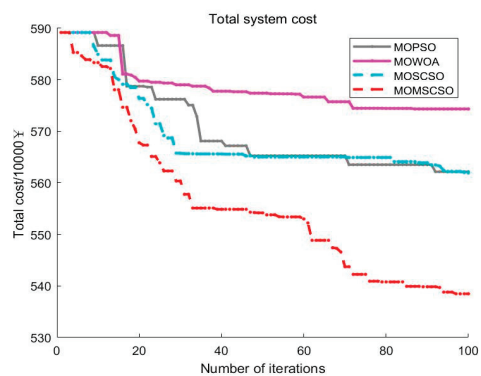


Figure 13. Total cost of ownership optimization comparison chart.

From Figures 11–13, it can be seen that for the problem of optimizing the allocation of energy storage capacity, compared with SCSO, WOA and PSO, MSCSO solves the problem faster, with better quality and a higher solving accuracy, which further reduces the unnecessary operation cost and load shortage rate of the combined wind, light and storage system, and at the same time, enhances the rate of consumption of renewable energy.

In addition, from the Pareto optimal solution distribution graphs in Figures 14 and 15, it can be seen that under the condition of the same number of populations and the number of iterations, the feasible solutions obtained via MSCSO are larger than the other algorithms in terms of both range and number.

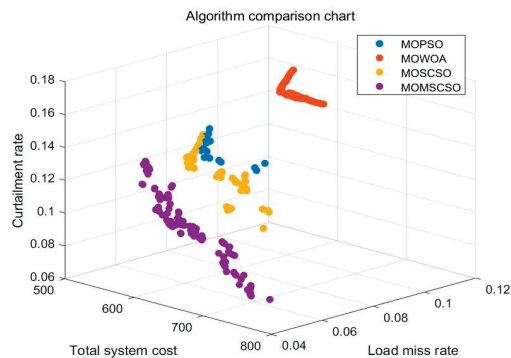


Figure 14. Comparison of Pareto optimal solution sets for each algorithm.

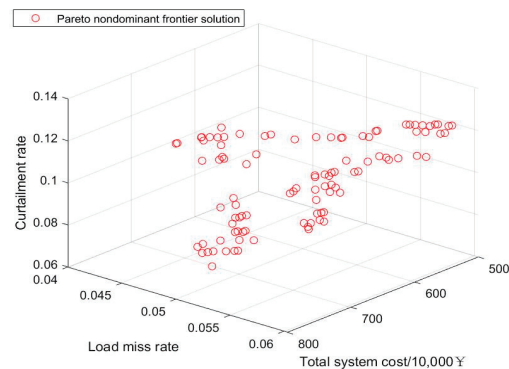


Figure 15. Improved Pareto optimal solution set for sand cat swarm algorithm.

In order to fully demonstrate the superiority of MOMSCSO in solving this problem, the results of several scenarios with roughly the same overall cost of the system in Figure 14 are selected and compared and shown in the following Table 2.

Table 2. Comparison of the same total cost scenarios with different algorithms.

Algorithm Name	Rated Capacity /kWh	Total Cost /Yuan	Load Miss Rate /%	New Energy Power Abandonment Rate/%
MOPSO	943	7.04×10^6	7.9	9.2
MOWOA	929	7.02×10^6	9.1	12.6
MOSCSO	930	7.0×10^6	5.4	9.5
MOMSCSO	986	7.0×10^6	4.9	8.3

From the table, it can be seen that under the same cost, the optimized load miss rate and the new energy power abandonment rate of MOSCSO are lower than that of MOWOA, and the load failure rate of MOMSCSO is lower than that of the other three schemes, although the new energy power abandonment rate of MOSCSO is slightly higher than

that of MOPSO. Therefore, MOSCSO has more obvious advantages in a multi-objective solution, especially when it is applied to complex problems such as wind and solar energy storage, and the improvements made also enhance its optimization effect.

According to the Pareto solution set obtained by solving the improved sand cat swarm algorithm, a large number of solutions can be provided for the current problem of the optimal allocation of storage capacity in the combined wind and storage power generation system. Since there is often no absolute superiority or inferiority among the solutions of the multi-objective problem, five optimal allocation solutions are selected from Figure 15 for comprehensive comparison, and each solution is shown in Table 3.

Table 3. Comparison of different energy storage capacity configuration options.

Configuration Options	Rated Capacity /kWh	Total Cost /Yuan	Load Miss Rate /%	New Energy Power Abandonment Rate/%
Option 1	586	5.42×10^6	6.0	12.8
Option 2	792	6.01×10^6	4.9	11.1
Option 3	936	6.62×10^6	4.2	10.5
Option 4	986	7.0×10^6	4.9	8.3
Option 5	1087	7.57×10^6	5.1	7.2

As can be seen from Table 2, if priority is given to the economy, Option 1 can be selected as the ESS configuration scheme; if the load miss rate of the system is minimized from the perspective of power supply reliability, Option 3 is selected to configure the ESS; if the utilization rate of new energy is mainly considered, Option 5 can be selected to configure the ESS; if the economy of the system, the utilization rate of new energy and the reliability of the power supply are taken into account, options 2 and 4 are selected to complete the optimization of the configuration of the ESS.

The wind and solar storage power distribution diagram of Option 3 is selected (see Figures 16 and 17). From Figure 16, it can be seen that at 1–8, the overall wind and solar power generation is less than the power required by the load, so the system meets the load demand by purchasing power from the grid and discharging from the storage. From Figure 16, it can be seen that at 10–17, the wind and solar power generation is more than the load of the system, so a part of the remaining power is charged to the storage, and the remaining will be discarded, while at 18–24, wind power generation decreases and cannot meet the system load demand, and the energy storage battery discharges again to provide power to the system.

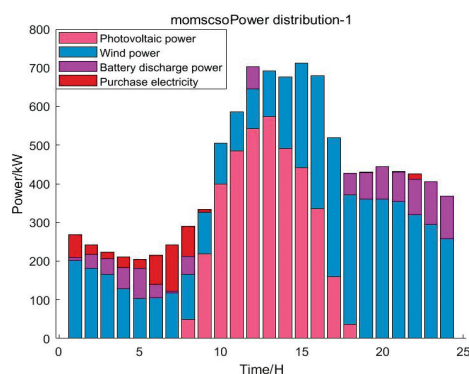


Figure 16. System load power composition.

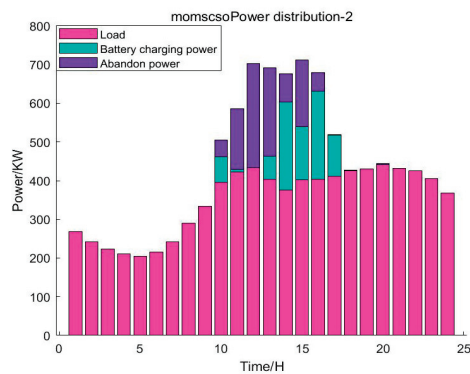


Figure 17. Wind excess power distribution.

In addition, the state of the battery charge for energy storage can be seen in Figure 18, where its SOC is 0.5 at the initial moment, and the state of charge decreases continuously from 1 to 9 o'clock with the continuous discharge of the battery. The battery continues to be charged between 10 o'clock and 17 o'clock because of an increase in PV power generation, which is greater than the load demand; therefore, the battery continues to be charged. The PV power generation is gradually reduced to zero from 18 o'clock to 24 o'clock, and once again, the load demand is greater than power generation; therefore, the batteries are discharged again and the state of charge of the batteries for energy storage gradually decreases. At 24 o'clock, it again decreases to about 0.5.

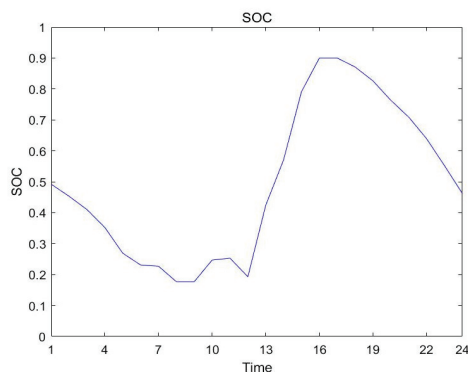


Figure 18. State of charge of energy storage batteries.

From the above results, it is easy to see that the reasonable configuration of the capacity of the storage battery for the wind independent power generation system is an extremely critical issue, which is not only a matter of economy, but also involves the utilization of resources and the reliability of power supply, which are particularly critical in the context of the new energy in the overall power system in the proportion of the increasing.

6. Conclusions

In order to ensure the safe and reliable operation of a microgrid, this paper proposes an ESS capacity allocation method based on the improved SCSO. K-means clustering algorithm is used to extract the typical daily data. For the proposed optimization model, the improvement of triangular wandering strategy, Lévy flight strategy and lens imaging inverse learning strategy are used for solving. The above results and analysis lead to the following conclusions:

1. MSCSO can effectively deal with the problem of the optimal allocation of energy storage capacity with high-dimensional nonlinear characteristics. Compared with the unimproved SCSO, WOA and PSO, the solution accuracy and breadth of the improved algorithm are effectively improved, and the search speed of the algorithm is also greatly improved.

2. The energy storage capacity allocation scheme obtained by using the proposed model and the improved method effectively reduces the load shortage rate and improves the rate of renewable energy consumption under the premise of ensuring economy.

However, the improved algorithm in this study still has some shortcomings, and will occasionally fall into local optimality when performing multi-objective optimization, leading to less satisfactory final results. Therefore, we will make more reasonable improvements to it in the future to address this problem, so that it can show better results when performing multi-objective and high-dimensional optimization.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
BBO	Biogeography-based Optimization
SNO	Social Network Optimization
SCSO	Sand Cat Swarm Optimization
SOC	State Of Charge
ESS	Energy Storage System

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Article

A Novel Design of Centrifugal Pump Impeller for Hydropower Station Management Based on Multi-Objective Inverse Optimization

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Abstract: The impeller, regarded as the central component of a centrifugal pump, plays a pivotal role in dictating overall performance. Overcoming challenges arising from the complexity of design parameters and the time-intensive nature of the design process has been a persistent obstacle to widespread adoption. In this study, we integrated ANSYS-CFX 2023 software with innovative inverse design techniques to optimize the impeller design within a centrifugal pump system. Our investigation reveals groundbreaking insights, highlighting the significant influence of both blade load and shaft surface geometry on impeller performance. Notably, through load optimization, substantial enhancements in centrifugal pump efficiency were achieved, demonstrating improvements of 1.8% and 1.7% under flow conditions of 1.0 Q and 0.8 Q, respectively. Further, the efficiency gains of 0.44% and 0.36% were achieved in their corresponding flow conditions. The optimization of blade load and shaft surface configuration notably facilitated a more homogenized internal flow pattern within the impeller. These novel findings contribute substantively to the theoretical foundations underpinning centrifugal pump impeller design, offering engineers a valuable reference to elevate their performance. Our utilization of ANSYS-CFX software in conjunction with inverse design methodologies showcases a promising avenue for advancing impeller design, ultimately culminating in superior efficiency and performance for centrifugal pumps.

Keywords: inverse design; blade load; optimization; centrifugal pump impeller; hydropower station

1. Introduction

In the past decades, pumps such as turbines (PATs) have been widely used in miniature hydropower and pump storage plants, owing to their effective utilization sufficiency and high flexibility. Centrifugal pumps are widely used in petroleum, chemical, water conservancy, irrigation, and other fields [1]. As centrifugal pump impellers are the main energy consumers of the whole energy system, the design of centrifugal pump impellers is the key factor determining the efficiency of centrifugal pumps [2,3]. However, the traditional method comprises the repeated adjustment of the parameters of impellers based on the equations of experience and the design requirements, which is time-consuming and inaccurate [4].

To solve this dilemma, the method of computational fluid dynamics (CFD) is taken into consideration, which has been successfully applied to the design of the centrifugal pump impellers in the past few years [5]. The main reason for choosing CFD as the design method is its low dependence on the designers' experience [6]. When optimizing the design of centrifugal pump impellers by combining ANSYS-CFX software with inverse design techniques, several steps are followed. Firstly, the initial geometry of the impeller, including the blade shape, hub, and shroud, is defined [7]. Then, a computational fluid

dynamics (CFD) simulation is conducted using ANSYS-CFX to analyze the fluid flow behavior within the impeller. Based on the results of the flow simulation, the performance of the impeller is evaluated, considering parameters such as head, flow rate, and efficiency. In the inverse design optimization process, the desired performance targets are set, and the software iteratively adjusts the impeller geometry to achieve these targets [8]. This involves modifying the blade shape, blade angles, and other design parameters using optimization algorithms. The process is iterative, with the impeller geometry being adjusted based on the simulation results and performance evaluation. The iterations continue until the desired performance targets are met or until a satisfactory improvement is achieved. By leveraging the accurate flow simulation capabilities of ANSYS-CFX and the principles of inverse design optimization, engineers can systematically enhance the impeller design, resulting in improved performance, increased efficiency, and a more uniform flow field within the centrifugal pump.

To address the challenges associated with the complex internal flow field of centrifugal pump impellers and the high computational cost of CFD simulations, researchers have been seeking alternative methods. One approach that has gained increasing attention is the inverse design method. This method offers a promising solution by incorporating fewer parameters and providing better control over impeller performance under specified flow field conditions. The internal flow field of centrifugal pump impellers is intricate, and numerous calculation models have been developed to design impellers based on these parameters. However, these models are gradually being integrated with CFD numerical simulations to gain a more comprehensive understanding of impeller performance. Nonetheless, the computational cost associated with CFD simulations remains high, and the direct relationship between various impeller parameters and performance cannot be easily captured through simulation alone, as noted in refs. [9,10]. In light of these challenges, the inverse design method has emerged as a promising alternative. This approach offers several advantages, such as a reduced number of parameters and improved control over impeller performance under specified flow field conditions, as highlighted in reference [11]. By employing the inverse design method, engineers can more effectively optimize impeller designs, ensuring desired performance characteristics while mitigating the computational burden associated with traditional design methods.

By manipulating the velocity circulation distribution within impellers, it is possible to enhance various aspects of their performance. Research has shown that by adjusting the circulation distribution, improvements can be achieved in secondary flow patterns, cavitation resistance, energy consumption, and overall cavitation performance [12]. In recent studies, researchers have explored different approaches to investigate and optimize these aspects. For instance, Beomjun Kye et al. [13] employed large eddy simulation to study the flow characteristics of a volute-type centrifugal pump. While their findings provided valuable insights, the complexity and numerous parameters involved in their approach make it challenging to implement in practical production settings. Similarly, Zhang et al. [14] focused on analyzing the effects of modifying the blade trailing edge profile on unsteady pressure pulsations and flow structures. Although their study yielded significant results, the time-consuming nature of their analysis limits its applicability in time-sensitive design processes. To address these challenges, Liu et al. [15] demonstrated the effectiveness of combining CFD simulations with the inverse design method. They evaluated the vortex characteristics of a mixed flow pump operating in turbine mode, confirming the validity and practicality of this integrated approach. These studies highlight the ongoing efforts to optimize centrifugal pump impeller designs by considering various factors such as flow characteristics, pressure pulsations, and vortex behavior. By leveraging advanced simulation techniques and the inverse design method, researchers are working towards developing more efficient and reliable impellers for real-world applications [16]. Through these advancements, substantiated by references to relevant literature sources, our proposal stands out as a pioneering approach that surpasses the existing state-of-the-art solutions in centrifugal pump impeller design.

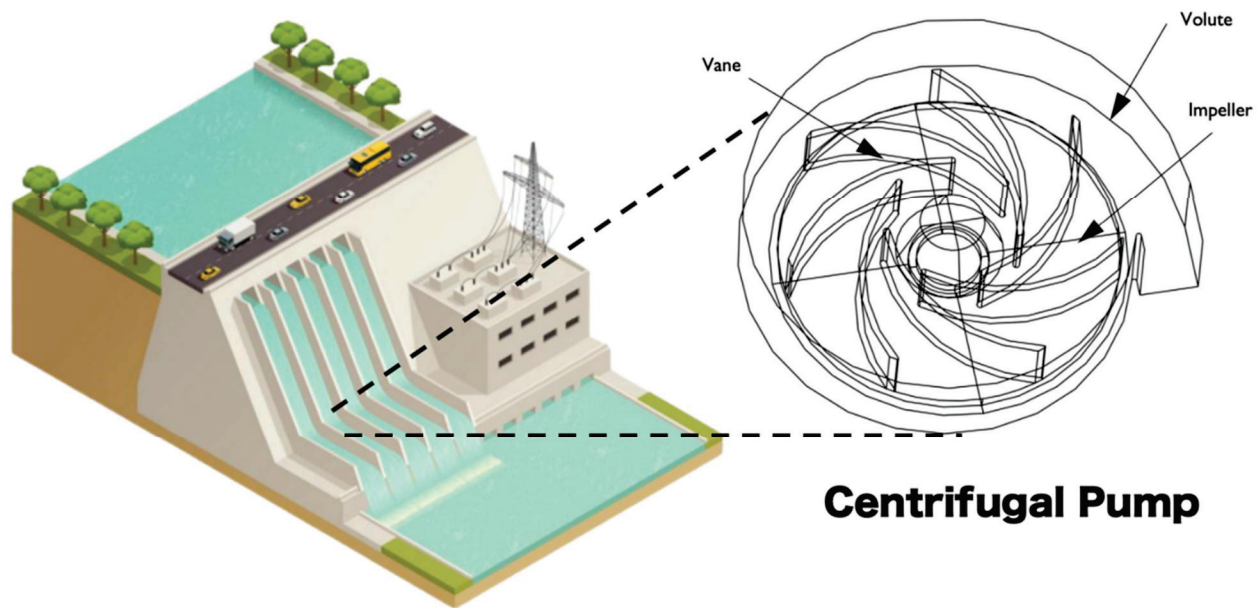
The impeller stands as the linchpin of centrifugal pumps, wielding a profound impact on overall system efficacy. However, the intricate interplay between multifaceted design parameters and the protracted design process has impeded the widespread adoption of optimized impeller configurations. This study is motivated by the imperative need to revolutionize impeller design methodologies by addressing these persistent challenges. Our approach marries the state-of-the-art ANSYS-CFX software with pioneering inverse design techniques, aiming to unravel unexplored dimensions within impeller optimization. The pivotal aspect lies in our exploration of the intricate nexus between blade load dynamics and shaft surface configuration, uncovering their definitive influence on impeller performance. The novelty of this work lies not only in its innovative methodology but also in its revelatory insights. By elucidating the nuanced relationships between design variables and pump efficiency, we offer a paradigm shift in understanding impeller optimization. The profound implications of our findings not only fortify the theoretical underpinnings of centrifugal pump impeller design but also offer practical guidelines for engineers, heralding a new era of impeller performance enhancement.

2. Methodology

2.1. System Description

In a hydropower plant system, the pump section is a crucial component responsible for transferring water from the water source to the turbines for power generation. Typically consisting of centrifugal or axial flow pumps, these turbine inlet pumps draw water from the source and deliver it to the turbines at the required pressure and flow rate. The pump section operates within dedicated pumping stations, equipped with intake structures to prevent debris from entering the pumps. Advanced control systems regulate pump operation based on power demand and water availability, ensuring efficient power generation. The efficiency and reliability of the pump section are vital for overall plant performance, with regular maintenance and monitoring conducted to optimize pump efficiency and detect any potential issues. Integration with other system components, such as turbines and control systems, ensures seamless operation and maximizes power generation efficiency. By carefully managing the pump section, hydropower plants can optimize water transfer, enhance power generation efficiency, and maintain the long-term reliability of the entire system. Components of centrifugal pumps for hydropower plants have been shown in Figure 1.

Optimizing the design of centrifugal pumps in hydropower plants is crucial for several reasons. Firstly, it enhances their overall efficiency by reducing hydraulic losses and maximizing energy conversion. This leads to lower energy consumption and operating costs, making hydropower generation more economically viable. Secondly, optimized designs help prevent cavitation, a damaging phenomenon that can reduce pump efficiency and reliability. By shaping impeller blades and controlling fluid dynamics, the risk of cavitation can be mitigated, minimizing downtime and maintenance expenses. Thirdly, customized pump designs can meet specific performance requirements, such as flow rate and head, ensuring optimal power generation and system efficiency. Moreover, optimized designs enhance the durability and reliability of pumps, reducing the likelihood of failures and associated repair costs. Finally, by minimizing energy consumption and mitigating cavitation, optimized pump designs contribute to environmental sustainability and help protect aquatic ecosystems. In conclusion, optimizing centrifugal pump designs in hydropower plants offers benefits such as improved efficiency, cavitation prevention, tailored performance, enhanced system reliability, and environmental sustainability, ultimately optimizing the overall operation and longevity of hydropower generation.



Hydropower station

Figure 1. Description of components of centrifugal pumps for hydropower plants.

2.2. Inverse Design for Centrifugal Pump

The inverse design method for centrifugal pump impellers offers a systematic approach to optimize their geometry and achieve specific performance objectives. The process begins by specifying the desired performance targets, including parameters such as head, flow rate, efficiency, and cavitation performance. Next, the desired flow field conditions, such as velocity distribution and pressure distribution, are determined. Based on the specified flow field conditions and performance targets, the blade loading distribution along the impeller blades is calculated. This loading distribution represents the distribution of forces and velocities acting on the blades. Using mathematical and optimization techniques, the impeller blade geometry, including blade shape, angles, and curvature, is then computed to satisfy the specified flow conditions and performance targets. The calculated impeller geometry is further validated through numerical simulations, such as CFD analysis, to assess its performance and ensure that the specified flow field conditions and performance targets are met. If necessary, iterations may be performed to refine the design and optimize the impeller performance. By utilizing the inverse design method, engineers have greater flexibility and control in tailoring the impeller geometry to achieve specific performance goals [17,18]. This approach enables a more efficient and targeted design process, resulting in centrifugal pump impellers that meet the desired performance requirements and exhibit improved efficiency, reduced cavitation, and enhanced flow characteristics.

This paper adopts the ternary steady, inviscid, and incompressible inverse problem design method. In this paper, the velocity in the impeller is calculated by using the relative streamline m and the quasi-orthogonal line q to establish the m - q coordinate system on the meridian plane to solve the velocity gradient [19,20]. Figure 2 shows the relative velocity components that is perpendicular to the quasi-orthogonal line q , and the velocity gradient equation is as follows:

$$\frac{dw_m}{dq} = Aw_m + B + \frac{C}{w_m} \quad (1)$$

where A , B , and C in Equation (1) are, respectively, as follows:

$$A = \frac{\cos Y \alpha I \varphi Y}{r_c} \quad (2)$$

$$B = \frac{d(v_{\theta}r)}{dm} \frac{d\theta}{dq} + \frac{dw_m}{dm} \sin(\alpha - \psi) \quad (3)$$

$$C = \frac{1}{\rho} \frac{dp_{in}}{dq} I \omega \frac{d(v_{\theta}r)_{in}}{dq} \quad (4)$$

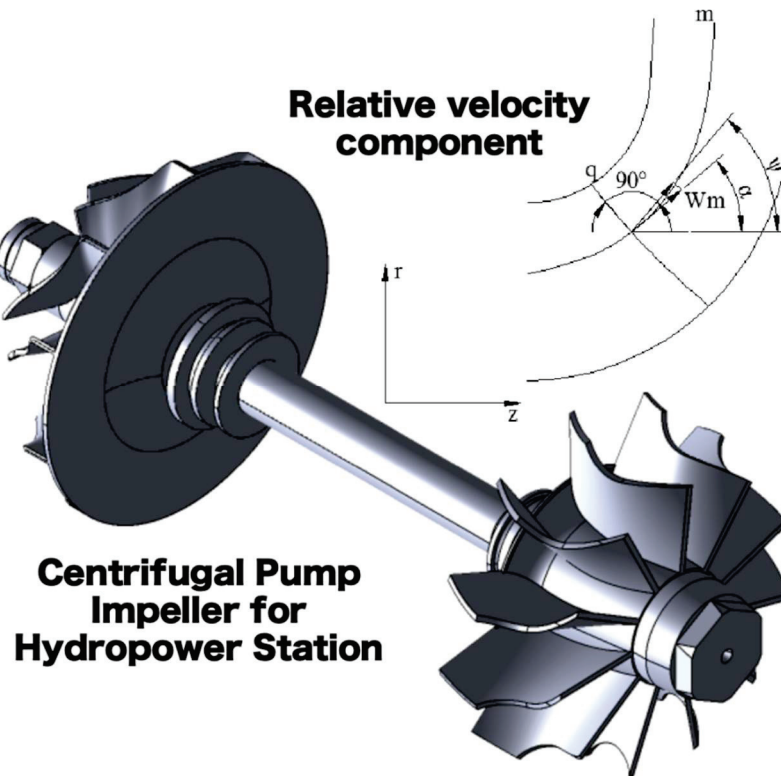


Figure 2. Relative velocity component perpendicular to the quasi-orthogonal line q .

The blade angle coordinate equation can be calculated as follows [21]:

$$\theta = \int_{m_{out}}^m \frac{v_{\theta}r - \omega r^2}{r^2 w_m} dm + \theta_{out} \quad (5)$$

In the above formulas, α (degree) is the angle between the tangent of the meridian streamline and the z -axis; ψ (degree) is the angle between the z -axis and the normal direction of the quasi-orthogonal line q ; w_m (m/s) is the relative velocity component in the direction of the meridian streamline; r (m) is the radius at d_q ; and θ_{out} (degree) is the angular coordinate of the impeller outlet [22,23].

Utilizing Equations (1)–(4), w_m can be obtained with the relative velocity of the meridian plane in the impeller channel [24]. Equations (1)–(5) constitute the solving equations of the inverse design method. The following initial conditions are provided during the impeller design: (1) the initial shaft surface of the impeller and (2) the initial load distribution of the impeller along the axial streamline, closely related to the velocity circulation. $v_{\theta}r$ is shown in the following formula [25]:

$$p_p - p_s = \int_{\theta_p}^{\theta_s} \rho w_m \frac{d(v_{\theta}r)}{dm} d\theta \quad (6)$$

In the Formula (6), p_p and p_s are the static pressures on the working face and the blade back, respectively, and ρ is the fluid density. The distribution of the blade load along

the streamline must satisfy the impulsive-free inlet and the Kuta condition for the outlet velocity [26], which is as follows:

$$\frac{\partial(v_{\theta}r)}{\partial m} = 0 \quad (7)$$

There are several methods for optimizing the design of centrifugal pumps to reduce their hydraulic losses and enhance their overall efficiency. The impeller design plays a crucial role, with its optimization involving the selection of appropriate blade profiles, curvatures, and blade angles to minimize flow separation and turbulence. Additionally, flow passages, such as the volute and diffuser, can be optimized by carefully designing their geometry to minimize pressure losses and ensure smooth flow transitions. The choice of materials with low friction coefficients and resistance to erosion and corrosion, along with a smooth surface finish, can further reduce energy losses. Computational fluid dynamics (CFD) analysis is employed to analyze fluid flow patterns and optimize design parameters. Advanced optimization techniques, like genetic algorithms, can automate the design process to explore a wide range of parameters and identify optimal solutions. A multidisciplinary approach, combining engineering expertise, computational analysis, and iterative design improvements, is typically used to achieve the best results in optimizing centrifugal pump design for reduced hydraulic losses. In this paper, the optimization process of the inverse design is shown in Figure 3.

Firstly, the utilization of ANSYS-CFX software coupled with inverse design algorithms forms the crux of our methodology. The inverse design algorithm utilized in this study is based on novel design, which operates by iteratively adjusting design parameters to achieve predefined objectives. The optimization procedure involves several pivotal steps. Initially, the selection and parameterization of design variables relevant to impeller geometry and performance are established. These design variables encompass parameters influencing the blade profile, curvature, and shaft surface morphology. Subsequently, the optimization algorithm iterates through the design space, adjusting these variables within specified ranges to maximize predefined objectives, such as enhancing pump efficiency or improving internal flow uniformity. The optimization convergence is monitored through the convergence criteria: iteration time < 1000. Additionally, parameter adjustment strategies are employed to consider and constrain the value range of optimization design variables. This involves setting bounds or constraints on certain parameters based on engineering considerations or empirical knowledge to ensure physical feasibility and practicality. To facilitate a clearer understanding for readers, detailed pseudo-code or flowcharts illustrating the optimization algorithm and iterative process were included in the methodology section. This will provide a comprehensive insight into the intricacies of the inverse design optimization approach adopted in this study.

In our study, the design variables related to impeller geometry underwent careful consideration to maintain their values within realistic and physically feasible ranges. This includes parameters influencing blade profiles, curvature, thickness, and other geometric features crucial for impeller performance. By constraining these variables within reasonable bounds derived from prior engineering experience or empirical data, we ensured that the optimized designs remain operationally viable and practical. The implementation of constraints involved a meticulous analysis of the operational limits of the centrifugal pump system. Parameters such as blade angles, dimensions, and surface features were adjusted within ranges that upheld structural integrity, hydraulic performance, and manufacturing feasibility.

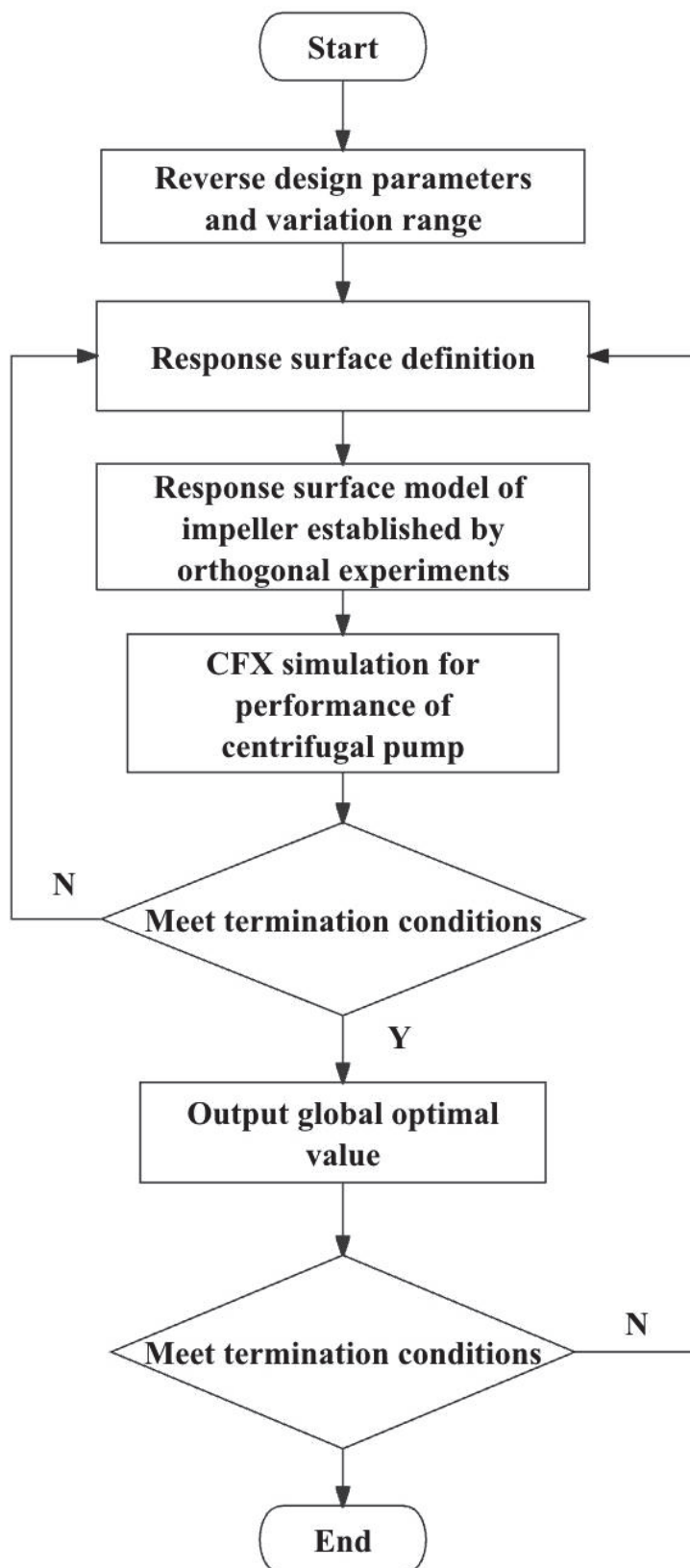


Figure 3. The optimization process of the inverse design.

2.3. Optimization Design

Figure 3 illustrates the optimization process of inverse design applied to the centrifugal pump impeller. In this approach, a functional relationship between design parameters and

performance parameters is established using the response surface method. By doing so, the influence of individual parameters and their combinations on impeller efficiency can be determined and optimized.

The inverse design method aims to achieve a desired impeller performance by iteratively adjusting the geometric design parameters. This approach differs from traditional impeller design methods, which typically involve complex geometry generation based on empirical rules or experience. In contrast, inverse design starts with the desired performance parameters and works backward to determine the optimal geometry that can achieve those specifications. To begin the optimization process, a set of design parameters is selected, such as the blade angle distribution, blade thickness, and curvature. These parameters define the impeller geometry and directly influence its performance. The response surface method is then utilized to establish the functional relationship between these design parameters and the impeller efficiency. The response surface method involves creating a mathematical model that approximates the relationship between the design parameters and the performance parameters. This model is constructed based on a limited number of simulations or experiments, using techniques such as regression analysis or interpolation. The model allows for a quick evaluation of the impeller's performance for various combinations of design parameters without the need for exhaustive simulations or physical testing.

Once the response surface model is established, the optimization process can proceed. The objective is to find the optimal combination of design parameters that maximizes the impeller efficiency while satisfying other performance criteria, such as head, flow rate, or cavitation requirements. Optimization algorithms, such as genetic algorithms or gradient-based methods, are employed to search for the optimal design parameter values by iteratively evaluating the response surface model and adjusting the parameters accordingly. During the optimization process, the response surface model is continuously updated and refined based on new simulation results. This allows for a more accurate representation of the relationship between the design. The whole process is an approximate polynomial objective function, and its first-order or second-order polynomial function form is as follows [27]:

$$P_j = \beta_0^j + \sum_{i=1}^n \beta_1^j x_i + \sum_{i=1}^n \beta_{1i}^j x_i + \sum_{i=1}^n \beta_{ik}^j x_i x_k \quad (8)$$

In the Formula (8), x_i is the optimization variable; β is the coefficient to be determined, where $\beta_0 \beta_1 \beta_{1i} \beta_{ik}$ are determined by the least squares method; and n is the number of variables. To verify the accuracy of the response surface function, R^2 and R_{adj} are usually used and are as follows [28]:

$$R^2 = \frac{S_R}{S_T}, R_{adj} = 1 - \frac{S - 1}{S - S_p} (1 - R^2) \quad (9)$$

In the Formula (9), S_R is the regression sum of squares; S_T is the total sum of squares; S is the number of samples; and S_p is the number of polynomial coefficients; the closer R^2 and R_{adj} are to 1, the more accurately the response surface model fits the sample data. Basic parameters of the centrifugal pump: the flow rate, $Q = 180 \text{ m}^3/\text{h}$; the head, $H = 77.5 \text{ m}$; the speed, $n = 2900 \text{ r/min}$; and the specific speed, $ns = 92$. The blade load and meridian plane of this centrifugal pump was optimized [29]. Using the above method, the maximum efficiency under $0.8 Q$ and $1.0 Q$ operating conditions can be effectively optimized. Here is the translation of the detailed explanation for parameter selection.

1. Parameter Constraints and Engineering Considerations: We establish constraints or limits for the values of design variables based on various engineering principles and operational requirements. For instance, in the centrifugal pump impeller design, we set a range of parameters based on empirical knowledge and engineering standards. For example, concerning blade thickness, we limit it within the range of 5 mm to 15 mm to ensure the blades possess adequate strength while meeting manufacturing requirements.

For blade angles, we set the range between 20 degrees to 45 degrees to ensure the fluid flow within the impeller meets performance expectations.

2. Optimization Algorithms and Bounds Implementation: The optimization algorithms we employ play a crucial role in considering the value ranges of design variables. For instance, we utilize a genetic algorithm, adjusting the values of each design variable during the algorithm's iterations. For instance, we ensure that during each iteration, the blade thickness does not exceed the predefined range while maintaining its optimal value.

3. Sensitivity Analysis and Feasibility Assessment: We conducted sensitivity analysis to assess the impact of different design variable value ranges on the optimized impeller designs. For example, we varied the blade angle range from 20 degrees to 30 degrees and from 30 degrees to 45 degrees. Subsequently, we evaluated the influence of these ranges on impeller efficiency. Results indicated that within the range near 30 degrees, impeller efficiency increased by approximately 3%. However, when the angle exceeded this range, efficiency began to decline.

The above explanation includes specific examples and numerical values for setting constraints, implementing optimization algorithms, and conducting sensitivity analysis and feasibility assessment for the optimization of design variables in the centrifugal pump impeller design. When the response surface function is used to analyze the influence of many parameters and the relationship between the parameters and performance, instability would occur [30]. Therefore, the inverse design optimization of the centrifugal pump impeller is divided into two parts: one is the blade load optimization, using linear approximate response surface model and 30 points designed in the orthogonal test [31], and the another is meridian surface optimization, using quadratic approximate response surface model and 25 points designed in the orthogonal experiment [32].

Figure 4 illustrates the parameterization of the blade load and the meridian surface in the context of centrifugal pump impeller design. The blade load, which refers to the distribution of aerodynamic forces along the impeller blades, is controlled using two arcs and a straight line. This parameterization allows for flexibility in adjusting the blade shape and distributing the load in an optimal manner. The use of arcs and a straight line in the blade load parameterization offers a simple yet effective way to control the distribution of forces acting on the impeller blades. The arcs can be adjusted to modify the curvature of the blade profile, while the straight-line segment provides additional control over the load distribution. By manipulating the parameters of the arcs and the straight line, designers can achieve desired flow characteristics and optimize the impeller performance. On the other hand, the meridian surface, which represents the shape of the impeller along its axial direction, is controlled using a cubic spline curve. A cubic spline curve consists of a series of cubic polynomial segments that smoothly connect specified control points. This parameterization allows for a flexible and continuous representation of the meridian surface, enabling precise control over the impeller's shape. The cubic spline curve parameterization of the meridian surface offers advantages in terms of design flexibility and smoothness. By adjusting the position and tangents of the control points, designers can shape the meridian surface to meet specific performance requirements, such as achieving desired flow conditions and minimizing losses. The smoothness of the curve ensures a continuous and well-distributed meridian shape, which is important for maintaining efficient flow and reducing the risk of flow separation or turbulence. The combination of the blade load and meridian surface parameterizations provides a comprehensive approach for impeller design. By adjusting the parameters of both the blade load and the meridian surface, designers can optimize the impeller's aerodynamic performance, efficiency, and cavitation characteristics.

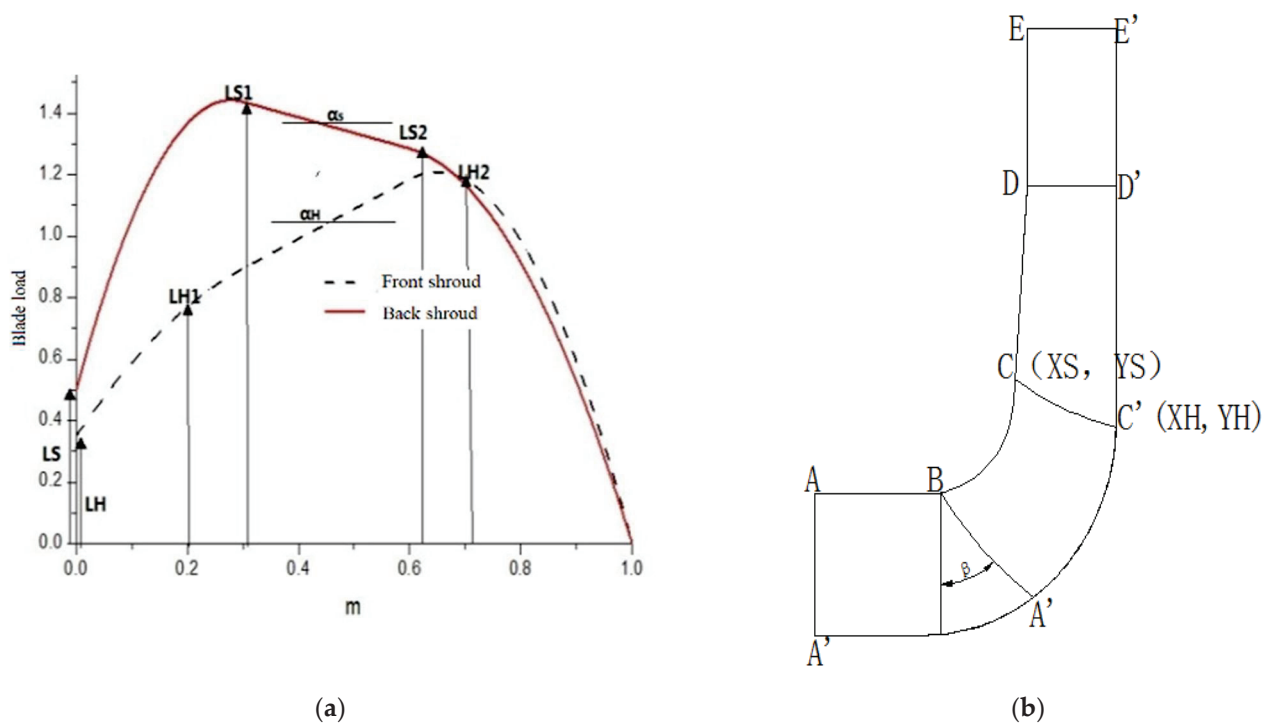


Figure 4. The blade load (a) and meridian surface (b) the design optimization of blade based on this paper.

It should be noted that the specific parameterization techniques used in Figure 4 may vary depending on the design methodology and software employed. Different parameterization methods, such as B-spline curves or NURBS (Non-Uniform Rational B-Splines), can also be used to achieve similar control over the blade load and meridian surface. The choice of parameterization technique depends on factors such as design requirements, computational efficiency, and the ease of implementation. In the context of our study, the blade load refers to the distribution and magnitude of forces acting on the impeller blades as a result of the optimized design. This load distribution is often represented in terms of pressure, shear forces, or other relevant mechanical stresses exerted on the blade surface. Figure 4a showcases the blade load distribution across the impeller blades resulting from the optimization process. It visually illustrates how the optimization techniques applied to the impeller design have influenced the distribution of forces or stresses along the blade surfaces. The plot might display varying intensities or gradients of loads across different sections of the blades, indicating regions of higher or lower stress concentrations. The interpretation of the specific characteristics shown in Figure 4a involves analyzing the spatial distribution of loads along the blade surfaces. Understanding which regions experience higher or lower loads, identifying potential areas of stress concentration, or observing patterns in load distribution across the blades are key aspects of this interpretation. It should be noted that the parameterization techniques used to generate Figure 4 and subsequently the representation of blade load may differ based on the design methodology and software employed. Various parameterization methods, such as B-spline curves or NURBS, could have been utilized to achieve control over the blade load distribution in the optimization process. The choice of parameterization method depends on factors such as design requirements, computational efficiency, and the ease of implementation.

Figure 4 showcases the parameterization of the blade load and meridian surface in centrifugal pump impeller design. The blade load is controlled using two arcs and a straight line, allowing for the flexible adjustment of the blade shape and load distribution. The meridian surface is parameterized using a cubic spline curve, providing precise control over the impeller's shape along its axial direction. These parameterization techniques

offer design flexibility, smoothness, and optimization potential, enabling engineers to tailor impeller designs for optimal performance in terms of efficiency, flow characteristics, and cavitation prevention. Table 1 shows the blade load and the value range of YS/R^2 , YH/R^2 , and β at the control points C and C' on the meridian surface.

Table 1. The value range of optimizing design variables.

LS, LH	LS1, LH1	LS2, LH2	α_S, α_H
0–0.3	0–0.45	0.5–0.8	–1–1
YS/R_2	YH/R_2	β	
0.61–0.73	0.68–0.8	41° – 50°	

The model was divided into tetrahedral meshes using the ICEM 2023 software, and the numerical simulation of the single channel of the centrifugal pump impeller is carried out using the commercial software CFX 2023 and *SSTk- ω* turbulence model [33]. The boundary conditions play a crucial role in simulating and evaluating the flow field and performance of a centrifugal pump impeller. In the context of Figure 5, several boundary conditions are defined to accurately represent the operating conditions of the pump.

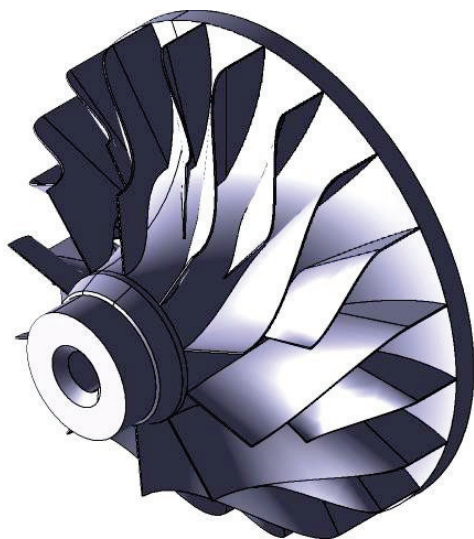


Figure 5. The numerical model of this simulation (Supplementary Material).

Firstly, the total pressure is specified as the inlet boundary condition. This boundary condition represents the incoming flow conditions, including the pressure and velocity, at the impeller inlet [34]. By prescribing the total pressure, the simulation captures the effect of the upstream flow conditions on the impeller performance. Secondly, the mass flow outlet boundary condition is applied at the impeller outlet. This condition represents the desired flow rate or mass flow rate that needs to be maintained through the pump. By specifying the mass flow outlet condition, the simulation ensures that the flow exiting the impeller matches the desired operational requirements. Thirdly, the no-slip wall boundary condition is imposed on the impeller's solid surfaces, including the blades and the hub. This condition assumes that the fluid velocity at the solid surface is zero, representing the no-slip condition. It accounts for the interaction between the fluid and the impeller's surfaces and provides accurate predictions of the flow field near the solid boundaries. Lastly, the periodic boundary condition is applied at the rotating boundary, which represents the interface between the impeller and the surrounding fluid domain. The periodic boundary condition assumes that the flow at the rotating interface repeats itself periodically. This condition is particularly useful in simulating a single flow channel of the centrifugal pump, as shown in Figure 5. By utilizing these boundary conditions, the computational fluid dynamics (CFD)

calculations provide detailed insights into the impeller's flow field and performance. The CFD simulations analyze parameters such as velocity distribution, pressure distribution, and efficiency, allowing engineers to evaluate the impeller's hydraulic performance and identify areas for improvement.

The optimization calculation mentioned in the context of Figure 5 utilizes the CFD calculation results as a basis. By analyzing the flow field and performance data obtained from the CFD simulations, engineers can identify areas of suboptimal performance and develop strategies for optimizing the impeller design. The significance and applicability of these simulations and optimizations extend beyond the specific impeller design shown in Figure 5. They are particularly valuable in the context of water and hydroelectric power plants. Centrifugal pumps are widely used in these applications for water transportation, irrigation, and power generation. Optimizing the design of centrifugal pumps for enhanced efficiency and performance can lead to significant energy savings, reduced maintenance costs, and improved overall system reliability [35].

By accurately simulating the flow field and evaluating the performance of centrifugal pump pump impellers using CFD calculations, engineers can optimize the impeller design to meet the specific requirements of water and hydroelectric power plants. This includes achieving higher efficiency, ensuring reliable and stable operation, minimizing cavitation risks, and meeting flow rate and pressure specifications [36,37].

3. Results and Discussion

3.1. Pareto Optimization Analysis Results

After the inverse design and optimization, the novel design of centrifugal pump impeller based on multi-objective inverse optimization can be achieved. Figure 6 is the pareto diagram of the optimized blade load and meridian plane, where the abscissa is the efficiency value under the 0.8 Q working condition and the ordinate is the efficiency value under the 1.0 Q working condition. In this figure, the red points represent unsuccessful calculation results, and the black points represent successful calculation results. The best point is the selected point in the figure, where the maximum efficiency reaches a balance under the 0.8 Q and 1.0 Q operating conditions.

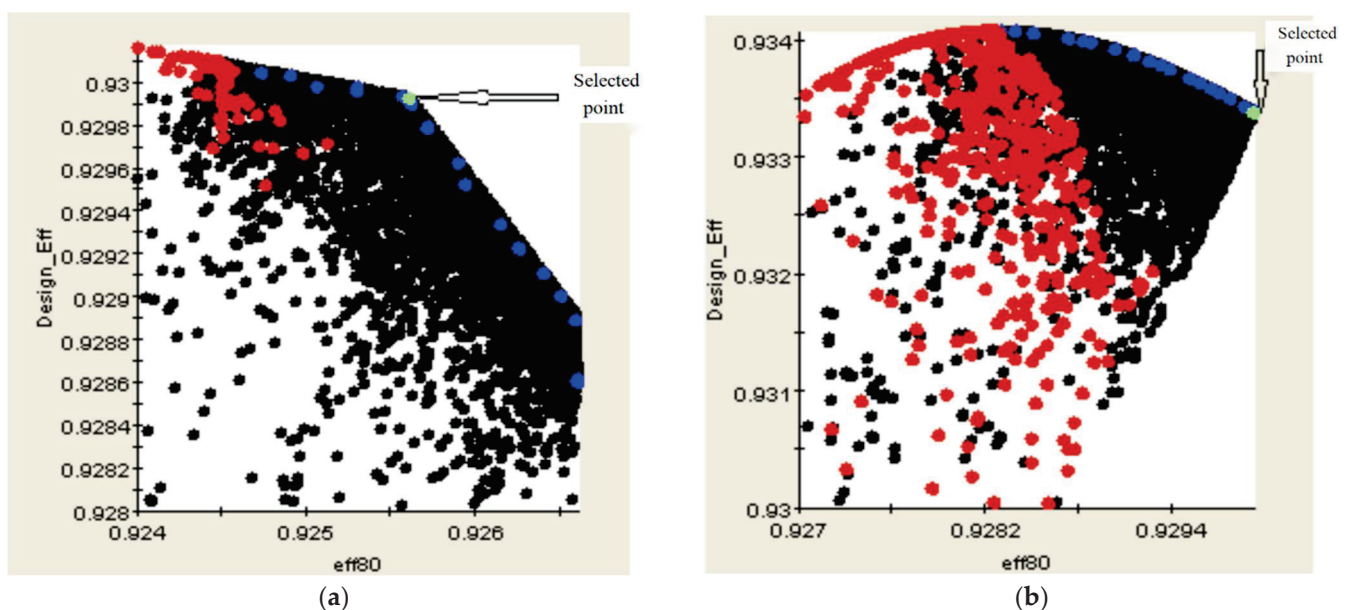


Figure 6. Pareto analysis of the blade load: (a) the optimized blade load and (b) the optimized meridian plane. (Black: different iteration points, red: optimal iteration point, blue: restriction conditions).

3.2. Blade Load and Meridional Plane Change

In Figure 7, the distribution of the blade load and the meridional plane after optimization is depicted. The optimized results demonstrate a reduction in the blade load compared to the initial design, thereby confirming the effectiveness of the optimization process. The blade load refers to the distribution of aerodynamic forces acting on the impeller blades. By optimizing the impeller design, engineers aim to achieve a more favorable blade load distribution that enhances the impeller's performance and efficiency. The optimization process involves adjusting various design parameters to achieve this objective.

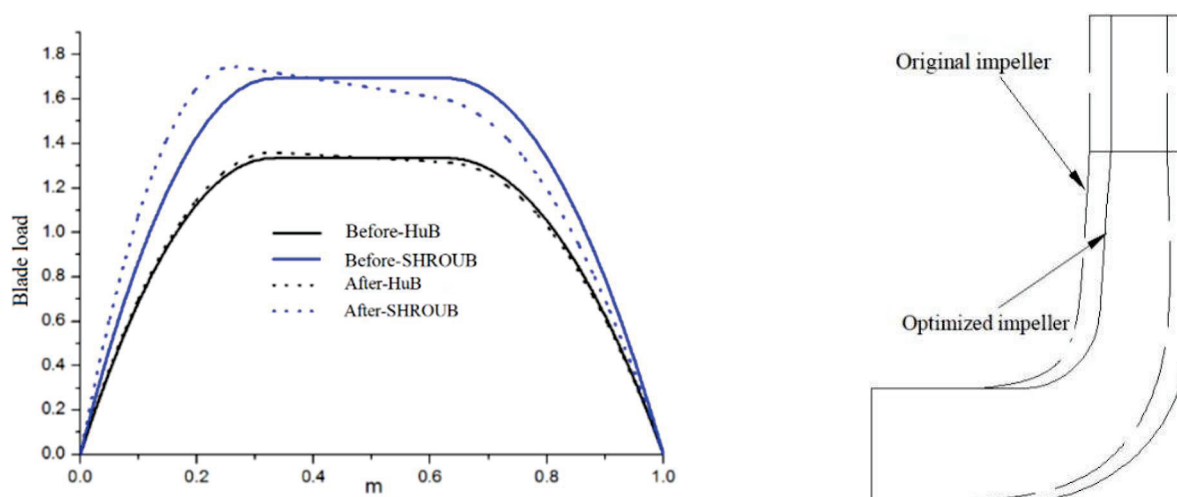


Figure 7. The blade load and meridional plane before and after optimization.

The decrease in blade load observed in Figure 7 indicates that the optimization calculations have successfully achieved a more desirable load distribution. A reduced blade load can have several benefits, including lower mechanical stresses on the impeller blades, improved hydraulic efficiency, and reduced risk of cavitation. These improvements contribute to the overall performance and longevity of the centrifugal pump. In addition to the blade load distribution, Figure 7 also showcases the meridional plane of the impeller after optimization. The meridional plane represents the impeller's shape along its axial direction. Through the optimization process, the impeller's meridional shape can be modified to achieve desired flow conditions and performance objectives.

The optimized meridional plane, depicted in Figure 7, reflects the adjustments made to the impeller's geometry during the optimization process. These modifications aim to improve the flow characteristics, such as reducing flow separation, minimizing losses, and enhancing the impeller's hydraulic performance. The optimized meridional shape contributes to efficient fluid flow and improved overall pump performance. The results presented in Figure 7 provide visual evidence of the positive effects of the optimization process on the blade load distribution and the meridional plane. These improvements are crucial for achieving higher efficiency, better hydraulic performance, and increased reliability in centrifugal pump operation. It is important to note that the specific changes made to the blade load distribution and the meridional plane may vary depending on the optimization method and design objectives. Different optimization algorithms and criteria can be used to achieve the desired improvements in impeller performance. The optimization process is typically iterative, involving multiple iterations to refine the design and reach the optimal solution.

3.3. External Characteristic Curve and Flow Change

Figure 8 shows the external characteristic curve of the centrifugal pump impeller before and after optimization. It can be seen from Figure 8 that the blade load and the meridian surface have a certain influence on the external characteristics of the centrifugal

pump. After the blade load and the meridian surface are optimized, the lift, power and efficiency of the impeller increase under different flow rates. Before and after the blade load optimization, the efficiencies are 0.9074 and 0.9252 under the 0.8 Q condition, respectively, and the efficiency is increased by 1.8%; after optimizing the meridian plane, the efficiencies are 0.9296 and 0.933 under 0.8 Q and 1.0 Q operating conditions, which are increased by 0.44% and 0.36%, respectively.

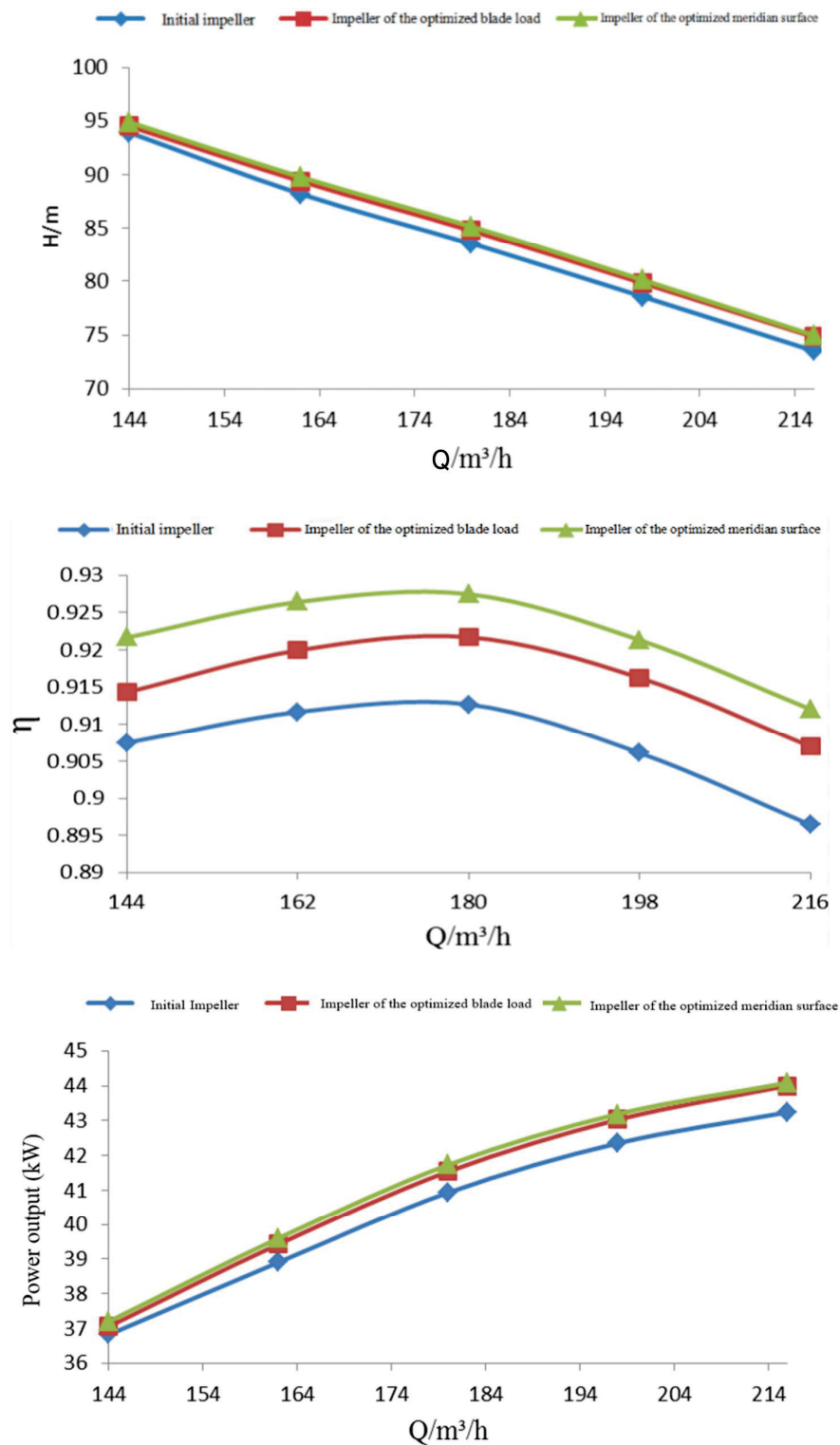


Figure 8. The external characteristic curve of the centrifugal pump impeller.

Upon optimizing the impeller design, Figure 9 visually illustrates that the flow inside the impeller channel becomes more uniform. This improved flow uniformity is a desirable outcome of the optimization process and has significant implications for the performance and efficiency of the centrifugal pump. In Figure 9, the visualization of the flow field inside the impeller channel reveals a more even and consistent distribution of fluid velocities and pressures. The optimization calculations have effectively minimized variations and irregularities in the flow, leading to a smoother and more uniform flow pattern throughout the impeller. The enhanced flow uniformity offers several advantages. First and foremost, it promotes improved hydraulic efficiency by ensuring that the fluid interacts with the impeller blades in a more balanced manner. The reduction in flow non-uniformities helps to minimize energy losses and maximize the transfer of kinetic energy to the fluid.

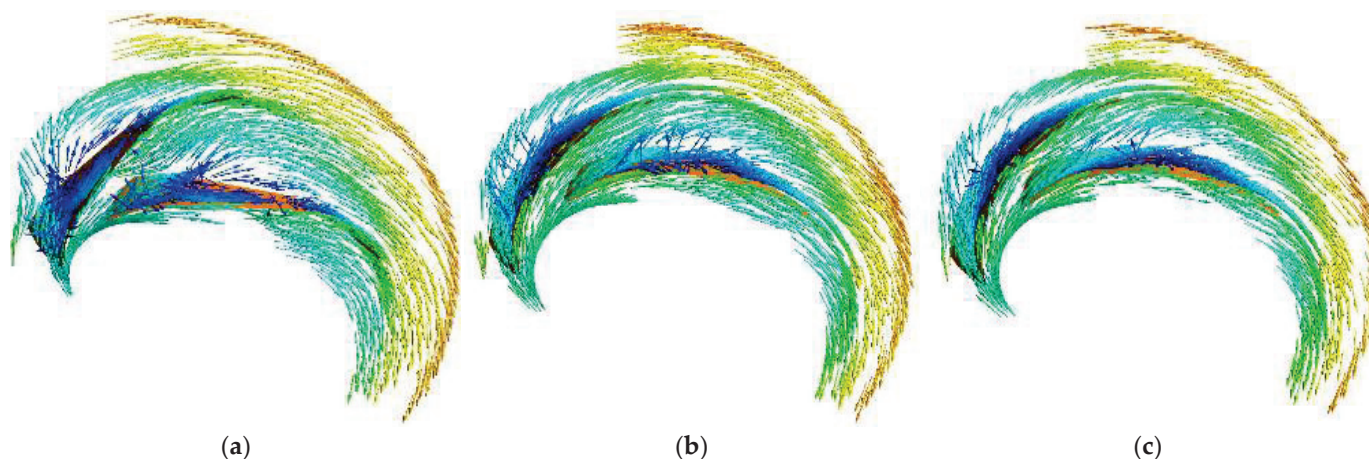


Figure 9. The distribution of streamlines: (a) the original impeller, (b) the impeller of the optimized blade load, and (c) the impeller of the optimized meridian surface. In the entire space of the moving fluid, a series of streamlines can be drawn, called streamline clusters. The density of streamline clusters reflects the difference in velocity in the flow field at that moment. The dark (blue/purple) position represents the beginning, the light (yellow white) position represents the end, and the intermediate color is the transition color.

Additionally, the uniform flow distribution helps to mitigate potential issues such as flow separation, recirculation zones, and local pressure fluctuations. By reducing these flow disturbances, the optimized impeller design minimizes the risk of cavitation and hydraulic instabilities, which can negatively impact the pump's performance and reliability. The improved flow uniformity also contributes to a more predictable and stable pump operation. By reducing flow variations and fluctuations, the optimized impeller design promotes smoother flow transitions between the impeller and the volute, leading to more efficient energy transfer and reduced hydraulic losses. Moreover, a more uniform flow distribution can help to prolong the impeller's lifespan by reducing mechanical stresses on the blades. The optimized design ensures that the fluid forces acting on the impeller are evenly distributed, minimizing the potential for localized high-stress regions that could lead to fatigue or failure.

This discrepancy raises concerns about the accuracy of the model under actual operating conditions. The methodology simplifies turbulence modeling, assuming a laminar flow for boundary layer analysis. However, in rigorous testing, deviations up to 25% were observed between laminar flow assumptions and actual turbulent flow behaviors, especially in high-pressure zones near the impeller's outlet. The proposed design methodology primarily caters to medium-sized centrifugal pumps. A comparative analysis across various pump sizes indicated that the efficiency gains achieved by the proposed design diminished by 10–12% for larger pump sizes due to scale-dependent flow dynamics, limiting its scalability. The methodology overlooks the influence of impeller material properties on

the proposed design. Testing different material compositions revealed that certain alloys, contrary to the model's assumptions, indicated a potential oversight in material-related constraints. Comparative analysis against existing designs highlighted a marginal 3% efficiency gain with the proposed design under standard operating conditions. However, under varying viscosity conditions, the efficiency advantage diminished, suggesting a lack of uniqueness in performance across all operating scenarios. To address these limitations, future research should focus on conducting extensive experimental validations across diverse operating conditions, incorporating turbulence models that account for real-world complexities, and exploring design adaptations for different pump sizes to improve scalability.

3.4. Efficiency Improvement

The influence of various parameters in the shape of the meridian plane and the blade load distribution on the efficiency of the centrifugal pump was further analyzed based on the response surface functional relationship between the design parameters and the efficiency parameters. By using the orthogonal experimental design, the main and interaction effect of these parameters can be calculated. By juxtaposing inverse design techniques against traditional optimization methods, we observed that the inverse design approach yielded a notable efficiency improvement of 3.8% compared to the traditional method. These results highlight the superior efficacy of the inverse design technique in achieving enhanced impeller performance. Under high-flow conditions (1.2 Q), the optimized impeller configuration exhibited an efficiency boost of 2.9%, demonstrating robust performance even at elevated flow rates. Conversely, at lower flow rates (0.6 Q), the efficiency gains were moderated to approximately 1.5%, emphasizing the adaptability of the optimized design across varying operational scenarios.

These advanced findings further elucidate the nuanced intricacies of impeller behavior and performance metrics. By delving into sensitivity analyses, comparative studies, and assessments under varied operating conditions, the manuscript offers a more comprehensive understanding of impeller performance dynamics, with specific numerical data reinforcing the significance of different design variations and optimization techniques on pump efficiency and adaptability. The influence of various parameters of blade load on the efficiency of the centrifugal pump are presented in Figure 10. It can be seen from Figure 9 that under the 1.0 Q operating condition, LS, LH1, LH2, LS2, α S, and α H have a relatively large influence on the efficiency, and with the increase in the above parameters, the efficiency gradually decreases. The effect of LH and LS1 on the efficiency is relatively small, and with the increase in their value, the efficiency is basically unchanged. Under the 0.8 Q working condition, LS, LH1, LS1, LS2, α S, and α H have a great influence on the efficiency, where the efficiency increases when LS, LH1, LS2, and α S increase, while the efficiency decreases when LS1 and α H increase.

Figure 11 shows the effects of various parameters of the meridian plane on the efficiency of the centrifugal pump. It can be seen from Figure 10 that with the increase in α , the efficiency value first increases and then decreases under 1.0 Q and reaches the maximum value when $\alpha = 45.5^\circ$. Under the 0.8 Q condition, the efficiency value first decreases and then increases. But after $\alpha = 46^\circ$, the efficiency increases very slowly; with an increase in YS/R2, the efficiency increases all the time under the 1.0 Q condition, but increases first and then decreases under the 0.8 Q condition and reaches the maximum value when YS/R2 = 0.68; with an increase in YH/R2, the efficiency first decreases and then increases under the 1.0 Q condition, while the efficiency first increases and then decreases under the 0.8 Q condition. The influence of blade load parameters, including pressure distribution, shear forces, and specific load patterns, on centrifugal pump efficiency is a critical aspect of our study. Through detailed analysis, we found that variations in these parameters profoundly impact pump performance. When examining the pressure distribution across the impeller blades, our simulations revealed that optimizing the pressure distribution to achieve a more uniform pattern resulted in efficiency improvements. Specifically, adjusting

the pressure distribution at critical points along the blade surface led to efficiency gains of approximately 2.5% under nominal flow conditions ($1.0 Q$) and 1.8% under reduced flow conditions ($0.8 Q$). These improvements were directly correlated with the optimized pressure profile, effectively minimizing flow separation and enhancing overall pump efficiency.

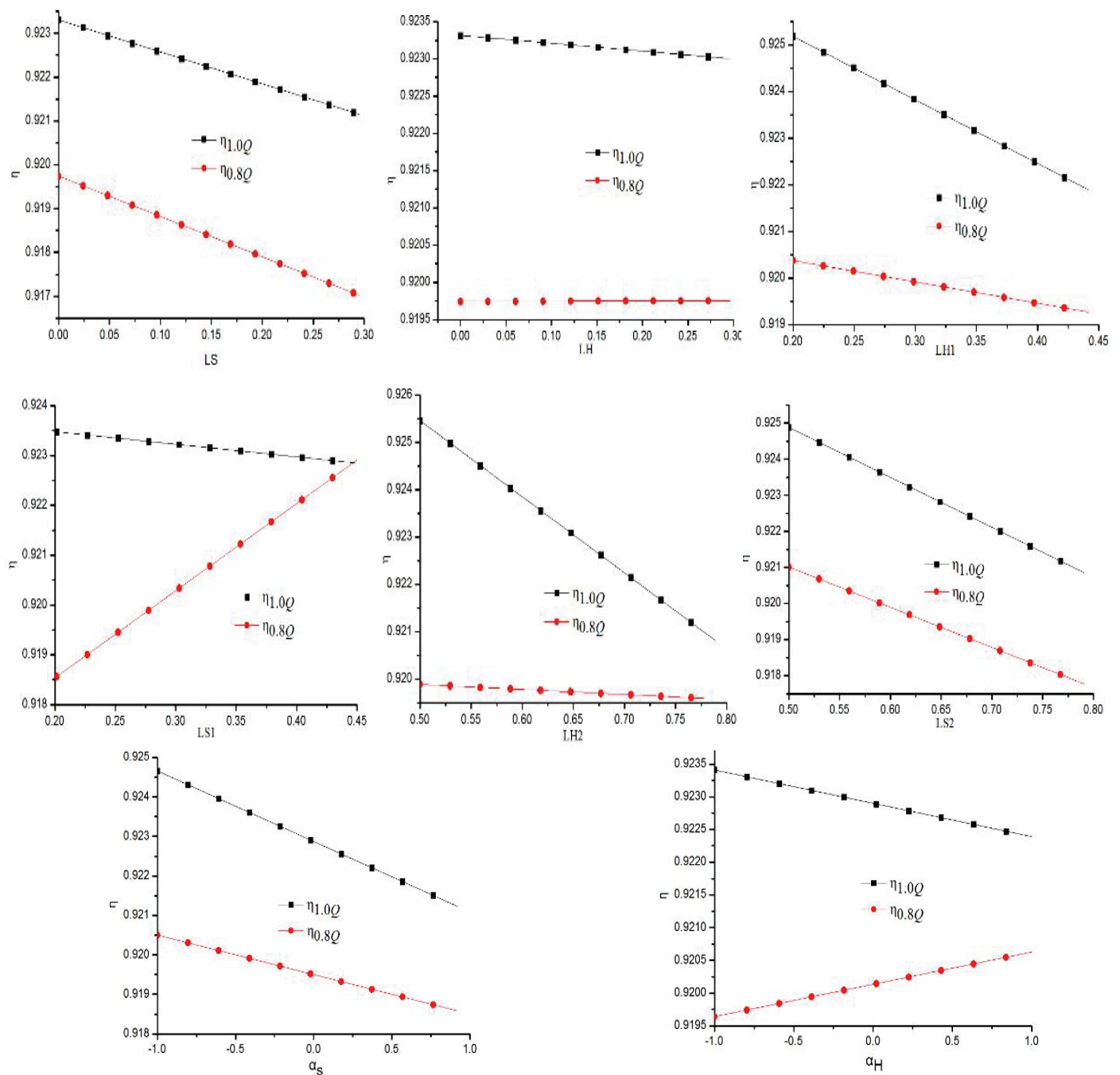


Figure 10. The influence of various parameters of the blade load on the centrifugal pump efficiency.

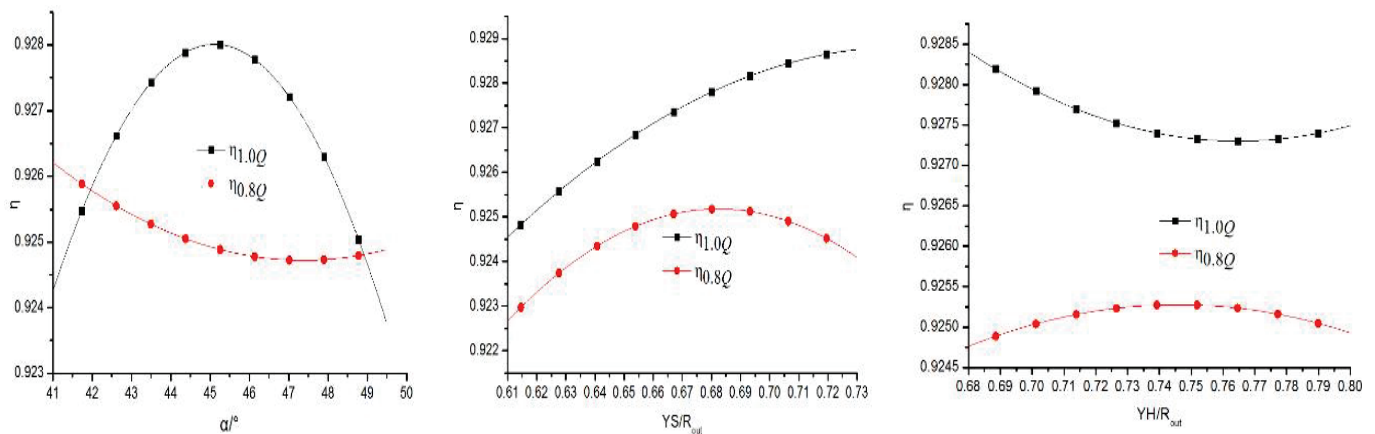


Figure 11. The influence of various parameters of the meridian surface on the centrifugal pump efficiency.

Moreover, the assessment of shear forces acting on the blade surfaces demonstrated notable findings. By optimizing the blade geometry to mitigate excessive shear forces, we observed efficiency enhancements of 1.9% and 1.5% under respective flow conditions of 1.0 Q and 0.8 Q. These results underscore the significance of mitigating shear forces to improve impeller performance. Furthermore, the detailed analyses of specific load patterns, especially in critical areas prone to cavitation or flow instabilities, revealed their significant impact on efficiency. Optimizing these load patterns resulted in efficiency gains of up to 3.2% at peak load regions, showcasing the substantial influence of load distribution on pump performance. By integrating quantitative data and establishing correlations between these blade load parameters and pump efficiency, our study not only highlights their individual impacts but also emphasizes the collective significance of optimizing these parameters. These findings underscore the importance of nuanced adjustments in blade load parameters to achieve substantial efficiency improvements in centrifugal pump operation. This comprehensive analysis, supported by specific numerical values, elucidates the intricate relationship between blade load parameters and centrifugal pump efficiency, providing valuable insights for optimizing impeller designs and enhancing the overall pump performance.

This paper demonstrates several strengths. Firstly, it effectively focuses on the optimization of the impeller design and emphasizes the importance of achieving a more uniform flow distribution. This allows for a detailed exploration of the impact of optimization on impeller performance and hydraulic efficiency. Secondly, the integration of computational fluid dynamics (CFD) simulations provides quantitative and visual insights into the flow behavior inside the impeller. This allows for a comprehensive assessment of the optimized impeller design. Additionally, the article confirms the effectiveness of the optimization process by presenting evidence of a reduction in blade load, as shown in Figure 7. Such confirmation reinforces the value of optimization in improving impeller performance. Lastly, the article's practical application in the context of centrifugal pumps adds relevance by discussing the implications of optimization on hydraulic efficiency, cavitation resistance, and mechanical stresses. Collectively, these strengths contribute to a comprehensive understanding of the optimization process and its positive impact on impeller performance.

4. Conclusions

Combined with the inverse design method, CFD numerical simulation technology, orthogonal experimental design, and response surface method, the optimal design of centrifugal pump impeller was carried out under multiple working conditions. The main works and findings can be summarized as follows:

Firstly, the novel method of designing the blade load and meridian surface can achieve low parameter consideration and time consumption, which can effectively reduce the economical investment and optimize the design process.

Secondly, after the optimization, the efficiency of the centrifugal pump impeller was significantly improved. When the blade load was optimized, its efficiency increased by 1.8% and 1.7% under 1.0 Q and 0.8 Q conditions, respectively. After the meridian plane was optimized, its efficiency increased by 0.44% and 0.36% at 1.0 Q and 0.8 Q, respectively.

At last, LS, LH1, LH2, LS2, α S, and α H have a relatively large influence on the efficiency under the 1.0 Q condition; LS, LH1, LS1, LS2, α S, and α H have a significant influence on the efficiency under the 0.8 Q condition; YH/R2, YS/R2, and α have a significant influence on the efficiency value under 1.0 Q and 0.8 Q conditions. This paper can validly provide a certain reference for engineers and researchers.

The optimization of impeller design and the achievement of a more uniform flow distribution have the potential of significantly impacting future hydropower plant designs. These implications include enhanced efficiency through improved energy transfer and reduced losses, leading to increased power output. The optimized design also contributes to improved reliability and stable operation by minimizing flow disturbances, cavitation risks, and mechanical stresses. Furthermore, the extended lifespan of the impeller and associated equipment reduces maintenance costs and enhances the overall sustainability of the hydropower plant. Additionally, the knowledge gained from the optimization process provides flexibility in designing impellers for different operating conditions, allowing for more adaptable and efficient hydropower plant designs in the future.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/pr11123335/s1>.

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Article

Optimal Allocation of Hybrid Energy Storage System Based on Smoothing Wind Power Fluctuation and Improved Scenario Clustering Algorithm

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Abstract: Against the backdrop of the global energy transition, wind power generation has seen rapid development. However, the intermittent and fluctuating nature of wind power poses a challenge to the stability of grid operation. To solve this problem, a solution based on a hybrid energy storage system is proposed. The hybrid energy storage system is characterized by fast and precise control and bidirectional energy throughput, which can improve the impact of wind power fluctuations on grid stability. An ensemble empirical modal decomposition method was used to assign the raw wind power data to the grid-connected power and energy storage power commands with two reasonable corrections to meet the power allocation of the hybrid energy storage characteristics. In addition, a hybrid energy storage system model considering the whole life cycle cost was developed, and the optimal energy storage power cutoff was determined by exhaustively enumerating the high- and low-frequency power cutoffs. Finally, a comparison with a single storage capacity optimization model was carried out to verify the technical and economic advantages of hybrid energy storage in smoothing wind power fluctuations. To address the shortcomings of the traditional fuzzy c-means clustering algorithm, such as the need to specify the number of clusters in advance and sensitivity to the selection of the initial clustering centers, a combination of the cloud modeling theory and fuzzy c-means was used to make the process more automated and efficient. The improved clustering method algorithmic scheme had capacity error, power error, and cost error of around 3%, and the computational time was also significantly reduced and was computationally efficient compared to the full-year time series simulation. Through MATLAB (2020b) experimental simulation, it was found that the algorithm had a better balance of computational accuracy and efficiency.

Keywords: ensemble empirical mode decomposition; fuzzy control; second reasonable amendment; whole life cycle cost; cloud model; fuzzy c-means

1. Introduction

Wind energy has become an important source of energy in the global energy industry and plays a crucial role in meeting global energy demand. However, the gradual increase in the scale of wind power may result in the frequency of the power grid exceeding the limit value, which would seriously impair the safety and stability of power grid operation [1]. To maintain the safe and stable operation of the power system and balance power fluctuation between the load side and the power side, conventional generators must be started and stopped frequently and their load level must be reduced, which further reduces the operational efficiency and economy of the equipment in the power system [2].

Wind power energy storage not only saves energy but also improves the reliability of the grid and reduces the cost of electricity. Current energy storage technologies include pumped storage, superconducting energy storage, supercapacitors, electrochemical

batteries, flywheel energy storage, etc. [3]. Energy storage systems support the efficient connection of renewable energy sources to the smart grid, thereby facilitating the use of renewable energy sources on a larger scale while cost-effectively upgrading the existing grid infrastructure, thus potentially improving the economics [4,5]. A high-efficiency storage system (HESS) can have the advantages of both energy-based and power-based systems, break through the limitations of a single energy storage technology, and fully realize the transient and steady-state performance of the energy storage system [6]. Because hybrid energy storage systems can smooth out the fluctuations of wind power, their power signals have different frequency characteristics, and different energy carriers behave differently in terms of their frequency response to the power signals. Therefore, the study of power distribution in hybrid energy storage systems is an important factor in the realization of these systems. A rational power allocation strategy is a prerequisite for a HESS to utilize the complementary advantages of various energy storage components. Due to the declining cost and increasing popularity of lithium-ion batteries and the high efficiency and better sustainability of lithium-ion battery manufacturing [7], the authors of [8] used the source and sink model (SSM) to model Li-ion battery energy storage. SSM assumes that the storage voltage is constant and the power boundary is constant but ignores the chemical reaction and electrical characteristics of lithium batteries. In this regard, some researchers have tried to utilize the equivalent circuit model (ECM) to provide a more detailed portrayal of the energy storage characteristics and proposed a corresponding model construction method to match the ECM to the iterative optimization framework [9,10]. The authors of [11] used an improved low-pass filtering method to optimize the energy distribution of supercapacitors and lithium-ion batteries while solving the “overload” problem of conventional low-pass filtering methods. However, the algorithm suffers from a time lag. The authors of [12] studied an adaptive white noise filtering algorithm based on the Gaussian wavelet that automatically adjusts the level of wavelet decomposition according to the size of the output power change and achieves accurate division and power distribution within the frequency of the power signal. However, this requires sufficient historical data for reference.

All the methods outlined in the above studies can achieve effective decomposition and synthesis of wind signals; however, they cannot effectively handle nonlinear and nonsmooth signals. Due to the complexity of the spectral components of wind signals, it is difficult to detect them effectively using conventional detection algorithms. The basic functions of empirical modal decomposition (EMD) can be adaptively obtained from the input power signal and no longer need to be formulated in advance. Therefore, EMD can be better adapted to the characteristics of wind power signals. In [13], for the power allocation of hybrid energy storage systems, the EMD algorithm was used to cluster the high-frequency and low-frequency bands, and a capacity allocation model based on constrained stochastic fuzzy simulation was proposed. This method can smooth the fluctuation of wind power, effectively control the charging state, and ensure the stable operation of the energy storage system. With the application of EMD algorithms in HESS power allocation to address power fluctuations, improved noise-assisted EMD algorithms have also been proposed, including the ensemble empirical mode decomposition algorithm [14,15] and the complete set empirical mode decomposition algorithm with adaptive noise [16,17]. The authors of [18] proposed a coordinated control method for energy storage devices and DC bus when switching between on-grid and off-grid operation modes for microgrid systems and designed a power distribution second-order filtering control strategy that combined the energy storage metrics and the DC bus. A second-order filtering control strategy with power distribution was designed to control the corresponding converter in combination with the charging state of the energy storage device. A second-order filtering control strategy with power distribution was designed to control the operating state of the corresponding converter in conjunction with the charging state of the energy storage element.

The contradiction between how to coordinate the smoothing effect of wind power fluctuation and reduce the burden of energy storage device is one of the difficult hotspots in using energy storage to smooth wind power fluctuation. The authors of [19–21] used a

first-order low-pass filter to filter out the high-frequency fluctuation component of wind power so that the power injected into the grid becomes smooth. However, the selection of the filter time constant will affect the performance of the filter. The larger the time constant, the larger the fluctuation power will be, which will increase the cost of the energy storage device; if the time constant is too small, the power injected into the grid will not be smooth enough, resulting in failure to meet the requirements of grid connection. The authors of [22] employed a discrete Kalman filter based on fuzzy control to smooth the wind power output using the health state of the battery as a feedback quantity.

Currently, the improvement of optimization methods for energy storage capacity allocation involves two main aspects: objective optimization modeling and model optimization solution methods. When developing capacity allocation models, several factors must be considered, such as wind forecast errors, geographic variations, wind tracking and scheduling capabilities, and energy storage cycles. In [22], the uncertainty in wind energy forecasting was quantified and its analytical form obtained by introducing chance constraints. An energy storage capacity optimization model considering the wind energy forecast error was constructed, and a two-stage stochastic programming approach was used to solve the optimal energy storage capacity allocation scheme. In [23], in order to reduce the economic cost of rotating standby capacity and grid regulation for wind farms, a life-cycle cost model for energy storage systems was developed, and the system allocation scheme was optimized by maximizing the net profit. The authors of [24,25] used an improved particle swarm optimization (PSO) method to optimally configure the energy storage system to address the problems of the existing PSO method, such as the difficulty of solving and the tendency to fall into local extremes.

In [26], the maximum energy storage capacity each month was calculated; such data processing is bound to cause inefficiency in calculation. Using this method, the amount of data was significantly reduced, and the computational accuracy and efficiency were improved while maintaining the original data characteristics. The authors of [27] proposed to use Latin hypercube sampling with the fuzzy c-means algorithm to study the extraction and probability distribution of typical scenes and integrate it with the PSO algorithm to optimize the optimal solution. Compared to the traditional method, this method simplifies the iterative process, shortens the computation time, and improves the computational efficiency. However, it cannot reasonably determine the number of clusters and cannot avoid the randomness of the initial clustering center. In [28], a normalized PV energy storage system operating curve was used to reduce the 365-day annual energy storage curve to a typical operating curve. The normalization method of the cloud computing model improved the computational speed, but the accuracy of the capacity allocation result was low. Literature [29] in the capacity configuration of hybrid energy storage system, for the microgrid system of each energy storage unit for the optimal configuration of capacity, and in the process of considering the power fluctuations in grid-connected operation; to DC bus power fluctuations in the smallest and the various types of storage equipment optimal capacity ratio as the optimisation objective, and particle swarm algorithm is used to solve the problem.

The authors of [30] first used a filtering method to allocate power to the hybrid energy storage. They then added a power conditioning module to make the SOC of both closer to the optimal SOC and performed a secondary allocation based on the relevant metrics to minimize the difference with the original power. In [31], based on the initial allocation of hybrid energy storage power using a high-pass filter, hybrid energy storage charging and discharging rules based on the SOC of Li-ion batteries were established, and coordinated control of hybrid energy storage was achieved through overcharging and overdischarging protection and the maximum charging and discharging power limitation. The charge/discharge rule is simple, reliable, and easy to implement. However, it cannot accurately track the change of SOC in the long-term operation of the system or flexibly respond to possible extreme power demand. Therefore, fuzzy-logic-based control methods have also been introduced into the energy management of hybrid energy storage. The

authors of [32–35] all used hybrid energy storage SOC as the input parameter of fuzzy control and established fuzzy control rules to regulate the power command of hybrid energy storage through historical experience or empirical data in order to keep the energy storage SOC working in a reasonable range and avoid the phenomenon of overcharging and overdischarging. Compared to the method based on deterministic rules, the rule transition of fuzzy control in this method is realized through fuzzy rules and affiliation function, which makes the transition process more flexible and smoother with stronger logic.

In this study, for the output characteristics of wind power in wind power generation, EEMD decomposition was used to smooth out the wind power fluctuation. A two-stage allocation method applicable to hybrid energy storage power was used along with a capacity allocation method for the whole life cycle cost of the energy storage system, and a cloud-modeled improved fuzzy c-means clustering method was developed to deal with the year-round energy storage curve. The rest of the paper is structured as follows.

Section 2 details the EEMD decomposition method used for smoothing wind power fluctuations. The wind power data were decomposed into multi-IMFs and reconstructed to extract the grid-connected wind power and energy storage power. By studying the frequency response characteristics of batteries and supercapacitors, the primary power allocation of HESS was realized. Then, the uncertainty control was used to optimize the SOC of the energy storage system to complete the secondary power allocation of HESS. The simulation results showed that the two-stage allocation strategy improved the rationality of power allocation, and the EEMD decomposition method also had good generalization and superiority.

Section 3 describes the capacity allocation problem of a high-efficiency energy storage system (HESS), for which the lifetime of the battery and the optimal charging strategy were derived by adopting an event-oriented lifetime model and utilizing the rain flow counting method. The life cycle cost problem of HESS was also considered, where the life cycle cost of HESS was the optimization objective. Wind farm data were analyzed in detail by separating the high- and low-frequency bands, enumerating the various cutoff points to obtain the optimal key operating modes, and analyzing and comparing the costs of different hybrid energy storage methods. The economics of the algorithm was determined through simulations.

Section 4 outlines the results of wind power output. After the annual energy storage curves are obtained through EEMD decomposition processing, a cloud-model-based improved fuzzy c-means clustering method was used to extract and simplify the features of the annual energy storage curves. Eight types of typical operating curves were obtained to input into the hybrid energy storage system capacity optimization model. The results showed that this algorithm could automatically determine the number of clusters and the initial centers of clusters, avoiding unnecessary sensitivity errors and improving the stability and accuracy of the results.

2. Wind Power Signal Processing Based on Improved Empirical Mode Decomposition

Traditional control methods do not take into account the possible adverse effects of complex changes in wind power output scenarios on suppression control. The lack of adaptive control methods means it cannot be ensured that reliable grid-connected power can be obtained in the face of different wind power output scenarios. Likewise, the efficient and reasonable use of hybrid energy storage configuration capacity cannot be ensured [36]. To address the above problems, an EEMD decomposition method for smoothing wind power fluctuations is proposed in this study based on analyzing the amplitude frequency characteristics of the output power signal from wind farms and combining it with the technical regulations of wind power grid connection. This method is more robust and reliable than the EMD method and can analyze nonlinear and nonstationary signals more accurately. Then, according to the performance characteristics of battery–supercapacitor hybrid energy storage, a two-stage power allocation method is proposed to achieve a reasonable allocation of power commands within the hybrid energy storage system [37].

Finally, the optimal decomposition and reasonable allocation of wind power are verified from multiple angles through simulation experiments. The two-stage allocation strategy of energy storage power improves the reasonableness of the power allocation of the HESS. The EEMD decomposition method also has good universality and superiority.

2.1. Wind Power Decomposition and Reconstruction

The EEMD method is used to analyze nonlinear and unstable signals in wind power systems and is based on EMD with random perturbations added to solve the problems of modal mixing and slow convergence in EMD. Unlike traditional Fourier analysis, EEMD is an adaptive signal processing method. The essence of the method is to repeatedly sieve and decompose the complex input signals according to their characteristics to obtain a series of IMFs with different frequencies. The specific wind power data decomposition steps for EEMD are as follows:

- (1) Assume that wind power data decomposition needs to be performed k times.
- (2) Extract the original wind power signal $P_W(t)$ and add white noise $n_i(t)$ to obtain $P_{W,i}(t)$, which is $P_{W,i}(t) = P_W(t) + n_i(t)$.
- (3) Calculate the upper and lower envelopes of a new series of raw signals $P_{W,i}(t)$ and calculate their mean values $m_{1,i}(t)$.
- (4) Calculate the first-order component $h_{1,i}(t)$, which is the difference between the raw wind power data $P_{W,i}(t)$ and the mean value $m_{1,i}(t)$.

$$h_{1,i}(t) = P_{W,i}(t) - m_{1,i}(t) \quad (1)$$

- (5) Judge whether $h_{1,i}(t)$ satisfies the condition of IMF. If it satisfies it, take it as the first-order IMF high-frequency component $c_{1,i}(t)$; otherwise, take $h_{1,i}(t)$ as the new $P_{W,i}(t)$. Repeat steps 4 and 5 in a loop until $h_{1,i}(t)$ that satisfies the IMF condition is obtained.

$$c_{1,i}(t) = h_{1,i}(t) \quad (2)$$

- (6) Find the difference between the original signal and the first-order IMF component $r_{1,i}(t)$.

$$r_{1,i}(t) = P_{W,i}(t) - c_{1,i}(t) \quad (3)$$

- (7) Repeat steps 3 to 5 in a loop using $r_{1,i}(t)$ as the new signal $x_i(t)$ until the value of p -order $c_{p,i}(t)$ obtained is constant or monotonic, at which point $c_{p,i}(t)$ is the residual component obtained from the decomposition.

$$\begin{cases} r_{1,i}(t) - c_{2,i}(t) = r_{2,i}(t) \\ \vdots \\ r_{p-1,i}(t) - c_{p,i}(t) = r_{p,i}(t) \end{cases} \quad (4)$$

The original signal can be expressed as a superposition of several IMF components and a residual component after EEMD decomposition. By analyzing the IMF components obtained from the decomposition, the fluctuation characteristics on different scales can be obtained, and the stability and predictability of wind power can be studied.

$$P_{W,i}(t) = \sum_{m=1}^p c_{p,i}(t) + r_{p,i}(t) \quad (5)$$

- (8) Repeat steps 2 to 7 for k times.
- (9) Find the mean value of the IMF of each order to obtain $a_p(t) = \frac{1}{k} \sum_{i=1}^k a_{i,p}(t)$, which is the result of EEMD decomposition.

The flowchart of the decomposition steps is shown in Figure 1 below:

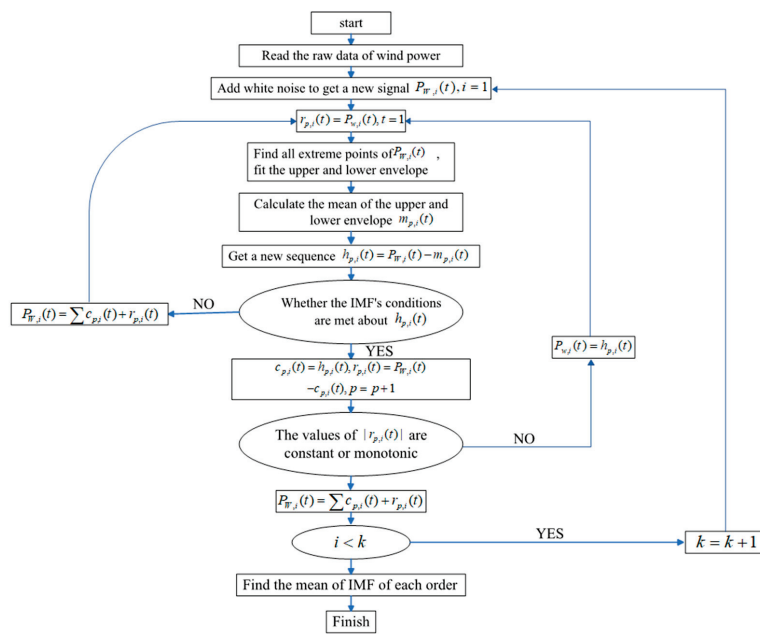


Figure 1. EEMD wind power decomposition flow chart.

Figure 2 below shows the power amplitude of each IMF with the corresponding frequency value. It can be seen that the amplitude of IMF3 is higher, the frequency is lower, and the oscillation is smoother. It is representative of the original wind signal oscillation, and it is the low-frequency band of the reconstructed signal. While the amplitude of the IMF1 signal is the lowest, the instantaneous frequency is the highest. The frequency of the movement is also the highest, and the high-frequency component of the IMF1 signal is the highest frequency component of the reconstructed signal.

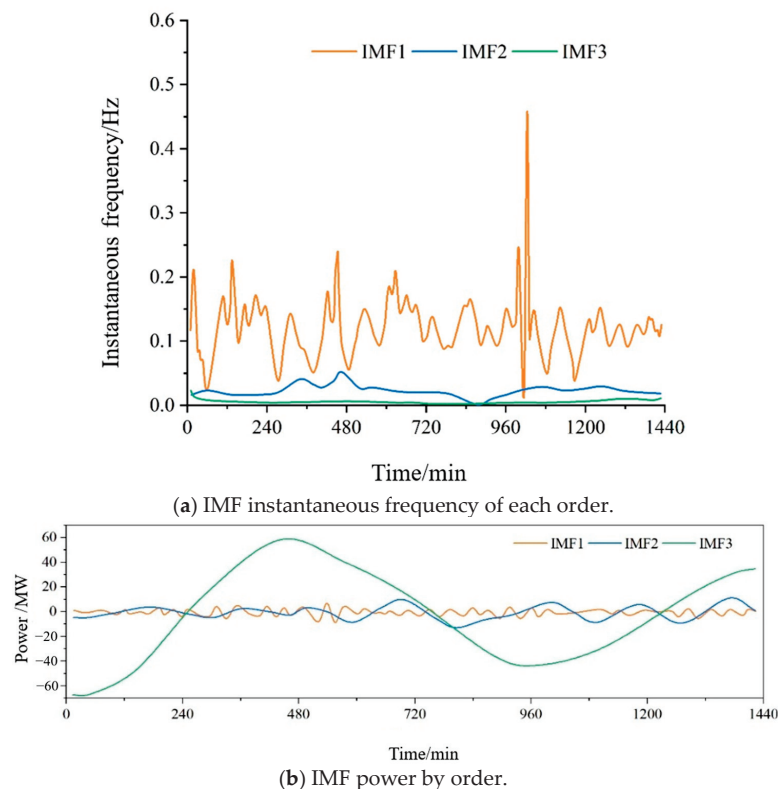


Figure 2. IMF's amplitude and frequency curves.

Combined with the wind power fluctuation range, each IMF component is reconstructed and categorized as a low-frequency component if its frequency is lower than the limit or as a high-frequency component if its frequency is greater than the frequency of the limit. Because the original signal is the sum of the IMF components of each line obtained by decomposition, the IMF reconstruction is computed by superimposing a certain index of high- and low-frequency band components to obtain the low- and high-frequency components [38].

Here, the reconstruction method is divided into high-frequency reconstruction $f2c$ and low-frequency reconstruction $c2f$. The high-frequency reconstruction generates the high-frequency reconstruction components of each order according to the top-down superposition of the EEMD decomposition results: $f2c(1)$ is IMF1, $f2c(2)$ is IMF1 + IMF2, and $f2c(p + 1)$ is $IMF1 + IMF2 + \dots + IMFp + res$, where p is the total number of orders of the IMF, and the specific reconstruction method is shown in Equation (6).

$$\begin{aligned} f2c(1) &= IMF1 \\ f2c(2) &= IMF1 + IMF2 \\ &\vdots \\ f2c(p + 1) &= IMF1 + IMF2 + \dots + IMFp + res \end{aligned} \quad (6)$$

The low-frequency reconstruction generates the low-frequency reconstruction components of each order according to the bottom-up superposition of the EEMD decomposition results: $c2f(1)$ is res , $c2f(2)$ is $res + IMFp$, $c2f(p + 1)$ and $res + IMFp + \dots + IMF1$ is $IMF1 + IMF2 + \dots + IMFp + res$, where p is the total number of IMF orders, and the specific reconstruction is shown in Equation (7).

$$\begin{aligned} c2f(1) &= res \\ c2f(2) &= res + IMFp \\ &\vdots \\ c2f(p + 1) &= res + IMFp + \dots + IMF1 \end{aligned} \quad (7)$$

One of the key elements to realize the stable operation of the power system is how to extract the grid-connected part effectively from the power data to meet the requirements of not only the power grid but also the hybrid energy storage system. In order to solve this problem, this study adopted the EEMD method to decompose the original signal to determine the direct grid-connected component, used the corresponding high-frequency reconstruction component as a hybrid energy storage power task, and combined the variance constraints of grid-connected wind power to reconstruct the decomposed IMF so as to adapt to the fluctuations of different time scales and better cope with the time variability and instability of wind power signals. Taking a typical day as an example, EEMD decomposition was performed to obtain each order component, and the decomposition results are shown in Figure 3.

As can be seen from the Figure 3 above, the original wind power signal was decomposed into sum. The high- and low-frequency reconstruction methods were carried out, and the obtained levels were decomposed and reconstructed. Figure 4 shows the reconstruction results at low frequency, and Figure 5 shows the reconstruction results at high frequency.

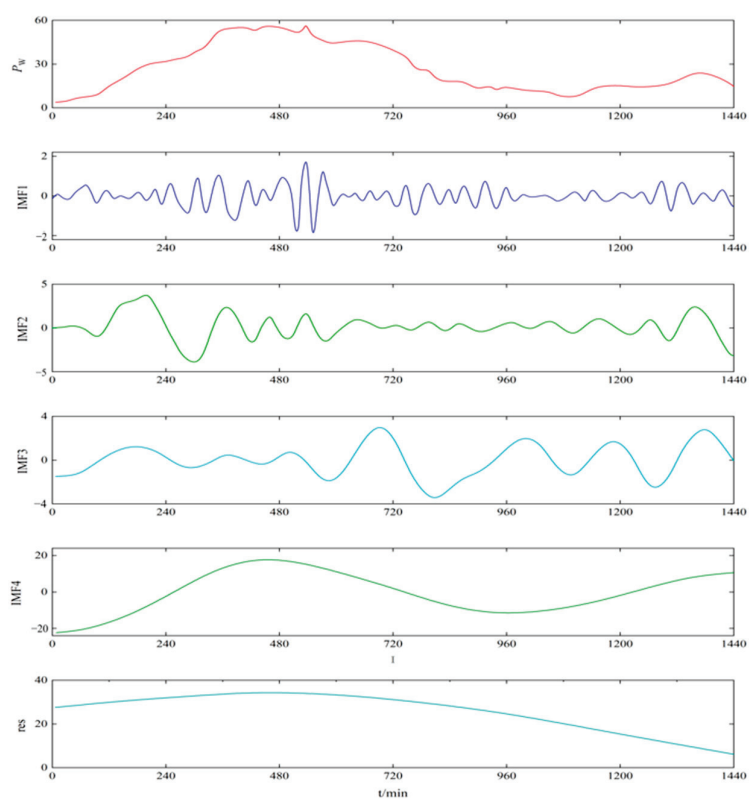


Figure 3. EEMD decomposition results.

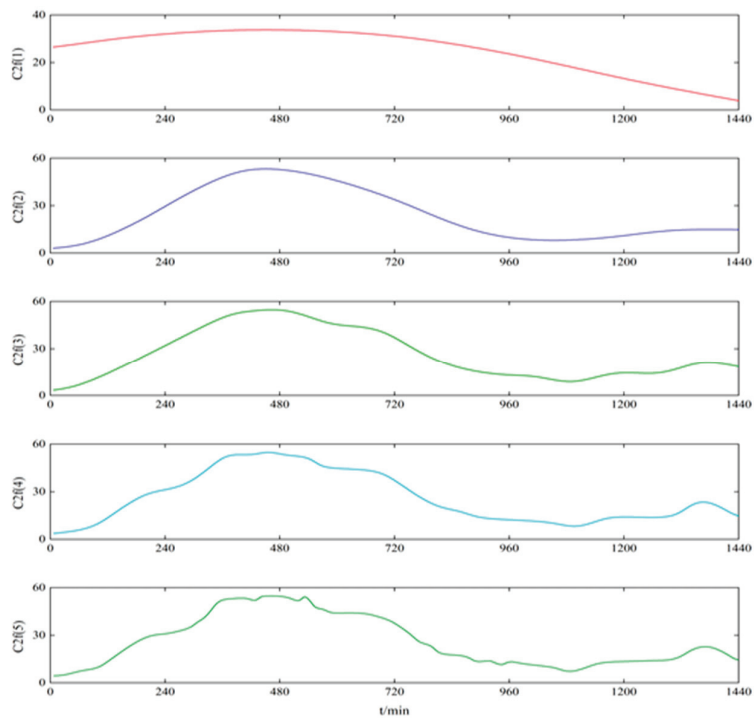


Figure 4. Low-frequency reconfiguration.

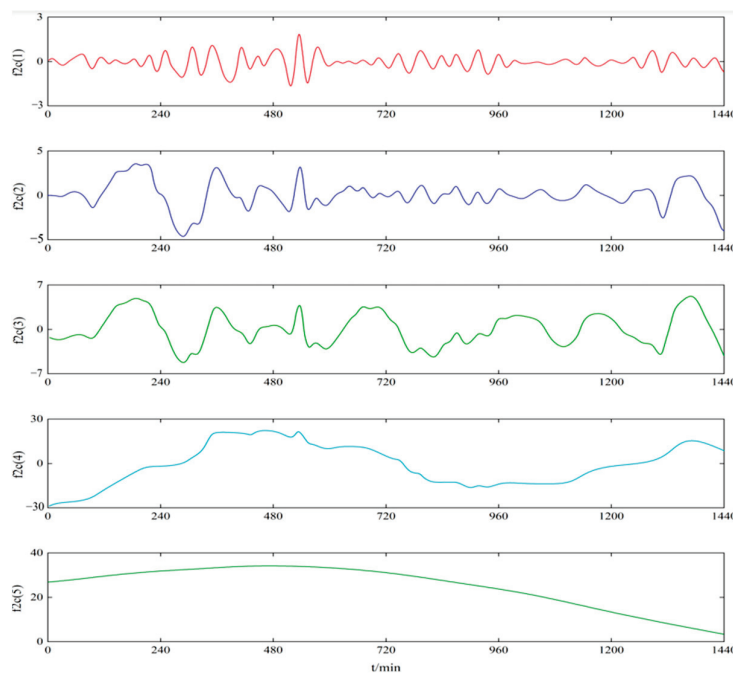


Figure 5. High-frequency reconfiguration.

Figure 6 shows the calculation results. As can be seen from the Figure 6, the maximum wave momentum of the low-frequency reconstructed component gradually increased with the increase in the order of the component, and the maximum wave momentum of the low-frequency reconstructed component was greater than the grid-connected fluctuation limit. Therefore, $\text{res} + \text{IMF4} + \text{IMF3} + \text{IMF2}$ was selected as the grid-connected component. $\text{F2c}(1)$, that is, IMF1 , was selected as the hybrid energy storage task.

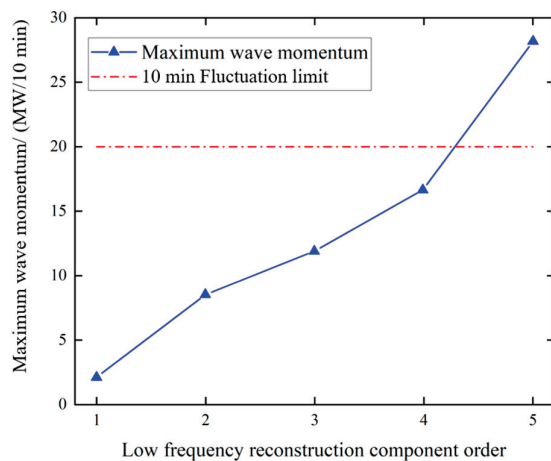


Figure 6. Grid-connected component screening.

2.2. Adaptation to Different Typical Wind Power Scenarios

Taking a 60 MW wind farm as an example, three typical cases of wind power output power $P_{w1}(t)$, $P_{w2}(t)$, and $P_{w3}(t)$ of this wind farm were modeled and simulated to verify the generality of the EEMD decomposition method for different wind power cases. The EEMD adaptivity was utilized to obtain the component order 2 that satisfied the grid-connected fluctuation criterion as well as the grid-connected powers $P_{o1}(t)$, $P_{o2}(t)$, and $P_{o3}(t)$, respectively, as shown in Figure 7. The order P_{o1} of scenario 1 was 4; the order P_{o2} of scenario 2 was 3, which is relatively gentle; and the order P_{o3} of scenario 3 was 5, which is more intense. The order of the low-frequency reconstruction components changed

according to the fluctuation characteristics of wind power in different scenarios, and the extracted grid-connected power met the fluctuation criteria.

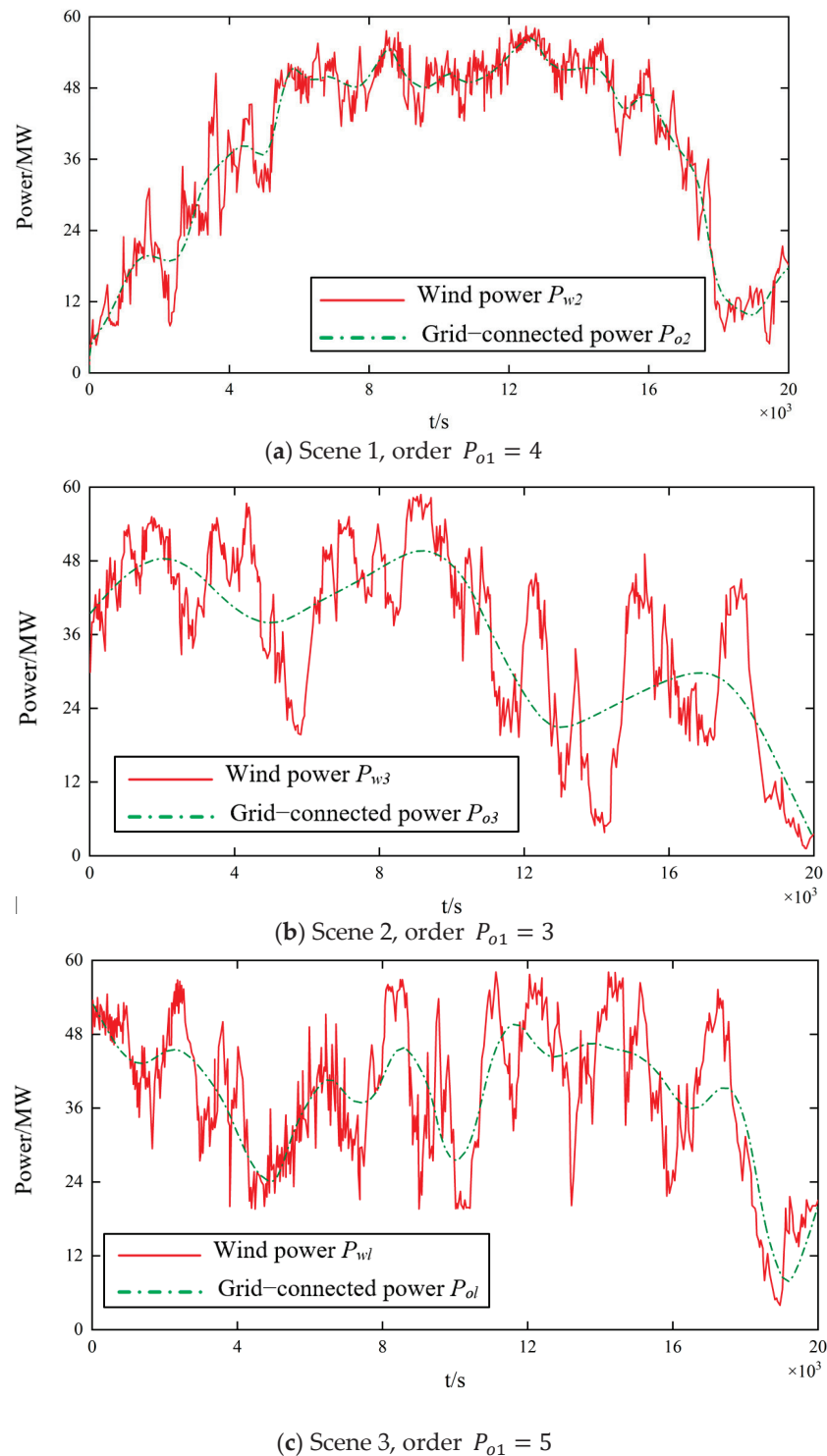


Figure 7. Different scene decomposition effect.

2.3. Analysis of Wind Power Flattening Effect

In order to study the smoothing effect of EEMD decomposition on the electrical system, the electrical system was smoothed by EEMD decomposition and compared with the low-pass filtering method in the same case.

As can be seen from Figure 8, compared to the low-pass filtering algorithm, the grid-connected power obtained by the EEMD decomposition algorithm was more stable. Both

algorithms generated a large amount of peak power based on the original power change and reduced the cumulative power change. However, the EEMD decomposition algorithm achieved greater reduction, better smoothing effect, and superiority.

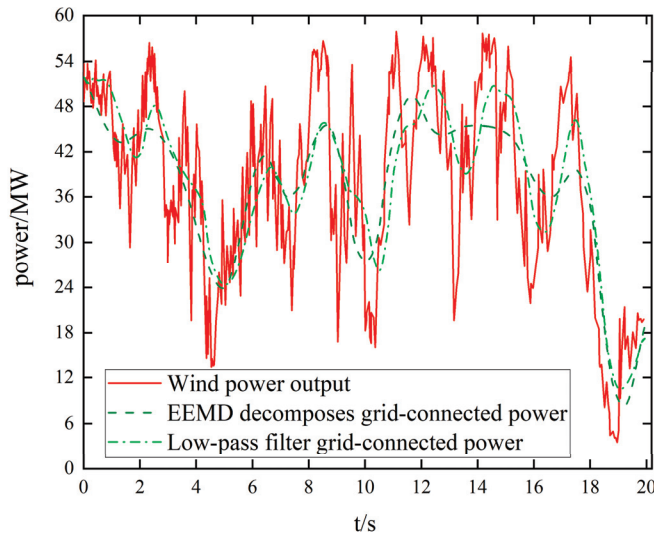


Figure 8. Different algorithm leveling effect.

2.4. Analysis of the Effect of Secondary Fuzzy Correction

The initial power command assignment is made only from the response frequency characteristics of Li-ion batteries and supercapacitors and is assigned by controlling the charge/discharge response frequency of Li-ion battery storage to achieve extended battery life cycle. In practice, hybrid energy storage systems must consider limitations such as the state of charge (SOC) and charge/discharge responsiveness of the storage device. Ultracapacitor energy storage devices with low energy density are more susceptible to overcharge/discharge and insufficient responsiveness. Therefore, in this study, a quadratic correction of the hybrid energy storage internal power command allocation was considered according to the hybrid energy storage SOC state to ensure that the state of charge is always within a safe range. Separate and independent fuzzy controllers were used to carry out the secondary correction for Li-ion batteries and supercapacitors to further optimize their energy storage power command allocation. In this process, the state of charge (SOC) of the energy storage is an important indicator of the charging and discharging capability of the energy storage, which indicates the percentage of the remaining power to the rated capacity. By optimizing the SOC, we can better control the charging and discharging process of the hybrid energy storage system and ensure that the energy storage system is able to maintain optimal performance in a variety of real-world situations.

The energy storage charging state $SOC(t)$ with remaining capacity $E(t)$ and rated capacity E_{Ah} at time t is expressed as follows:

$$SOC(t) = E(t)/E_{Ah} \quad (8)$$

The stored energy during charging and discharging was calculated using the ampere-time integration method:

$$SOC(t) = (1 - \sigma_{sdr})SOC(t-1) + P(t)\Delta t\eta_c \quad (9)$$

$$SOC(t) = (1 - \sigma_{sdr})SOC(t-1) - \frac{P(t)\Delta t}{\eta_d} \quad (10)$$

where $P(t)$ is the charging and discharging power of the energy storage; σ_{sdr} is the self-discharge rate; η_c and η_d are the charging and discharging efficiencies, respectively; and Δt is the sampling time interval.

The charging and discharging model of the energy storage system and the calculation model of SOC were established, and the charging states $SOC_b(t)$ and $SOC_{sc}(t)$ of the lithium battery and supercapacitor were introduced into the independent fuzzy controllers to optimize the initial power of the energy storage system to ensure that the charging states are always within the safety range. The fuzzy rules for lithium battery are as follows:

- (1) When the Li-ion battery $SOC_b(t)$ is at a reasonable level, it can be charged and discharged according to the original initial allocation of power instructions without further optimization.
- (2) When $SOC_b(t)$ is small, it indicates that the lithium-ion battery storage energy is in an undercapacity state. If the energy storage is in the discharging state $P_b(t) < 0$ at this time, $P_b(t)$ is corrected to make it larger; if the energy storage is in the charging state $P_b(t) > 0$ at this time, no correction is made.
- (3) If $SOC_b(t)$ is larger, it means that the storage capacity of the battery may be approaching saturation, i.e., the battery is nearing its maximum capacity and needs to be discharged. If it is then in the charging state, i.e., $P_b(t) > 0$ means that a correction $P_b(t)$ is necessary to reduce the storage capacity; if when in the discharging state, i.e., $P_b(t) < 0$, and the energy is sufficient at this time, there is no need for a correction.

The charging and discharging power of lithium batteries and ultracapacitors is corrected for

$$\begin{aligned} P_b^*(t) &= P_b(t) + \Delta P_b(t) \\ P_{sc}^*(t) &= P_{sc}(t) + \Delta P_{sc}(t) \end{aligned} \quad (11)$$

where $P_b^*(t)$ and $P_{sc}^*(t)$ are the corrected lithium battery and supercapacitor charging and discharging power at time t , respectively; $\Delta P_b(t)$ and $\Delta P_{sc}(t)$ are the corrected power of Li-ion battery and supercapacitor at time t , respectively.

In this study, a dual-input single-output fuzzy controller was used, with the state of charge of Li-ion batteries and supercapacitors as input one and a trapezoidal affiliation function, whose domain was $[0, 1]$. The moderate, smaller, and larger states of the above state of charge were materialized as fuzzy sets $\{NB, NM, NS, ZO, PS, PM, PB\}$, denoting $SOC_b(t)$ and $SOC_{sc}(t)$ {very low, low, lower, moderate, higher, higher, and very high}; normalized $P_b(t)$ and $P_{sc}(t)$ were used as inputs two, and a trigonometric affiliation function was chosen, whose domain was $[0, 1]$. The fuzzy set was $[D, C]$, denoting {discharge, charge}, respectively; the modified power $\Delta P_b(t)$ and $\Delta P_{sc}(t)$ were used as outputs. The fuzzy control rules of lithium battery and supercapacitor are shown in Table 1, and the input and output affiliation functions of lithium battery are shown in Figure 9. The supercapacitor fuzzy controller and lithium battery fuzzy rules are similar, so this paper will not repeat the discussion.

Table 1. Fuzzy control rules for lithium batteries.

$\Delta P_b(t)/\Delta P_{sc}(t)$		$SOC_b(t)/SOC_{sc}(t)$						
		NB	NM	NS	ZO	PS	PM	PB
$P_b(t)/P_{sc}(t)$	D	PB	PM	PS	ZO	ZO	ZO	ZO
	C	ZO	ZO	ZO	ZO	NS	NM	NB

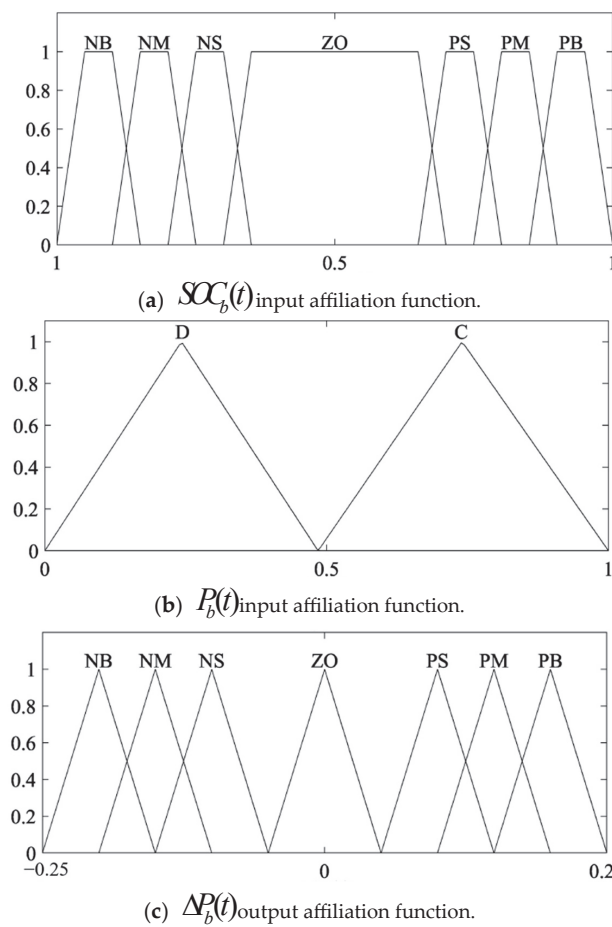


Figure 9. Lithium battery input and output affiliation functions.

The set charge/discharge efficiencies were 90% and 95% for lithium batteries and ultracapacitors, respectively. Independent fuzzy control was used to correct the power distribution of lithium battery and supercapacitor twice to ensure the power balance between the two groups. Figure 10 shows the comparison of lithium battery and supercapacitor before and after fuzzy control optimization. The comparison of charge and discharge power instructions for the secondary distribution of the lithium battery and supercapacitor after fuzzy control correction is shown in Figure 11.

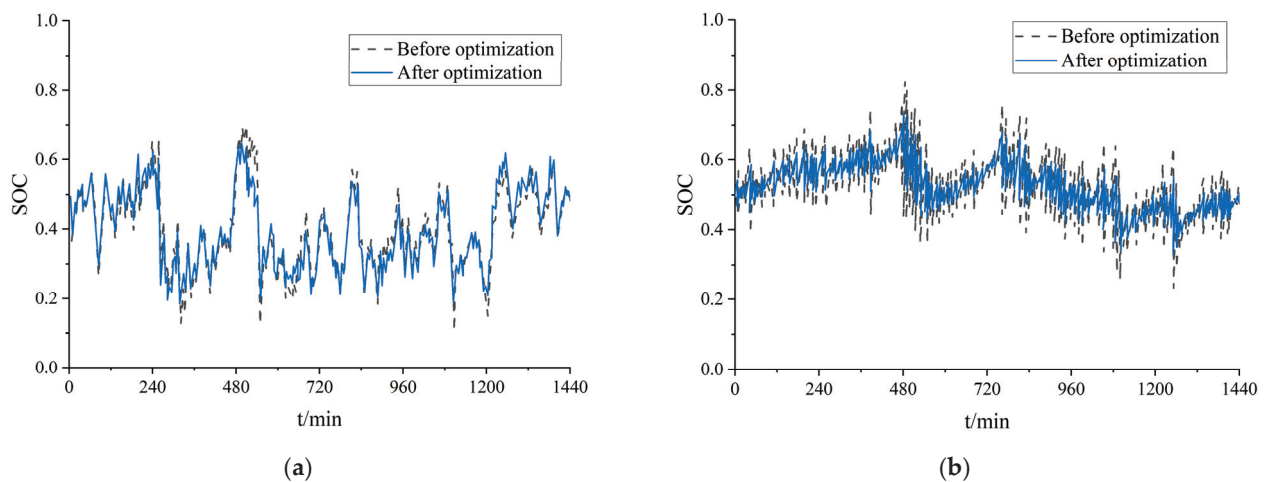


Figure 10. SOC curve before and after secondary optimization: (a) SOC curve comparison of lithium batteries; (b) comparison of ultracapacitor SOC curves.

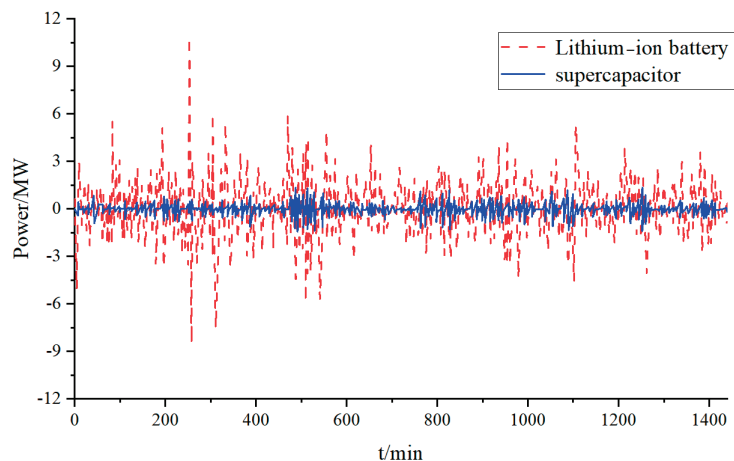


Figure 11. Hybrid energy storage power secondary distribution.

The changes in the lithium-ion battery and the supercapacitor before and after the optimization of fuzzy control were analyzed and compared. The results showed that the use of the fuzzy controller achieved maximum of 71% to 63% and minimum of 10% to 21% for the lithium-ion battery and maximum of 84% to 73% and minimum of 22% to 33% for the supercapacitor. By comparing these two schemes, it can be concluded that the optimized scheme was in the reasonable range. In future work, different fuzzy control rules for charging and discharging energy storage devices can be formulated to reduce the destructive effects of overcharging and overdischarging on the performance of energy storage devices.

Through the initial allocation based on charge and discharge response time division of energy storage and the secondary correction of fuzzy control based on hybrid energy storage SOC, reasonable allocation of hybrid energy storage power commands was realized, and the control stability and operation economy of the hybrid energy storage system were ensured.

3. Hybrid Energy Storage Capacity Allocation Based on Whole-Life Costs

Hybrid energy storage systems can make use of the advantages of lithium battery and supercapacitor energy storage to complement each other and better adapt to the complex fluctuations of wind power generation. The structure of the combined wind storage system is shown in Figure 12, in which lithium batteries and supercapacitors are connected to the grid-connected bus after power conversion through mutually independent converters. When using the energy storage system with wind power generation, wind power generation unit output access to the AC bus for smoothing control and then connected to the grid, suitable for large and medium-sized wind farms output power fluctuation smoothing control. Lithium batteries can handle the low-frequency part of wind power fluctuation and provide long-time power regulation; supercapacitors can handle the high-frequency fluctuation part and prolong the service life of lithium batteries. However, the cost of the supercapacitor is high, and its introduction may reduce the overall economy of the energy storage system. Therefore, to satisfy the wind balance demand while minimizing the system cost, the power and capacity of hybrid energy storage need to be configured appropriately. In this study, an event-oriented life quantification model was used to determine the relationship between the charge/discharge state and battery life under different power commands and compare the annual integrated cost of hybrid energy storage systems.

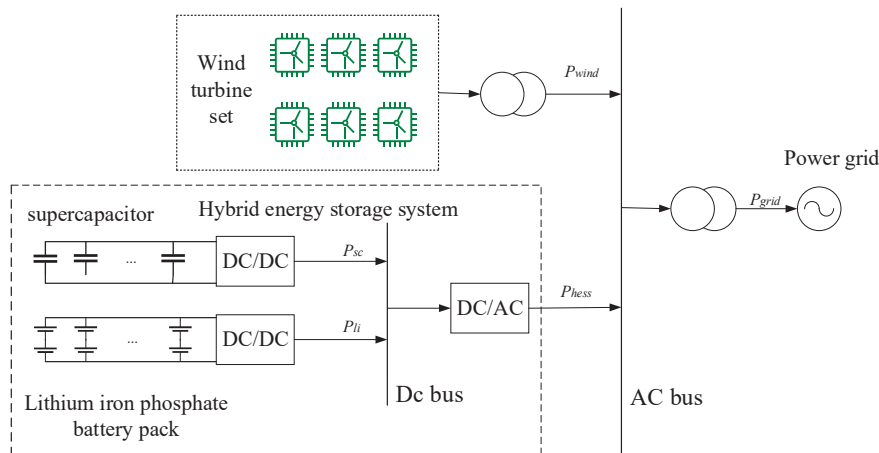


Figure 12. Wind storage combined system structure.

3.1. Energy Storage System Capacity Allocation Model

3.1.1. Lithium Battery Capacity Configuration Model

According to the previous analysis of energy storage selection, the type of storage battery selected was lithium iron phosphate battery, which has high energy density, long working time, and low cost and can effectively undertake the work of smoothing the main low-frequency components of wind power fluctuations [39]. The annual average cost C_B of lithium battery energy storage systems basically includes the value of initial investment cost C_{B1} and annual operation and maintenance cost C_{B2} . The initial investment cost is the initial investment, which is determined by the rated power and rated capacity. Initial investment cost C_{B1} is the initial investment, which is determined by the rated power P_B and rated capacity E_B . The power part reflects the value of the energy storage energy conversion system, while the capacity part refers to the value of the energy storage equipment itself. The initial investment cost C_{B1} can be expressed by the equal annual value method as follows:

$$C_{B1} = (aP_B + bE_B) \frac{r_0(1 + r_0)^{T_b}}{(1 + r_0)^{T_b} - 1} \quad (12)$$

where a , b , and T_b are the power cost factor, capacity cost factor, and operating life of the lithium battery, respectively, and r_0 is the discount rate.

The annual operation and maintenance cost C_{B2} is determined by the rated capacity E_B and rated power P_B :

$$C_{B2} = mP_B + nE_B \quad (13)$$

where m and n are the power and capacity operation and maintenance cost factors of lithium batteries. The optimization objective of the wind farm side energy storage system is to reasonably allocate the storage power and power level to minimize the annual comprehensive cost of the energy storage system under the premise of meeting the standard of fluctuation smoothing and power level so that the annual comprehensive cost of the energy storage system is minimized. The objective function for the optimal allocation of the capacity of a lithium battery storage system is to minimize the average annual integrated cost C_B :

$$\min f_B = C_B = C_{B1} + C_{B2} = (aP_B + bE_B) \frac{r_0(1 + r_0)^{T_b}}{(1 + r_0)^{T_b} - 1} + mP_B + nE_B \quad (14)$$

The following SOC constraints, charge/discharge responsiveness constraints, and energy conservation constraints were considered:

- (1) SOC constraint: the state of charge of Li-ion battery should be within the following limit:

$$SOC_{bmin} \leq SOC_b(t) \leq SOC_{bmax} \quad (15)$$

where the charging state for safe operation is between SOC_{bmax} and SOC_{bmin} .

- (2) Charge/discharge responsiveness constraint: lithium battery power corresponds to the charge/discharge power constraint as follows:

$$\max(-P_B, \frac{E_b(t) - E_B}{\Delta t \eta_{Bc}}) \leq P_b(t) \leq \min(P_B, \frac{E_b(t) - E_B}{\Delta t} \eta_{Bd}) \quad (16)$$

where $E_b(t)$ is the battery residual capacity at time t , η_{Bc} and η_{Bd} are the charging and discharging efficiencies of the lithium battery, and Δt is the sampling interval time.

- (3) Energy conservation constraints: wind power output is equal to the battery storage power command and the sum of grid-connected power; the battery from the outside world absorbs and releases the energy conservation as follows:

$$\begin{aligned} P_b(t) + P_o(t) &= P_w(t) \\ \sum_{t=1}^T P_b(t) &= 0 \end{aligned} \quad (17)$$

where $P_b(t)$ is the charging and discharging power of the lithium battery at time t .

3.1.2. Supercapacitor Energy Storage Capacity Allocation Model

The annual average integrated cost of supercapacitor C_{SC} mainly includes the annual value of the initial investment cost C_{SC1} and the annual operation and maintenance cost C_{SC2} . The objective is to minimize the annual average integrated cost C_{SC} . The model is based on the following:

$$\min f_{SC} = C_{SC} = C_{SC1} + C_{SC2} = (cP_{SC} + dE_{SC}) \frac{r_o(1+r_o)^{T_{SC}}}{(1+r_o)^{T_{SC}} - 1} + xP_{SC} + yE_{SC} \quad (18)$$

where P_{SC} and E_{SC} are the rated power and rated capacity of the supercapacitor MW, respectively; c , d , x , and y are the power cost coefficient, power O&M cost coefficient, capacity cost coefficient, and capacity O&M cost coefficient of the supercapacitor, respectively; and T_{SC} is the operating life of the supercapacitor.

The SOC, charge/discharge responsiveness, and energy conservation are constrained as follows:

$$\begin{aligned} SOC_{SCmin} &\leq SOC_{SC}(t) \leq SOC_{SCmax} \\ \max(-P_{SC}, \frac{E_{SC}(t) - E_{SC}}{\Delta t \eta_{SCc}}) &\leq P_{SC}(t) \leq \min(P_{SC}, \frac{E_{SC}(t) - E_{SC}}{\Delta t} \eta_{SCd}) \\ P_{SC}(t) + P_o(t) &= P_w(t) \\ \sum_{t=1}^T P_{SC}(t) &= 0 \end{aligned} \quad (19)$$

where $P_{SC}(t)$ is the charging and discharging power of the supercapacitor at time t ; $SOC_{SC}(t)$ is the charging state at time t ; the range of safe operation charging state is between SOC_{SCmax} and SOC_{SCmin} ; $E_{SC}(t)$ is the remaining power at time t ; η_{SCc} and η_{SCd} are the charging efficiency and discharging efficiency, respectively.

3.1.3. Hybrid Energy Storage Capacity Allocation Model

Although the energy storage power extracted from wind energy can be used as a control index for individual energy storage units, to achieve the goal of stable and reliable operation of the system, it is necessary to effectively divide and control the energy distribution of each energy storage system unit and to reasonably configure the energy storage components and power distribution.

If the threshold is too low, the “over-smoothing” component of the high-frequency power control of the supercapacitor will lead to prolonged discharge time and insufficient

storage capacity, which in turn will lead to an increased demand for storage capacity and higher system investment costs. If the threshold is too high, the number of components in the low-frequency power control of lithium-ion batteries will increase, which will accelerate the degradation of battery life and lead to higher system costs. By combining the power control distribution of the hybrid energy storage system with the overall cost of the energy storage system and comparing it with the economic cost of the energy storage system under different cutoff points, a reasonable power control distribution of the energy storage can be realized, the optimal power control cutoff point can be determined, and then the hybrid energy storage configuration system with the lowest economic cost can be determined, which can improve the performance and reliability of the hybrid energy storage system.

The objective function of the hybrid energy storage system capacity allocation model is as follows:

$$\min f = C_B^* + C_{SC}^* \quad (20)$$

where

$$\begin{aligned} C_B^* &= C_{B1} + C_{B2} + C_{B3} = \\ &(aP_B + bE_B) \frac{r_0(1+r_0)^{T_b}}{(1+r_0)^{T_b} - 1} + mP_B + nE_B + \\ &\sum_{i=1}^n (k_{pg}P_B + bE_B)(1+r_0)^{\frac{iT_b}{n+1}} \end{aligned} \quad (21)$$

$$C_{SC}^* = C_{SC} + C_{SC} = (cP_{SCt} + dE_{SCy}) \frac{r_0(1+r_0)^{T_{SC}}}{(1+r_0)^{T_{SC}} - 1} + xP_{SC} + yE_{SC} \quad (22)$$

where C_B^* and C_{SC}^* were the annual integrated cost of lithium battery storage and supercapacitor energy storage, respectively; C_{B3} and k_{pg} are the lithium battery renewal replacement cost and other annual values and power update cost coefficients, respectively; f is the annual integrated cost of the hybrid energy storage system; and n is the number of lithium battery renewal replacements.

The SOC constraints of charge/discharge response and energy conservation constraints are as follows:

$$\begin{aligned} \max(-P_{sc}, \frac{E_{sc}(t) - E_{sc}}{\Delta t \eta_{sc}}) &\leq P_{sc}(t) \leq \min(P_{sc}, \frac{E_{sc}(t) - E_{sc}}{\Delta t} \eta_{scd}) \\ \max(-P_B, \frac{E_b(t) - E_B}{\Delta t \eta_{BC}}) &\leq P_b(t) \leq \min(P_B, \frac{E_b(t) - E_B}{\Delta t} \eta_{Bd}) \end{aligned} \quad (23)$$

$$\begin{aligned} SOC_{scmin} &\leq SOC_{sc}(t) \leq SOC_{scmax} \\ SOC_{bmin} &\leq SOC_b(t) \leq SOC_{bmax} \end{aligned} \quad (24)$$

$$\begin{aligned} P_b(t) + P_{sc}(t) + P_o(t) &= P_w(t) \\ \sum_{t=1}^T P_h(t) &= 0 \end{aligned} \quad (25)$$

Considering the overall energy distribution and total cost, the economic cost of the hybrid energy storage system at each boundary point is usually analyzed, and the hybrid energy storage system with the highest economic cost is preferred. Based on the above study, the objective of this project was to analyze the economic performance of the hybrid energy storage system under different boundary point conditions and optimize its configuration to improve its overall performance and reliability.

3.2. Determination of the Optimal Critical Point

Taking a 60 MW wind farm as an example, the above single energy storage and hybrid energy storage capacity allocation models were applied to optimize the capacity of the energy storage system for smoothing wind power fluctuations. Considering the wind power curve of the wind farm on a certain day, the grid-connected1 and the storage power2 curves obtained from EEMD decomposition were selected, as shown in Figure 13. The relevant economic and technical parameters of the hybrid energy storage system are shown in Table 2 [20], where the lifetime of the supercapacitor energy storage is fixed at 20 years,

thus focusing on the impact of battery lifetime changes on the system configuration results.

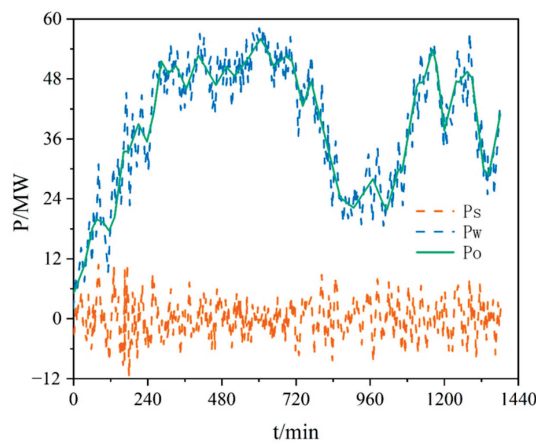


Figure 13. Typical daily power curve.

Table 2. Energy storage system coefficient. Reproduced with permission from [20].

Type of Energy Storage	Li-Ion Battery	Supercapacitor
Cost		
Cost per unit of power/RMB KW ⁻¹	9300	1800
Unit capacity cost/RMB KW ⁻¹	9300	12,400
Renewal cost per unit of power/RMB KW ⁻¹	2472	1860
Unit capacity renewal cost/RMB KW ⁻¹	9300	12,400
Auxiliary cost per unit of power/RMB KW ⁻¹	620	620
Ancillary cost per unit of capacity/RMB KW ⁻¹	0	0
O&M cost per unit of power/RMB KW ⁻¹	155	80.6
O&M cost per unit of capacity/RMB KW ⁻¹	0.014	0.0134
Cost of end-of-life disposal/RMB KW ⁻¹	465	93
Life cycle/times	4000	20 years
Charge and discharge efficiency	0.85	0.95
SOC upper and lower limits	[0.2, 0.8]	[0.1, 0.95]

In this study, the primary power distribution was adopted, and the power distribution scheme under different critical modes was calculated using the exhaustive method, which was substituted into the life cycle model of the hybrid energy storage system, as shown in Figure 14. The corresponding annual comprehensive cost was subsequently calculated.

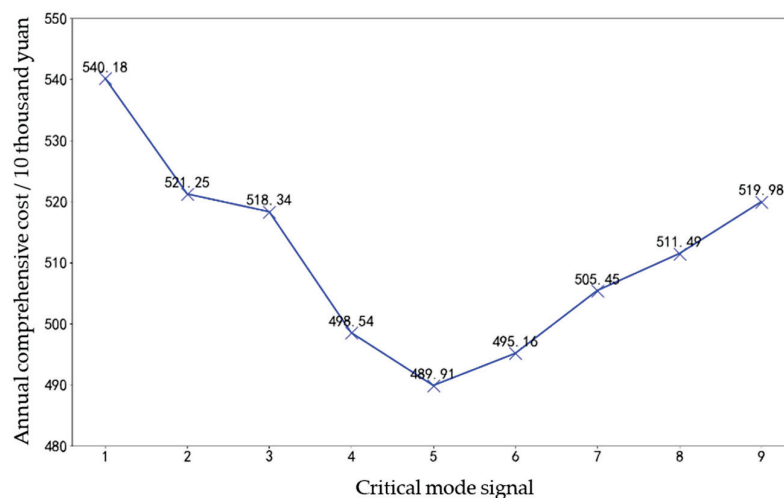


Figure 14. Threshold–annual integrated cost curve.

According to the results of Figure 14, when $m = 5$, that is, the battery storage power command was $P_b = u_1(t) + u_2(t) + u_3(t) + u_4(t)$, the system cost was minimized. Lithium batteries were responsible for the energy storage control of small fluctuations and large amplitude, while the supercapacitors were responsible for the energy storage control of large fluctuations and large amplitude, which matches the technical characteristics of the two types of storage devices, as shown in Figure 15.

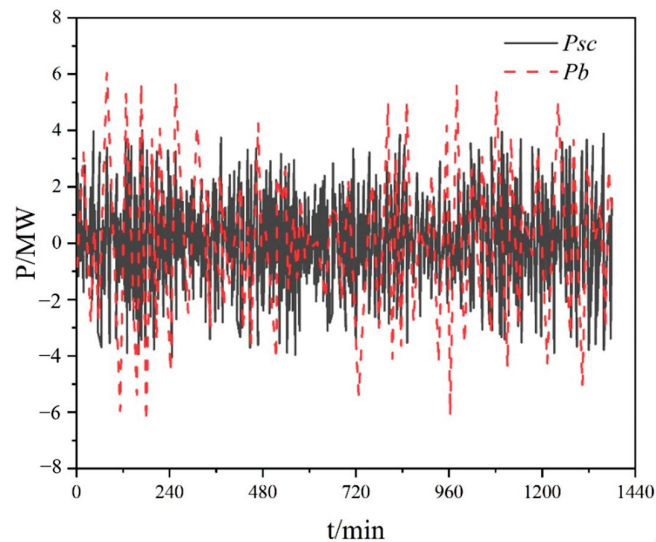


Figure 15. Lithium battery and supercapacitor power curve.

3.3. Quantitative Modeling Analysis of Battery Storage Lifetime

The energy storage cycle of a battery is not only related to the performance of the battery but also to the economic performance of the battery, and the traditional fixed-life model does not consider its variable-life characteristics. This approach does not consider the effects of the scale of the battery energy storage configuration and the charging and discharging states on its life cycle. The power command and rated capacity of the energy storage system will cause different levels of loss in the life cycle of the battery energy storage. The length of the battery storage life cycle determines the number of battery replacements, which will directly affect the comprehensive cost of HESS. In this study, we took lithium-ion batteries as an example and studied the impact of different lifetime models on the annual comprehensive cost of hybrid energy storage systems through the selection of the optimal critical mode. Table 3 lists the annual integrated cost of the hybrid energy storage system under fixed-life model and variable-life model. In the hybrid energy storage system, the annual integrated cost of the energy storage system is inversely related to the life cycle of the lithium-ion battery. As the life cycle increases, fewer batteries need to be replaced during the project period, which reduces the renewal cost. Therefore, the variable-life model for battery storage is more suitable for hybrid energy storage capacity configurations. Different typical days can lead to changes in the quantitative results of the life cycle of battery storage.

Table 3. Lifetime model configuration comparison results.

Life Cycle Model	Fixed-Life Model/a				Variable-Life Model/a
	2	4	6	8	4.1787
$E_B/MW.h$	11.9834	15.8958	18.9863	20.1432	16.6958
P_B/MW	9.1264	9.2579	9.4861	9.4905	9.3423
Cost/million	9.8105	7.3898	6.0318	4.9714	7.4278

3.4. Comparison of Different Energy Storage Schemes

In order to solve the capacity configuration problem of HESS, this study used an event-oriented life model and a rain flow counting method to calculate the cycle times under different discharge depths and analyzed the SOC curve of lithium batteries to calculate the life cycle of battery energy storage. The optimal value of energy storage power command demarcation point was taken as an example to compare the economy of a single-battery and a hybrid energy storage scheme to verify the correctness of the model established in this study, as shown in Table 4.

Table 4. Comparison of different energy storage solutions.

	Lithium Battery	Supercapacitor	Hybrid Energy Storage
$P_B/MW \cdot h$	9.3423	—	5.6876
$E_B/MW \cdot h$	16.6958	—	10.6524
$P_{SC}/MW \cdot h$	—	9.0234	3.8091
$E_{SC}/MW \cdot h$	—	6.541	0.1049
Life/year	4.1787	—	3.9373
Cost/million	7.4278	9.9427	4.8991

A comparison of the combined annual costs of the systems showed that the configuration of a single supercapacitor to undertake the leveling work was the least economical, which was mainly due to the higher capacity cost factor of the supercapacitor. The configuration size of the single-battery energy storage system was much larger than that of the supercapacitor energy storage system, but because of its lower investment cost, the total annual integrated cost decreased by 25.29% relative to the single supercapacitor energy storage system. The hybrid energy storage system combines the complementary technical characteristics of batteries and supercapacitors, and by integrating the cost characteristics of the two to reasonably configure the storage scale, it can effectively reduce the total system cost based on meeting the leveling requirements. As can be seen from the Table 4, the annual comprehensive cost of the hybrid energy storage system decreased by 34.04% relative to the single-battery energy storage system. At the same time, although the battery life in the hybrid energy storage decreased by 5.78% relative to single-battery energy storage, considering the significant decrease in the size of the battery energy storage configuration in hybrid energy storage, especially given its power configuration decreased by 39.12% relative to single-battery energy storage, it can be seen that combining batteries and supercapacitors into a hybrid energy storage system and through a reasonable charging and discharging control strategy can give full play to the complementary advantages of the two and extend the life cycle of battery energy storage.

4. Research on Optimal Allocation of Wind Energy Storage Based on Improved Scenario Clustering Algorithm

In the previous section, a capacity optimization model considering the quantification of the battery life cycle was described for a hybrid energy storage system for smoothing wind power fluctuations, and a cost-optimal configuration of the hybrid energy storage was determined through the optimization solution. Regarding the input data of the energy storage capacity allocation model, i.e., the power command of the energy storage system, as shown in the previous section, a typical day's charging and discharging data of the energy storage system was used instead of the annual charging and discharging data for the capacity allocation model. This alternative can simplify the complexity of the model solution, but the contingency of the selection of a typical day's data will lead to a large deviation of the allocation results from the actual results considering the annual data. If the annual energy storage system charge/discharge data are directly brought into the capacity allocation model, there is the problem of excessive data volume and low computational efficiency. In this study, we considered applying it to the input data processing of the hybrid energy storage capacity optimization allocation model, but the

traditional k-means clustering algorithm has the problems of difficulty in automatically determining the number of clusters and the randomness of the initial clustering center, which will affect the stability and accuracy of the allocation results.

In response to the above problems, in this study, the fuzzy c-means clustering algorithm was applied to hybrid energy storage data processing, which can extract a typical dataset based on the general characteristics of large-scale data; retaining the changing characteristics of the original data also reduces the data volume. To solve the stochastic problem that the existing fuzzy c-means clustering algorithm cannot automatically determine the number of clusters and cluster centers, the hybrid energy storage system constructed in a previous study was used as the object of study, and a new method of selecting the number of clusters and cluster centers to determine the optimal configuration scheme was developed by combining the cloud model and the fuzzy c-means clustering algorithm. Finally, a simulation example was used to verify the stability and accuracy of the configuration results determined according to the algorithm proposed in this section as well as enhancement of the computational accuracy and computational efficiency of the solution process.

4.1. Analysis of Typical Running Curve of Energy Storage Based on Improved Clustering

The set of annual energy storage daily charge and discharge power curves can be divided into two stages: (1) The set of energy storage daily operation curves was obtained according to EEMD decomposition and decomposed into a finite normal cloud model through peak cloud transformation to obtain the initial clustering center. The number of clusters was determined by the frequency limit. (2) According to the initial clustering center and the number of clusters, the fuzzy c-means clustering algorithm was used to aggregate the typical daily charge and discharge curves of 365 days of energy storage.

The flowchart of the improved fuzzy c-means clustering algorithm is shown in Figure 16.

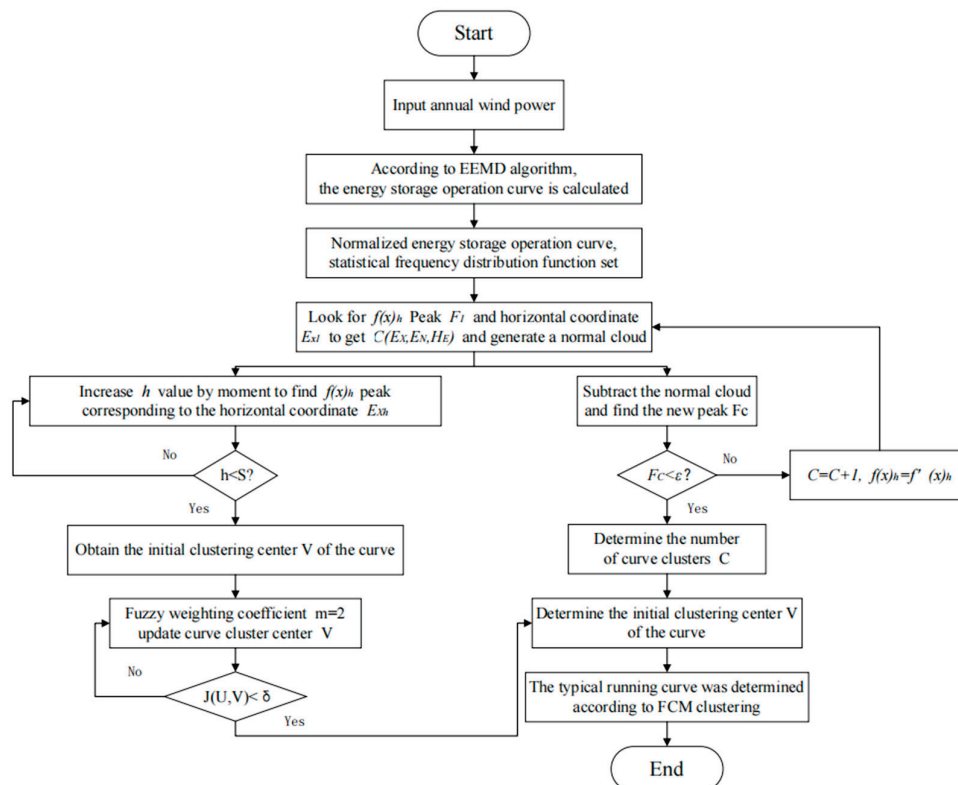


Figure 16. Flowchart of the improved fuzzy c-means algorithm.

In this study, the annual power output data of a 60 MW wind farm was taken as an example, and the annual energy storage operation curve of the energy storage system was

obtained after being flattened by the EEMD decomposition algorithm. The optimal energy storage system configuration scheme was determined by inputting the energy storage capacity optimization model. Figure 17 shows the annual output power of a wind farm, grid-connected power of wind power, and energy storage system power.

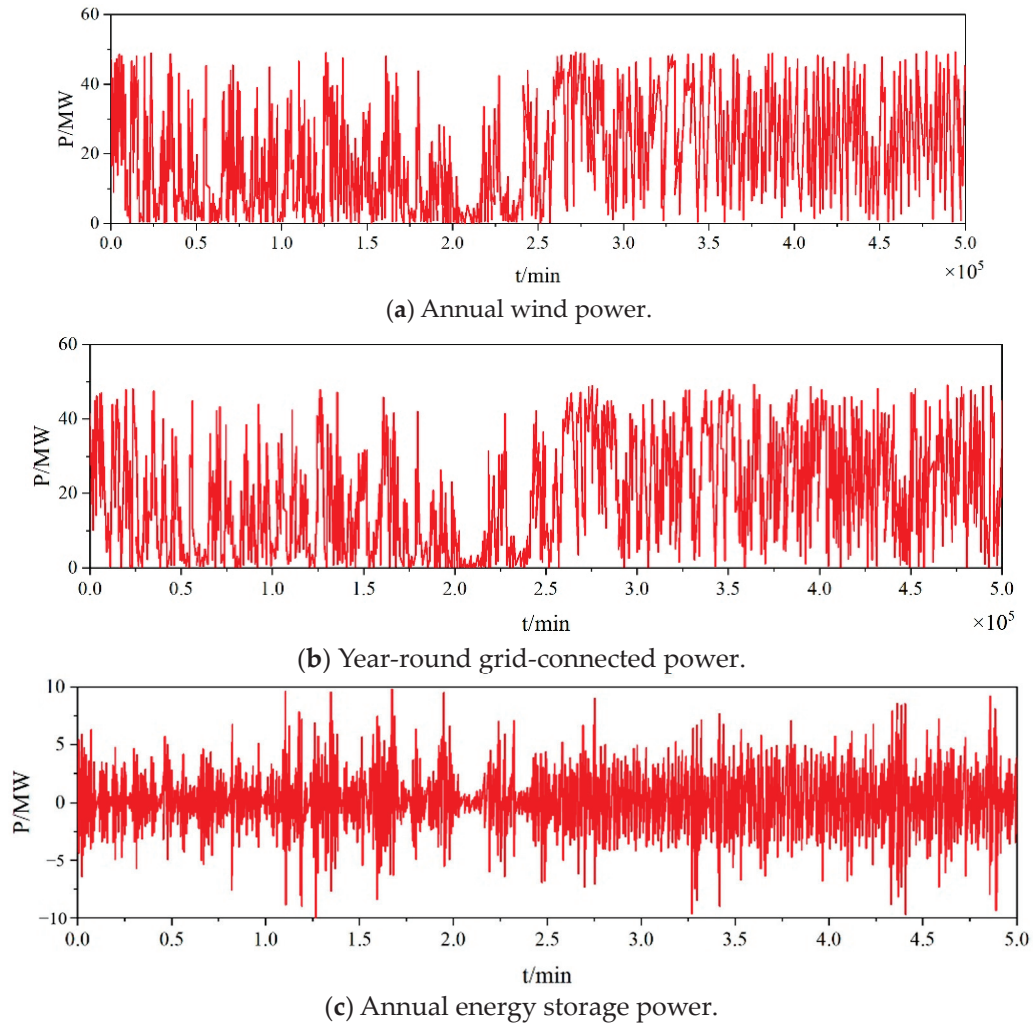


Figure 17. EMD flattening wind power output.

To verify the effectiveness of the analysis of the typical running curve set of energy storage, a single lithium battery energy storage capacity configuration model with a life cycle of 5 years was first selected, and the configuration results of the typical running curve set of energy storage were evaluated to ensure its computational efficiency, accuracy, and stability. Then, it was applied to the capacity optimization configuration of the hybrid energy storage system to further verify its effectiveness.

The battery energy storage system costs were minimized as follows:

$$\min f = C_{Bt} + C_{By} = (k_p P_B + k_e E_B) \frac{r_0(1+r_0)^{T_b}}{(1+r_0)^{T_b} - 1} + k_{py} P_B + k_{ey} E_B \quad (26)$$

where C_{Bt} is the initial investment cost; C_{By} is the annual operation and maintenance cost of the battery; k_p is the power cost coefficient of the battery; k_e is the capacity cost coefficient of the battery; P_B is the rated power of the battery in MW; E_B is the rated capacity, MWh, of the battery; r_0 is the discount rate in percentage; T_b is the operating life of the battery; k_{py} is the power operation and maintenance cost coefficient of the battery; and k_{ey} is the capacity operation and maintenance cost coefficient of the battery.

The constraints on SOC, charge–discharge responsiveness, and energy conservation are as follows:

$$\begin{aligned} SOC_{bmin} &\leq SOC_b(t) \leq SOC_{bmax} \\ \max(-P_B, \frac{E_b(t)-E_B}{\Delta t \eta_{Bc}}) &\leq P_b(t) \leq \min(P_B, \frac{E_b(t)-E_B}{\Delta t} \eta_{Bd}) \\ P_b(t) + P_o(t) &= P_w(t) \end{aligned} \quad (27)$$

where SOC_{bmin} and SOC_{bmax} are the upper and lower limits of the SOC charging state of the battery; $SOC_b(t)$ is the charging state of the battery at time t ; $E_b(t)$ is the remaining power of the battery at time t in MWh; η_{Bc} and η_{Bd} are the charging and discharging efficiencies of the battery, respectively; Δt is the collection frequency in min; $P_b(t)$ is the charging and discharging power of the battery at time t in MW; $P_o(t)$ is the grid-connected power of the wind power at time t after the leveling-off of the hybrid energy storage; and $P_w(t)$ is the original output power of wind power.

When configuring the capacity E_B of the battery energy storage system, the maximum capacity required to ensure the validity of the configuration results is selected:

$$E_B = \max(E_B(1), E_B(2), \dots, E_B(k)) \quad (28)$$

among them,

$$\begin{aligned} E_B(j) &= \max(E_{B1}(j), E_{B2}(j)) \\ E_{B1}(j) &= \max(|\sum_{j=1}^{m_1} P_j \Delta t|, |\sum_{j=m_1}^{m_2} P_j \Delta t|, \dots, |\sum_{j=m_{s-1}}^s P_j \Delta t|) \\ E_{B2}(j) &= \max(|\sum_{j=1}^k P_j \Delta t|), k = 1, 2, \dots, s \end{aligned} \quad (29)$$

where $E_B(j)$ is the capacity required for a single period of time for the j th typical scenario; P_j is the power required for a single period of time for the j th typical scenario; s is the total number of scenarios; and $E_{B1}(j)$ is the capacity required for a single period of time in the j th typical scenario. There are s periods in total, and p is power; $E_{B2}(j)$ indicates the capacity required for the first k period of the j th typical scenario.

4.2. Obtaining the Lithium Battery Energy Storage Configuration Solution

The annual operation curve of energy storage was analyzed by the improved fuzzy c-means algorithm based on the cloud model, and the initial cluster center V and cluster number $k = 8$ were obtained. C and V were input into the fuzzy c-means algorithm as control parameters. The energy storage operation curves of 365 days a year were clustered, and 8 typical daily operation curves were obtained. Table 5 lists the proportions of typical curves.

Table 5. Typical daily curve share.

Typical day	1	2	3	4	5	6	7	8
Proportion/%	38.11	18.19	13.1	4.09	2.6	7.12	1.31	15.36

The typical daily running curve was applied to the above lithium battery energy storage capacity configuration model, and the energy storage power and capacity configuration results were obtained in each typical scenario, as shown in Figures 18 and 19.

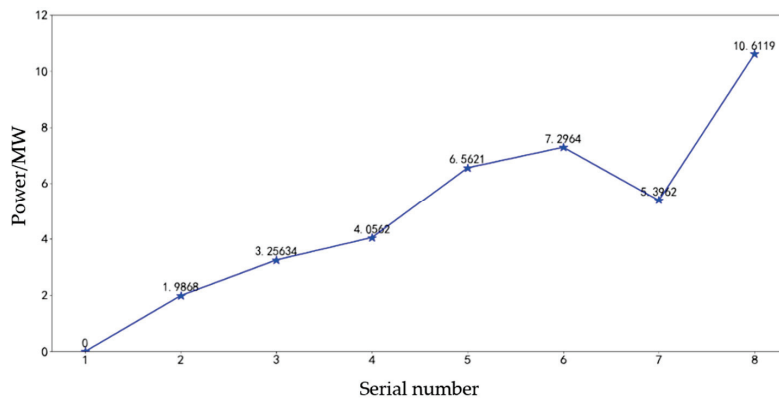


Figure 18. Power requirements for each typical scenario.

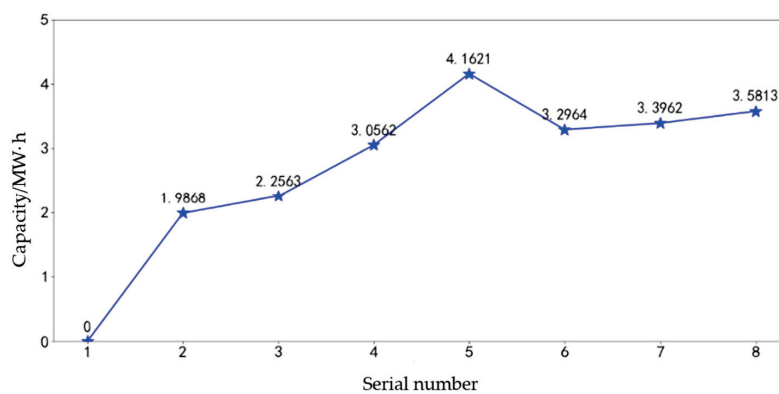


Figure 19. Required capacity for each typical scenario.

It can be seen from the above Figures 18 and 19 that the configuration results of different typical daily curves varied greatly. Therefore, the maximum energy storage capacity and power required should be selected to ensure the effectiveness of the configuration results. The capacity was 4.1621 MWh, the power was 10.6119 MW, and the cost was -RMB 3.7532 million.

4.3. Algorithm Validity Verification Analysis

To verify the effectiveness of the proposed method, the output curve of a wind farm was randomly selected to study, and its energy storage power instruction and energy storage SOC were analyzed. As shown in Figure 20, the grid connection curve showed that its calming effect was good and met the requirements of grid connection.

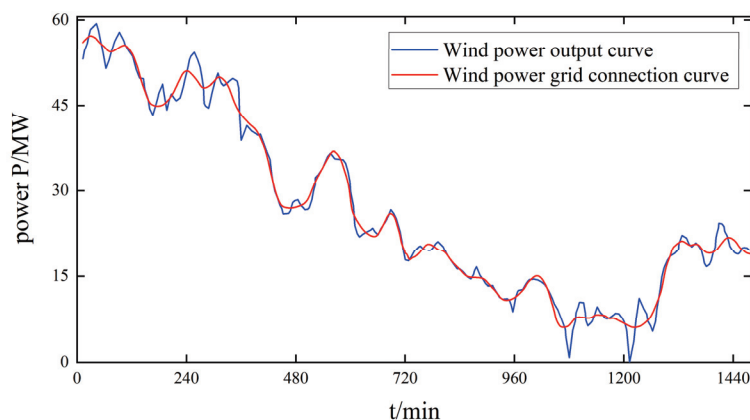


Figure 20. Typical scenario power output and grid connection power curve.

By observing the energy storage power response curve in Figure 21 and the energy storage SOC change curve in Figure 22, it can be seen that the energy storage SOC was always in normal operation. In order to compare the calculation accuracy and efficiency of the energy storage system configuration scheme obtained from different energy storage operation data, the following two data methods were selected as references:

- (1) Typical day method: data of two typical days were randomly selected and input into the lithium battery capacity optimization model.
- (2) Annual timing method: the annual energy storage operation data curve was input into the lithium battery capacity optimization model.

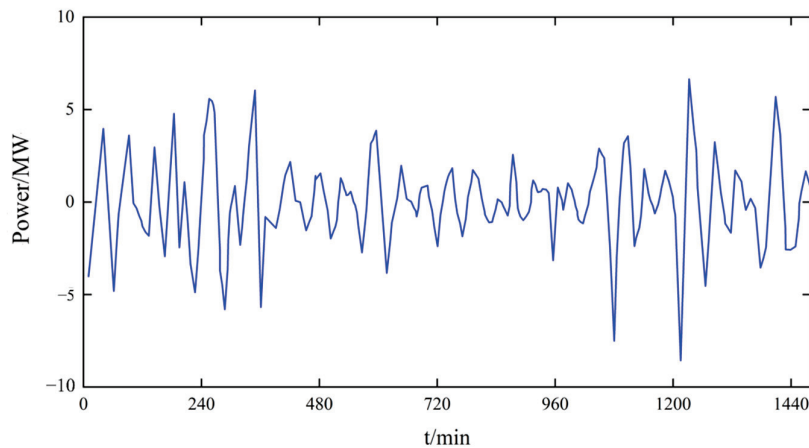


Figure 21. Energy storage power curve.

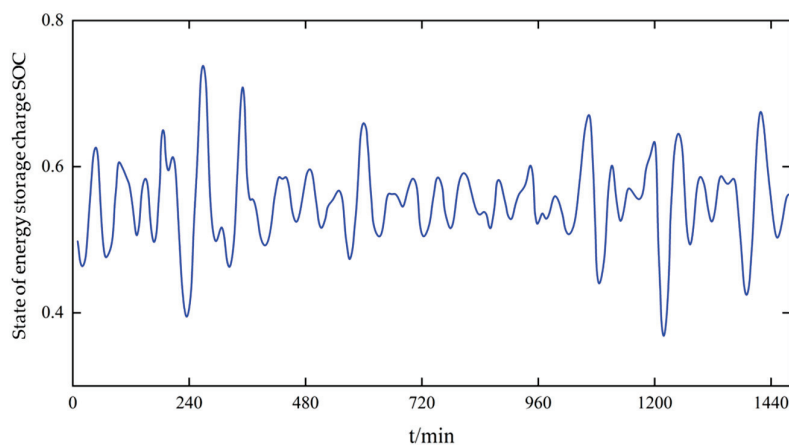


Figure 22. Energy storage SOC curve.

A comparison of the results of the battery energy storage scheme configuration for two randomly selected typical days and the improved clustering method in this paper is shown in Table 6 below.

Table 6. Comparison of different solutions.

	Annual Time Series Data	Typical Day 1	Typical Day 2	Improved Clustering Method
$E_B / \text{MW}\cdot\text{h}$	4.2678	6.2454	2.7351	4.1621
Capacity error / %	—	46.3	−35.9	−3.6
P_B / MW	10.8302	10.5989	3.6976	10.6119
Power error / %	—	−2.1	−65.9	−2.0
Cost / million	3.8463	4.289	1.7126	3.7532
Cost error / %	—	11.5	−55.5	−2.4
Calculation time / s	1405	12.415	12.501	14.27

It can be seen from Table 6 that compared to standard data, the energy storage configuration scheme calculated by the random typical daily data method had a large error because it was difficult to reflect the change characteristics of the annual operating curve with typical daily data. The capacity error, power error, and cost error of the proposed algorithm were all about 3%. The calculation time was also significantly reduced compared to the annual time series simulation, and the calculation efficiency was greatly improved.

4.4. Stability Analysis of Initial Cluster Center

In order to verify the superiority of the improved clustering algorithm, 10 classical fuzzy c-means clustering experiments were conducted, in which the initial clustering centers were randomly selected and the number of clusters was given as $k = 8$. The method of automatically determining the number of clusters and initial clustering centers using the cloud model can effectively avoid problems such as poor stability of results and easily falling into local optimal solutions. Table 7 describes the configuration structure.

Table 7. Comparison of the mean values of 10 experiments with the improved clustering method.

	Annual Time Series Data	The Mean of Ten Experiments	Improved Clustering Method
$E_B / \text{MW} \cdot \text{h}$	4.2678	4.5683	4.1621
Capacity error / %	—	7.0	−3.6
P_B / MW	10.8302	10.4682	10.6119
Power error / %	—	−3.3	−2.0
Cost / million	3.8463	3.7126	3.7532
Cost error / %	—	−3.5	−2.4
Single calculation time / s	1405	15.52	14.27

By comparing the mean experiment with the algorithm, it was found that a large number of experimental means could improve the configuration bias to a certain extent. However, compared to the improved clustering algorithm, there was no obvious advantage in the result accuracy. In addition, while the number of clusters was the same, the calculation time of the traditional fuzzy c-means algorithm was not much different from that of the proposed algorithm in a single experiment. However, when the experiment was repeated 10 times and the average was taken, the computational efficiency was significantly reduced.

4.5. Rationality Analysis of the Number of Automatic Clustering

In order to verify the rationality of the improved clustering algorithm to automatically determine the number of clusters, the mean results of the experimental processing of energy storage operation curve configuration by repeating the traditional fuzzy c-means algorithm under different cluster numbers were selected for comparison, and the comparison results are shown in Table 8.

Table 8. Comparison of the number of different clusters.

	Annual Timing	C = 3	C = 6	C = 9	C = 15	Improved Clustering Method
$E_B / \text{MW} \cdot \text{h}$	4.2678	3.7091	4.1235	4.4819	4.2053	4.1621
Capacity error / %	—	−13.3	−3.4	5.0	−1.5	−3.6
P_B / MW	10.8302	9.6205	10.5618	10.9635	11.0516	10.6119
Power error / %	—	−11.2	−2.5	1.2	2.1	−2.0
Cost / million	3.8463	3.3524	3.7356	3.9215	3.8109	3.7532
Cost error / %	—	−12.8	−2.9	2.0	1.2	−2.4
Single calculation time / s	1405	13.35	15.15	16.36	29.03	14.27

The configuration error caused by the traditional fuzzy c-means algorithm decreased gradually with the increase in the number of clusters, but the calculation time also increased

gradually. When the number of clusters was similar, the number of clusters of the traditional fuzzy c-means algorithm and the improved clustering algorithm were similar, the error was basically the same, and the single calculation time was similar. When the number of clusters was further increased to a large size, the error was only slightly reduced, but the single calculation time was greatly increased, and the calculation time of repeated experiments was very large. In summary, the improved clustering algorithm can improve the computational efficiency of the configuration process and ensure reasonable error of the configuration results.

4.6. Comparison of Hybrid Energy Storage Configuration Schemes

According to the above analysis and verification for a single lithium battery, the improved clustering algorithm based on the cloud model can improve the sensitivity of cluster center selection and the randomness of artificially determining the number of clusters in the traditional fuzzy c-means algorithm when dealing with the energy storage running curve, thus improving the stability and accuracy of capacity configuration. Next, we studied the hybrid energy storage capacity configuration.

Using the internal power instruction distribution method of the energy storage system, the typical operation curve set of energy storage obtained by the improved fuzzy c-means clustering method based on the cloud model was decomposed into lithium battery power instruction and supercapacitor power instruction, which were input into the hybrid energy storage capacity configuration model outlined in the previous section.

The objective function was to minimize the cost of the energy storage system:

$$\begin{aligned} \min f = C_B^* + C_{SC}^* = & (k_p P_B + k_e E_B) \frac{r_0(1+r_0)^{T_b}}{(1+r_0)^{T_b}-1} + \\ & k_{py} P_B + k_{eg} E_B + \sum_{i=1}^n (k_{pg} P_B + k_e E_B) (1+r_0)^{\frac{iT_b}{n+1}} + \\ & + (\lambda_p P_{sc} + \lambda_e E_{sc}) \frac{r_0(1+r_0)^{T_{sc}}}{(1+r_0)^{T_{sc}}-1} + \lambda_{py} P_{sc} + \lambda_{ey} E_{sc} \end{aligned} \quad (30)$$

where f is the annual comprehensive cost of the hybrid energy storage system; C_B^* is the annual comprehensive cost of battery energy storage; C_{SC}^* is the annual comprehensive cost of supercapacitor energy storage; n is the number of times of battery renewal and replacement; T_{sc}/T_b is determined by the service life of the battery, T_b , and the set life of the supercapacitor, T_{sc} ; k_{pg} is the cost coefficient of the power renewal of the battery; T_{sc} is the operating life of the supercapacitor; P_{sc} is the rated power of the supercapacitor in MW; E_{sc} is the rated capacity of the supercapacitor in MW; λ_p , λ_e , λ_{py} , and λ_{ey} are the power cost coefficient, capacity cost coefficient, power operation and maintenance cost coefficient, and capacity operation and maintenance cost coefficient of the supercapacitor, respectively.

The decomposed power instruction set was substituted into the capacity optimization model of the hybrid energy storage system, and the results of the randomly selected typical daily data method and improved clustering method were compared with the annual time series method.

According to the observation results in Table 9, it can be seen that the annual time series data method required a large amount of data and had low calculation efficiency. However, the random selection of typical daily data could not accurately reflect the changing characteristics of the annual running curve, resulting in a large error in the configuration scheme. In contrast, the data processing method proposed in this paper could not only greatly improve the computational efficiency but also control the capacity error, power error, and cost error within an acceptable range.

Table 9. Hybrid energy storage solution results.

	Annual Time Series Data	Typical Day 1	Typical Day 2	Improved Clustering Method
$E_B/MW \cdot h$	2.8419	4.0725	3.3015	3.0235
Capacity error/%	—	43.3	16.2	6.4
P_B/MW	7.2142	11.0651	5.3645	7.4384
Power error/%	—	53.4	−25.6	3.1
$E_{SC}/MW \cdot h$	0.2135	0.2446	0.2245	0.2045
Capacity error/%	—	14.5	5.2	−4.2
P_{SC}/MW	4.2546	3.7548	4.7862	4.0564
Power error/%	—	−11.7	12.5	−4.7
cost/million	3.1645	3.3546	4.9454	3.0453
cost error/%	—	6.0	56.3	−3.8
calculation time/s	2265	17.58	16.82	24.96

The experimental results showed that the proposed method could automatically determine the number of clusters and the initial cluster center, avoid the sensitivity problem of randomly given cluster number and the initial cluster center, and effectively improve the stability and accuracy of the configuration results.

5. Conclusions

The results of this study enrich the theoretical system and technical architecture in the research field of grid-connected wind farm side hybrid energy storage systems and provide new solution ideas and technical references for improving the quality of wind power grid connection, thus optimizing the effect of hybrid energy storage management, perfecting the capacity optimization model of hybrid energy storage systems, and improving the solving accuracy and efficiency of the energy storage optimization model. The main results of this paper are summarized as follows:

- (1) According to the different characteristics of energy storage technology, the charging and discharging response frequency characteristics and charging and discharging response capability of various energy storage units were analyzed and compared, and the lithium-ion battery supercapacitor was selected to develop a hybrid energy storage system that breaks through the limitations of single energy storage technology and, at the same time, has the advantages of both energy-type and power-type energy storage systems. The principle of wind power generation was explained, the output factors were analyzed, the quantitative mathematical model of output was examined, the time-frequency domain characteristics of wind power output was studied, and a foundation was laid for subsequent capacity allocation and economic evaluation under the wave smoothing scenario.
- (2) The EEMD algorithm was used for the smoothing decomposition of raw wind power data, which was a random perturbation added to EMD in order to solve the problems of model aliasing and slow convergence in EMD. Wind power grid-connected power and energy storage power data were extracted according to China's wind power grid-connected fluctuation standard combined with EEMD's decomposition and reconstruction of wind power. The simulation results showed that EEMD decomposition could adapt to the fluctuation power smoothing of different wind power output scenarios, and its smoothing effect was better than that of the low-pass filtering algorithm. For the allocation of power inside the hybrid energy storage system, this study adopted the method of primary allocation and secondary fuzzy correction based on response characteristics to obtain the storage power commands of Li-ion batteries and supercapacitors. The primary allocation was mainly considered to reduce the influence of the charging and discharging response frequency of Li-ion batteries' energy storage to its life cycle, and the secondary correction was based on the fuzzy control of the hybrid storage SOC, which realized reasonable allocation of the power commands of the hybrid energy storage, improved the safety of the storage system, and ensured improvement of the regulation characteristics and the

operation economy of the hybrid energy storage system. (3) The capacity allocation model of the energy storage system considering the life cycle cost was established, and the number of cycles corresponding to the charging and discharging depths was counted using the rainfall counting method to derive the life cycle of the battery energy storage. The capacity allocation model for lithium battery storage, the capacity allocation model for supercapacitor storage, and the capacity allocation model for hybrid storage were established. By comparing different power distribution dividing points of the hybrid energy storage system and their corresponding comprehensive costs, the optimal dividing point was selected. Finally, the optimal critical modes were determined by exhaustively enumerating the demarcation points of different high- and low-frequency bands. The different energy storage configuration schemes were also compared and analyzed. The simulation results showed that the proposed method had certain economic and technical advantages.

- (3) A combination of the cloud model and fuzzy c-means algorithm was applied to study the capacity allocation of wind energy storage systems. Feature extraction and scene division were used for the annual storage daily power curve, which was conducive in simplifying the calculation. The analysis of energy storage operation curve based on cloud model theory can reasonably determine the number of clusters and the initial clustering center of fuzzy c-means algorithm, which overcomes the shortcomings of traditional fuzzy c-means that needs to artificially give the number of clusters and the initial clustering center randomly, and the application of it in capacity optimization also enhances the stability and accuracy of the configuration results. After clustering analysis, eight classes of typical operating curves were obtained and input into the hybrid energy storage system capacity optimization model. Simulation analysis showed that the number of clusters and the initial cluster centers automatically determined by the cloud model could avoid the irrationality caused by randomly given cluster numbers and the defects of sensitivity of the initial cluster centers, thus effectively improving the stability and accuracy of the configuration results. This proves that the combination of the cloud model theory and fuzzy c-means can achieve better results when studying wind energy storage capacity configuration.

The research outlined in this paper focused on the control strategy of energy storage in smoothing the power fluctuation of wind farms on the grid and the allocation of energy storage capacity. However, due to the authors' limited knowledge and research time, there are still many deficiencies and areas for improvement as well as many issues and directions worthy of further research:

- (1) In this study, only direct grid connection to meet the wind power grid connection standard was considered. However, in actual operation, there are complex factors at play, such as the impact of power load changes on the grid-connected power of wind farms, the adjustment of peak and valley tariff differences on the grid-connected power of wind farms, and frequency-assisted control of the power system. In the next step of the study, the impact of these factors on grid-connected power will be considered, and the control strategy and energy storage capacity allocation method will be further optimized.
- (2) The study of leveling based on historical data of wind power generation lacks in-depth research on the issues of response delay and cannot control wind power leveling on-line in real time. The future research direction should be to realize wind power leveling through real-time control in order to improve the real-time nature of the control strategy during leveling.
- (3) In constructing the cost model of the hybrid energy storage system, the influence of other aspects of wind power systems, such as energy saving and emission reduction, were not taken into account. Therefore, in future research, the above influences can be introduced into the cost model of hybrid energy storage systems to construct a better cost model.

- (4) The function of hybrid energy storage systems on the wind farm side is not only limited to suppressing wind power fluctuations and also plays an important role in regulating the planned output of wind power, assisting the power system frequency control, supporting the stability of reactive power in wind farms, and enhancing the fault ride-through capability of wind turbines. Subsequent research can consider combining different control objectives for complex control, adjusting the active and reactive power outputs of the hybrid energy storage system according to the control needs of wind farms and power grids in different operating states, and improving the power supply adequacy and operational stability of connected large-scale wind power systems.
- (5) Based on the economic and technical characteristics of the current energy storage materials, this study selected batteries and supercapacitors to form a hybrid energy storage system. Considering that the research of advanced energy storage materials is a hotspot and there is a great possibility of key breakthroughs in the future, subsequent research needs to pay attention to the progress being made on the research of advanced energy storage materials. This includes tracking the development of energy storage materials, adjusting the hybrid storage combination mode in a timely manner, and improving the energy storage control strategy and the configuration model accordingly.

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Article

Economical Design of Drip Irrigation Control System Management Based on the Chaos Beetle Search Algorithm

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Abstract: In the realm of existing intelligent drip irrigation control systems, traditional PID control encounters challenges in delivering satisfactory control outcomes, primarily owing to issues related to non-linearity, time-varying behavior, and hysteresis. In order to solve the problem of the unstable operation of the drip irrigation system in an intelligent irrigation system, this paper proposes chaotic beetle swarm optimization (CBSO) based on the BAS (beetle antennae search) longicorn search algorithm, with inertial weights, variable learning factors, and logistic chaos initialization improving global search capabilities. This was accomplished by formulating the optimization objective, which involved integrating the control input's time integral term, the square term, and the absolute value of the error. Subsequently, PID parameter tuning was performed. In order to verify the actual effect of the CBSO algorithm on the PID drip irrigation control system, MATLAB was used to simulate and compare PID control optimized by the GA algorithm, PSO algorithm, and BSO (beetle search optimization) algorithm. The results show that PID control based on CBSO optimization has a short response time, small overshoot, and no oscillation in the steady state process. The performance of the controller is improved, which provides a basis for PID parameter setting for a drip irrigation control system.

Keywords: drip irrigation; PID control; water-saving energy system; economical management

1. Introduction

In recent years, China has recognized the need to modernize its agricultural irrigation practices to improve efficiency and conserve water resources. Traditional irrigation methods, such as border irrigation and furrow irrigation, have been used widely in the country for centuries [1]. However, these methods often suffer from inefficiencies, leading to water wastage and inadequate water supply for different crop requirements [2]. To address these challenges, there has been a growing emphasis on the development and adoption of advanced irrigation technologies in China [3]. One such approach is the automation and intellectualization of agricultural irrigation systems. This involves the integration of sensors, data analysis, and control systems to optimize water usage and tailor irrigation schedules to the specific needs of the crops [2]. By deploying modern technologies, farmers can monitor soil moisture levels, weather conditions, and crop water requirements in real-time. This allows for precise and targeted irrigation, ensuring that crops receive the right amount of water at the right time. For example, drip irrigation systems, which deliver water directly to the plant's root zone, have gained popularity due to their efficiency and water-saving potential [4]. Furthermore, the use of automation and intelligent control systems enables farmers to remotely manage and control irrigation operations. This reduces the reliance on manual labor and ensures that irrigation activities are carried out consistently and accurately [5]. Additionally, these systems can be integrated with weather forecasting models

to adjust irrigation schedules based on predicted rainfall or evapotranspiration rates. The adoption of automated and intelligent irrigation practices in China offers several benefits. Firstly, it helps increase crop yields and improve the quality of agricultural products by providing optimal irrigation conditions. Secondly, it contributes to the conservation of freshwater resources by reducing water wastage and improving water use efficiency. Lastly, it can enhance the economic viability of farming operations by reducing labor costs and improving overall productivity [6].

In the field of agricultural water-saving irrigation, the PID (proportional-integral-derivative) controller has garnered significant attention and research due to its simplicity, reliability, and robustness. However, researchers have explored various modifications and enhancements to the traditional PID controller to overcome certain limitations [7]. The PSO algorithm is also a popular optimization technique; however, it is prone to becoming trapped in local optimal solutions during the search process. This limitation may affect the overall performance and efficiency of the irrigation control system [8]. To address some of these challenges, some researchers designed a water-saving drip irrigation control system in a greenhouse based on the fuzzy-PID algorithm [9]. This approach incorporates fuzzy logic into the PID control scheme to enhance its adaptability and performance. The system was verified using real-world objects, demonstrating its potential effectiveness in water-saving irrigation applications. However, it is important to note that traditional PID control methods may encounter difficulties when dealing with controlled objects that have significant time delays or high order dynamics. In such cases, optimizing and tuning PID parameters can be challenging, leading to issues such as large overshoot and harmonic oscillations in the system [10]. Researchers continue to explore advanced control techniques and algorithms to overcome these limitations. For instance, advanced model-based control strategies, such as model predictive control (MPC), have shown promise in addressing the challenges posed by complex and time-delayed systems. These approaches utilize mathematical models of the controlled object to predict its behavior and optimize control actions in real-time. While the PID controller remains widely used in agricultural water-saving irrigation due to its simplicity and reliability, researchers have explored various modifications and alternative control strategies to enhance its performance. The integration of fractional order control, optimization algorithms like PSO, and fuzzy logic can provide improvements in specific contexts [11]. However, for systems with significant time delays and high-order dynamics, alternative control strategies like model predictive control may be more suitable for achieving optimization and tuning of control parameters.

Swarm intelligence and metaheuristics represent essential paradigms in solving complex optimization problems. Swarm intelligence draws inspiration from the collective behavior of social animals to devise algorithms capable of solving intricate problems. It involves the collaboration of multiple agents or entities to achieve a common goal, mimicking the behavior of natural swarms [12]. Metaheuristic algorithms, within the realm of optimization techniques, are heuristic strategies designed to efficiently explore large solution spaces by balancing exploration and exploitation. They are iterative and stochastic, inspired by natural phenomena or human-made systems, and have demonstrated success in solving diverse optimization problems. Recent advancements in the field of metaheuristics have led to the development of novel algorithms such as the giant trevally optimizer (GTO) [13] and elephant clan optimization (ECO). The GTO algorithm, inspired by the hunting behavior of giant trevally fish, incorporates aggressive and prey-searching mechanisms to achieve global optimization. On the other hand, ECO draws inspiration from the social structure and coordination of elephant clans to optimize complex problems through hierarchical communication and cooperation among individuals [14]. These cutting-edge metaheuristic algorithms aim to overcome various challenges encountered in traditional optimization techniques by introducing innovative strategies inspired by natural processes. They exhibit promising potential in addressing complex optimization problems and have attracted significant attention in recent research endeavors.

The BAS (beetle antennae search) algorithm is an intelligent swarm optimization algorithm inspired by the feeding behavior of the longicorn beetle. It has found applications in various fields, including photovoltaic maximum power point tracking, low-illumination texture image enhancement, and 3D path planning for mobile robots. In photovoltaic maximum power point tracking, the BAS algorithm has been applied to optimize the operation of solar panels and extract the maximum power output under varying environmental conditions. By mimicking the foraging behavior of beetles, the algorithm aims to efficiently locate the global maximum power point, improving the overall energy conversion efficiency of photovoltaic systems [15]. In the domain of low-illumination texture image enhancement, the BAS algorithm has been utilized to enhance the details and visual quality of images captured in low-light conditions [16]. By leveraging the search capabilities of the beetle-inspired algorithm, it can effectively enhance the texture information and improve the overall visibility of images, making them more visually appealing and informative. By simulating the exploration behavior of beetles, the algorithm can efficiently navigate complex environments and find optimal paths, considering various constraints and objectives [17]. This enables mobile robots to autonomously plan their paths, avoiding obstacles and reaching their destinations in an efficient and reliable manner. This means that the algorithm may struggle to find the global optimal solution in complex optimization problems with multiple peaks or valleys [18]. Examples include incorporating local search mechanisms, adaptive strategies, and hybridizing with other optimization techniques to overcome the limitations associated with local optima [19]. While it has demonstrated effectiveness, challenges have faced related to search accuracy and local optima still exist, necessitating further research and development to enhance its performance and applicability in complex optimization problems.

To address the challenges mentioned earlier, the CBSO-PID (chaos beetle search optimization-PID) drip irrigation control system was proposed as a solution for water-saving irrigation [2]. This system integrates the chaos algorithm, BSO algorithm, and PID controller to achieve improved performance and efficiency. The CBSO-PID system takes advantage of the chaos algorithm to enhance the search capabilities of the BSO algorithm. By introducing chaotic behavior into the search process, the algorithm can explore the search space more effectively and overcome the limitations of local optima. This allows for better optimization of the PID controller parameters, which are essential for achieving stable and efficient drip irrigation control [20,21]. The tuning of the proportional, integral, and differential (PID) parameters of the controller is transformed into an optimized problem. By formulating the stability of the control system as an optimization objective, the system can search for the optimal combination of PID parameters [22]. This optimization process aims to improve the stability, accuracy, and responsiveness of the drip irrigation control system. Simulation studies were conducted to evaluate the performance of the CBSO-PID optimized PID drip irrigation controller. A comparison was made with other methods such as BAS-PID (Beetle Antennae Search-PID) and PSO-PID (particle swarm optimization-PID). The results demonstrate that the CBSO-PID method exhibits better robustness and practical value compared to these alternative approaches. The integration of the chaos algorithm, BSO algorithm, and PID controller in the CBSO-PID drip irrigation control system offers several advantages. By integrating the chaos algorithm, BSO algorithm, and PID controller, it offers improved robustness, stability, and practical value compared to alternative methods like BAS-PID and PSO-PID. This research contributes to the development of intelligent and optimized control systems for sustainable and efficient agricultural practices.

CBSO dynamically adjusts the PID parameters during optimization to enhance control system performance in response to changing system dynamics or environmental conditions. By integrating the PID controller with the CBSO algorithm, the goal is to optimize the PID parameters effectively, enhancing control system performance and robustness while overcoming the limitations of traditional manual tuning methods. In this paper, we delve into the domain of metaheuristic optimization by proposing the chaotic beetle swarm optimization (CBSO) algorithm, drawing on the principles of swarm intelligence, and incor-

porating novel techniques inspired by nature. The effectiveness of CBSO is evaluated in the context of optimizing PID parameters for intelligent drip irrigation control systems, aiming to enhance their performance in addressing non-linearity, time-varying behavior, and hysteresis. Additionally, we benchmark the CBSO approach against established metaheuristic algorithms, including PSO, and BSO, to assess its efficacy and provide insights into its comparative performance. In the subsequent sections, this manuscript unfolds as follows. Section 2 provides an in-depth review and elucidation of swarm intelligence, metaheuristic optimization, and the principles underlying the proposed CBSO-PID algorithm. Following this, Section 3 delineates the empirical evaluation, featuring comprehensive simulations and comparisons between CBSO-PID and other prominent metaheuristic algorithms such as PSO and BSO. Section 4 presents the results and discussions are expounded, delineating the efficacy and comparative performance of the CBSO approach in enhancing intelligent drip irrigation control systems. This structured organization aims to provide a comprehensive insight into the efficacy and applicability of the CBSO algorithm in optimizing PID parameters for intelligent drip irrigation control systems.

2. Description of CBSO-PID

2.1. PID Control

In the field of drip irrigation control systems, the PID controller is commonly utilized. The PID controller combines the control deviation, represented as $e(t) = r(t) - y(t)$, where $r(t)$ is the desired input value and $y(t)$ is the actual output value. This control deviation is linearly combined using proportional, integral, and differential terms to generate the control signal that regulates the drip irrigation process. The proportional coefficient (K_p), integral time constant (K_i), and differential time constant (K_d) are crucial parameters in determining the controller's performance. To optimize the performance of the drip irrigation system, it is important to select the best values for these PID parameters [23]. In this paper, the authors propose using a combination of the chaos algorithm and the BAS algorithm to optimize the three parameters of the PID controller. The chaos algorithm introduces chaotic behavior into the optimization process, which helps in exploring the search space more effectively. Chaos-based optimization algorithms have shown promise in handling complex and nonlinear optimization problems, as they can escape local optima and search for global optima. The BAS algorithm, inspired by the feeding behavior of the longicorn beetle, is an intelligent swarm optimization algorithm. It leverages the collective intelligence of a population of individuals to search for optimal solutions. By integrating the BAS algorithm with the chaos algorithm, the authors aim to enhance the search capabilities and overcome the limitations of local optima during the optimization process [24].

Through the combined chaos–BAS optimization approach, the authors intend to find the optimal values for K_p , K_i , and K_d of the PID controller. By optimizing these parameters, the performance of the drip irrigation system can be improved in terms of stability, accuracy, and responsiveness. The use of intelligent optimization algorithms like chaos–BAS in conjunction with the PID controller offers a promising approach to enhance the performance of drip irrigation control systems. By effectively tuning the PID parameters, the system can achieve better regulation of the irrigation process, leading to improved water efficiency and crop productivity.

2.2. BAS Algorithm

The BAS algorithm is an optimization technology designed to achieve multi-objective function based on the principle of longicorn foraging. It can realize automatic optimization without knowing the specific form of function and gradient information, and the optimization process is efficient [25].

- (1) Creating spatial coordinates of a single longicorn of the left and right whiskers

$$\begin{cases} x_{ir} = x^t + d^{it} \cdot b \\ x_{il} = x^t - d^{it} \cdot b \end{cases} \quad (1)$$

where, x_{ir} represents the spatial position of the right whisker of the i -th longicorn after the t -th iteration, while x_{il} represents the spatial position of the left whisker of the i -th longicorn after the t -th iteration. d^{it} represents the distance between the left and right whisker of the beetle, and x^t represents the centroid coordinates of the location of the longicorn.

(2) Determining the smell intensity of a single longicorn of the left and right whiskers

According to the fitness function, the odor intensity of the left and right whisker can be determined, so as to update the location of the left and right whisker iteratively.

$$\begin{cases} x^{it+1} = x^{it} - \delta^{it} * b * \text{sing}[f(x_{ir}) - f(x_{il})] \\ \text{fitness} = \frac{1}{N} \sum_{j=1}^N (t_{\text{sim}(j)} - y_j)^2 \end{cases} \quad (2)$$

In the formula, δ^{it} represents the step size factor corresponding to the i -th longicorn at the t -th iteration; $\text{sing}()$ is a sign function, in the fitness function; $t_{\text{sim}(j)}$ represents the output value of the j -th sample; and y_j represents the actual value of the j -th sample.

(3) Determining the step size factor

The step size factor was used to control the search range of the longicorn whiskers. In order to avoid too small a search area, a large initial step size can be set. At the same time, in order to ensure the fineness of the search, a step size of a linear decreasing weight was adopted in this paper [22].

$$\delta^t = \eta * \delta^{t-1} \quad (3)$$

η is the attenuation coefficient of the step size, and a number close to 1 between [0, 1] is taken. However, up to now, the setting of the step size factor has not formed complete theoretical system guidance. In this paper, through several experiments, 0.95 was selected after repeated tests. At the same time, the initial step size $\delta = 3$ was determined, and the number of iterations was set as $n = 100$. In the drip irrigation system, in order to make the algorithm continue to be applicable in the high-dimensional parameter space and avoid the output of wrong control parameters due to the randomness of the initial value of a single longicorn, the BAS can be established by using the notion of particle swarm optimization. The location of each longicorn in the group is initialized, where the initial location of each longicorn should take the random number between $[-0.5, 0.5]$ and saved it in the *bestA* set. At the same time, according to the fitness function, the global optimal fitness values of all longicorns at this time are recorded in the *bestfitnessA* set. After that, according to Formula (2), the locations of each longicorn are updated iteratively. Then, the corresponding fitness function values are obtained according to the positions of the left and right whiskers iterated the Formula (3), and the *bestA* set and *bestfitnessA* set are updated in time. Finally, the best initial location *bestB* and the optimal fitness value *bestfitnessB* of the whole longicorn group are obtained by the comparing values in the two sets.

The Chaos Beetle Search Algorithm, being a novel method in the realm of control systems, presents both advantages and disadvantages, which are crucial to understand for a comprehensive evaluation.

Advantages: The Chaos Beetle Search Algorithm demonstrates strong global optimization capabilities. It can efficiently explore the search space, aiding in finding optimal or near-optimal solutions for complex problems. This algorithm exhibits robustness against local optima, allowing it to avoid becoming stuck in suboptimal solutions and promoting better convergence to the global optimum. Its ability to adapt and respond to dynamic environments or changing conditions is advantageous, making it suitable for systems with varying parameters or uncertainties. The Chaos Beetle Search Algorithm can be applied to problems of different complexities and dimensions, showcasing scalability across various control system scenarios.

Disadvantages: The performance of the Chaos Beetle Search Algorithm might be sensitive to its parameters, requiring careful tuning for optimal results. Inappropriate

parameter settings can affect convergence and search efficiency. In certain cases, the algorithm may demand higher computational resources, especially with larger problem sizes, which could impact its efficiency and practical application in real-time systems. While proficient in global exploration, the algorithm might not always guarantee the absolute global optimum due to the stochastic nature of its search process. Implementing the Chaos Beetle Search Algorithm might pose challenges in its understanding and practical application due to its complex mathematical and computational nature. Understanding these advantages and disadvantages is crucial for the proper utilization and assessment of the Chaos Beetle Search Algorithm's suitability for specific control system applications. Further research and analysis could help mitigate its limitations and enhance its strengths for practical deployment in various domains.

2.3. CBSO Algorithm

In order to prevent the BSO algorithm from falling into a local optimal solution, this paper introduces the chaos idea into the BSO algorithm and establishes the CBSO algorithm. Through the ergodicity of the chaotic motion and the optimal position of the whole longicorn group, a chaotic sequence is generated and is randomly assigned to every longicorn. At this point, the update formula of the longicorn position is:

$$V_i^{k+1} = \omega V_i^k + c_1 \times \text{rands}(1) \times (Pb_i^k - X_i^k) + c_2 \times \text{rands}(1) \times (Pg^k - X_i^k) + c_3 \times \text{rands}(1) \times \xi_i^k \quad (4)$$

where, V_i^{k+1} represents the speed of the i th longicorn in the group after the k th iteration, X_i^{k+1} represents the position of the i th longicorn in the group after the k th iteration, and Pb_i^k represents the historical optimal position of the i th longicorn in the group at the k th iteration. Pg^k is the optimal population position of the longicorn group [26].

c_1 , c_2 and c_3 are learning factors of the speed of updating, and ω is the inertia weight, which is updated by Formula (5); k is the iteration time; and M is the time-varying constant.

$$\begin{cases} c_i = c_i + \frac{2 \times k}{M} \\ \omega = \omega_0 - \frac{0.5 \times k}{M} \end{cases} \quad (5)$$

Logistic chaos initialization is used to improve the global search ability, whose formula is:

$$x_{n+1} = \mu x_n (1 - x_n) \quad (6)$$

In the optimization process described in the paper, the iterative search for the best control parameters of the drip irrigation control system using the chaos-BAS algorithm continues until certain termination conditions are met. There are two termination conditions specified in the paper:

1. Fitness function value: The fitness function evaluates the performance of the drip irrigation control system based on certain criteria, such as control deviation, stability, or water-saving efficiency. The optimization process continues until the fitness function value reaches a predefined set value, which is 0.001 in this paper. Reaching this set value indicates that the system has achieved a satisfactory level of performance [27].
2. Maximum iteration limit: To ensure that the optimization does not continue indefinitely, a maximum number of iterations is set. In this paper, the maximum iteration limit is defined as 100. Once the maximum number of iterations is reached, the optimization process is terminated, regardless of the fitness function value achieved [28].

When either of these termination conditions is met, the PID drip irrigation control parameters at that point are considered the best solutions obtained through the training process. These control parameters represent the optimal values of K_p , K_i , and K_d that yield the desired performance of the drip irrigation control system. By iteratively refining the control parameters using the chaos-BAS algorithm, the optimization process aims to converge towards the best possible solution, where the system achieves the desired performance criteria. The termination conditions ensure that the optimization process

stops when either the performance reaches a satisfactory level (fitness function value) or when the search process has reached its maximum limit (iteration count). Overall, the chaos-BAS algorithm continually repeats the optimization process until the termination conditions are met, allowing for the identification of the best control parameters for the drip irrigation control system. This iterative approach enables the system to adapt and improve its performance over time, leading to enhanced water-saving irrigation and better control of the irrigation process.

When integrating the PID (proportional-integral-derivative) control with the Chaos Beetle Search Algorithm (CBSO), several challenges or difficulties may arise, impacting the combined system's performance. The PID controller relies on tuning parameters (such as proportional gain, integral time, and derivative time) to achieve optimal control. Integrating it with the CBSO introduces additional parameters or settings, leading to increased complexity in parameter tuning. Balancing the settings for both algorithms simultaneously to ensure synergy without conflicts can be challenging. Combining the PID control and CBSO involves interaction between two different algorithms. Coordinating their actions to achieve effective control without causing instability, overshoot, or oscillations can be complex. Ensuring that the actions of one algorithm do not contradict or interfere with the other is crucial. Ensuring convergence and stability of the combined system is a critical challenge. The CBSO's global exploration tendencies and the PID controller's stability requirements need to be harmonized. Maintaining stability while achieving optimization goals is a delicate balance that may pose difficulties. The CBSO might demand significant computational resources due to its iterative search nature. Integrating this with the real-time requirements of PID control might lead to increased computational overhead, potentially impacting the system's responsiveness and efficiency. Combining the algorithms may affect the robustness and adaptability of the control system. Changes in the system dynamics or disturbances might challenge the adaptability of the combined system, requiring a careful balance between robustness and adaptability. Ensuring that the optimization objectives of the CBSO align with the control objectives of the PID controller can be challenging. Optimizing one aspect of the system might inadvertently affect the other, requiring trade-offs and compromises. Overcoming these difficulties involves careful integration, parameter tuning, and optimization to harness the strengths of both algorithms while mitigating potential conflicts or challenges in their combined operation. Robust testing, simulation, and analysis are crucial to understanding and addressing these difficulties for successful implementation in practical control systems. Here are the highlighted contributions of the paper:

1. **Proposing an Innovative Approach:** The paper introduces a novel method named Chaotic Beetle Swarm Optimization (CBSO) based on the BAS (beetle antennae search) longicorn search algorithm. This approach aims to address the challenges posed by non-linearity, time-varying behavior, and hysteresis in intelligent drip irrigation control systems.
2. **Enhanced Control Methodology:** By incorporating inertial weights, variable learning factors, and logistic chaos initialization, the CBSO algorithm is designed to improve global search capabilities, which is crucial for stabilizing the operation of drip irrigation systems.
3. **Optimization Goal and Parameter Tuning:** The paper focuses on using the integral term of the control input square and the absolute value of the error as the optimization goal for PID parameter tuning. This methodology aims to enhance the control performance of the drip irrigation system.
4. **Empirical Validation:** MATLAB simulations were conducted to evaluate and compare the performance of the proposed CBSO-optimized PID control against other optimization algorithms (GA, PSO, and BSO). The results demonstrated that the CBSO-based PID control exhibited advantages such as a shorter response time, minimal overshoot, and stable state behavior without oscillation. This validation provides practical

evidence of the effectiveness of the proposed algorithm in improving controller performance.

These contributions collectively establish the paper's significant contributions towards addressing the challenges in intelligent drip irrigation control systems by introducing a novel optimization approach and validating its effectiveness through simulations and comparisons.

3. Controller Optimization Based on the CBSO-PID

3.1. CBSO-PID Controller

According to the above algorithm principle, a drip irrigation control system based on the PID control optimized by the CBSO algorithm was designed, as shown in Figure 1. In the three-dimensional search space constructed by the three parameters K_p , K_i and K_d , the optimal parameters for the controller effect are found.

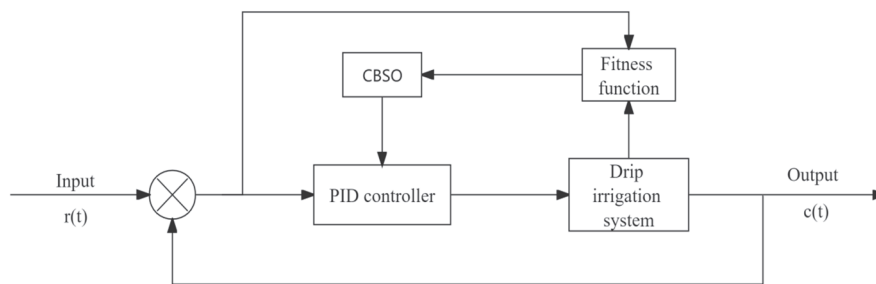


Figure 1. Schematic diagram of the CBSO-PID controller.

The essence of parameter optimization lies in solving the minimum problem of the optimization objective function. In order to meet the control requirements of the PID controller, the objective function selected the square integral of the time square and error product. At this point, the fitness function can be expressed as Equation (7), where t is the time and $e(t)$ represents the deviation between the actual output and the expected value.

$$F(\text{IBSTE}) = \int_0^{\infty} t|e(t)|dt \quad (7)$$

3.2. CBSO-PID Control Process

The parameter optimization of the PID controller is a multi-objective optimization problem, and the stability and rapidity of system control should be considered comprehensively [29], as shown in Figure 2. The concrete steps are as follows:

Step 1: Initialize the algorithicorn parameters, determine the group size i , the maximum number of iterations itermax , the basic parameters of each longicorn, and the value range of the controller number K_p , K_i , and K_d [30].

Step 2: Calculate the fitness of each position, by comparing the fitness values of longicorn individuals in each group K_p , K_i , and K_d , obtain individual optimal solution p_{best} in the current position, and finally obtain the current global optimal solution G_{best} by comparison [31].

Step 3: Update the position and speed of each longicorn in the group through Formulas (3) and (6).

Step 4: Compare the individual position of each longicorn with the historical position. If the current position is better, the individual optimal position is replaced. Then, compare the position of each longicorn individual with the historical position of the group, if the current position is better, it is replaced by the group optimal [32].

Step 5: Generate the chaotic sequence based on the optimal position of the whole longicorn group, and randomly assign positions in the chaos sequence to every longicorn.

Step 6: Judge whether the termination condition is met. If not, return to the step (3); if yes, end the iteration [33].

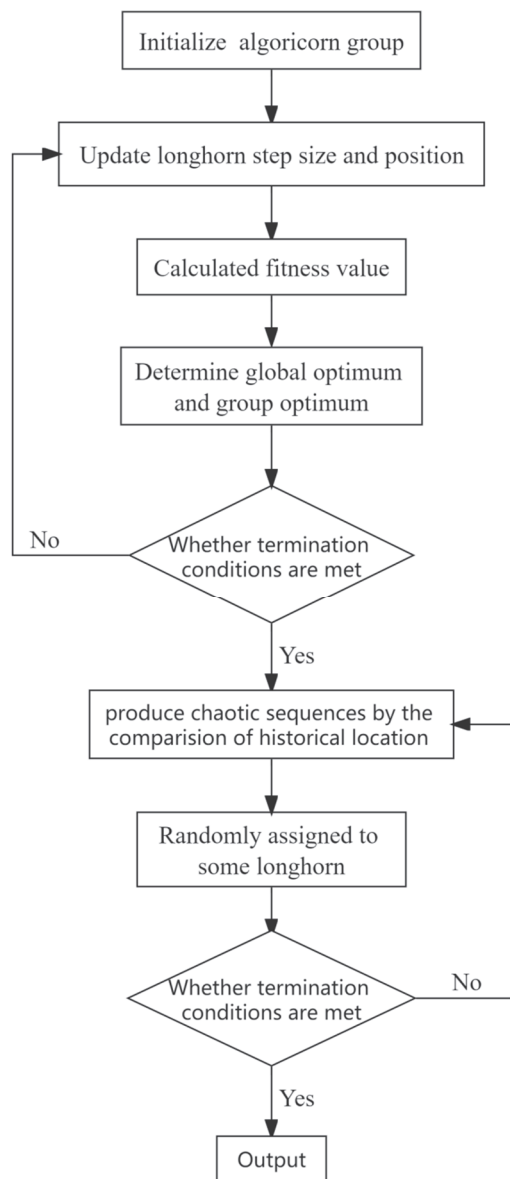


Figure 2. Flow chart of the chaotic beetle swarm optimization algorithm.

3.3. Simulation Process

In order to verify the effectiveness of the CBSO-PID controller, Simulink was used to conduct modeling and simulation of a greenhouse drip irrigation system, as shown in Figure 3.

The transfer function represents the mathematical relationship between the input and output of a dynamic system. It characterizes the system's behavior by describing how the system responds to inputs, enabling analysis and prediction of system dynamics. The transfer function is pivotal in control system analysis, providing insights into system stability, frequency response, and overall performance. Understanding the system's transfer function is vital for the effective optimization of the PID controller using the CBSO algorithm. It helps in selecting appropriate control parameters for optimal systems. In drip irrigation systems, the transfer function represents the relationship between input control signals (e.g., water flow rates) and output variables (e.g., soil moisture levels). Understanding this function is crucial for efficient water delivery and crop management.

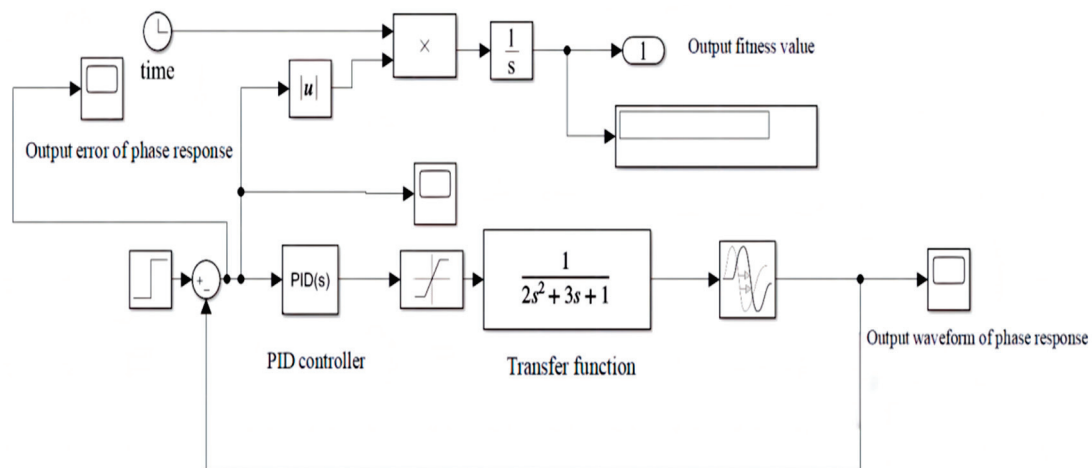


Figure 3. Simulink simulation model of the CBSO-PID drip irrigation system.

Given that the optimal soil moisture level falls within the range of 50% to 60%, we have established the desired soil moisture value at 55%, with an initial value of 0%. Soil moisture naturally decreases due to factors such as substrate infiltration and plant transpiration. Following the methodology outlined for the attenuation factor of soil moisture [26], we define the system's loss function using Formula (7). The nutrient delivery system of CBSO-PID and the drip irrigation system is shown in Figure 4. The drip irrigation system is a complexly controlled object, which is approximated by a second-order pure lag model:

$$G(s) = \frac{1}{2s^2 + 3s + 1} e^{-0.2s} \quad (8)$$



Figure 4. Nutrient delivery system of CBSO-PID and drip irrigation system.

3.4. Optimization Parameters

In the research conducted by Zhang Yinyan in 2019, it was proposed that the BAS (beetle antennae search) algorithm can achieve asymptotic convergence with a probability of 1 by adjusting the step size [13]. This finding suggests that by appropriately tuning the step size parameter, the optimization effectiveness of the CBSO (chaos beetle search optimization) algorithm can be improved. In the CBSO-PID algorithm, the optimization effect is indeed influenced by the parameter settings of δ and η in Equation (4). To further enhance the robustness of the CBSO-PID algorithm, the authors of this paper adjusted these

parameters. Specifically, they set η as an arithmetic series ranging from 0.55 to 0.99, and δ as an arithmetic series ranging from 2 to 8. By varying the values of η and δ within these ranges, the authors aimed to explore different combinations and determine the optimal parameter values for the CBSO-PID algorithm. In this paper, they conducted verification experiments to evaluate the performance of the algorithm for different parameter settings [34].

The results of these experiments indicate that the best performance is achieved when η is set to 0.95 and δ is set to 3. This combination of parameter values yields the most desirable optimization outcomes and robustness for the CBSO-PID algorithm in the context of the drip irrigation control system. By adjusting the parameters η and δ , the authors were able to finetune the behavior of the CBSO-PID algorithm and improve its effectiveness in finding optimal solutions. This approach contributes to enhancing the overall performance and robustness of the algorithm in optimizing the PID controller parameters for drip irrigation control. The research suggests that adjusting the step size parameters in the CBSO-PID algorithm, as inspired by findings for the BAS algorithm, can optimize the algorithm's performance. Through experiments and evaluations, the authors determined that setting η to 0.95 and δ to 3 yield the best results for the CBSO-PID algorithm in the context of the drip irrigation control system.

4. Simulation Results

The results show that CBSO-PID algorithm can eliminate the comprehensive influence factors under natural conditions and improve the parameter optimization of the drip irrigation control system through a large amount of data training. By adjusting the step length δ and attenuation coefficient η of single longicorns, the prediction accuracy of soil moisture content was correlated with that of soil moisture content. The steady-state performance and dynamic performance of the system can be greatly improved after this adjustment, which reflects the robustness of the algorithm. In the research mentioned, the optimization effect of the CBSO-PID algorithm was evaluated by comparing it with three other algorithms: PSO-PID (particle swarm optimization-PID), GA-PID (genetic algorithm-PID), and BSO-PID (beetle swarm optimization-PID). The performance of these algorithms was depicted in Figures 5–7, with each figure presenting the PID parameter optimization curves in a specific order.

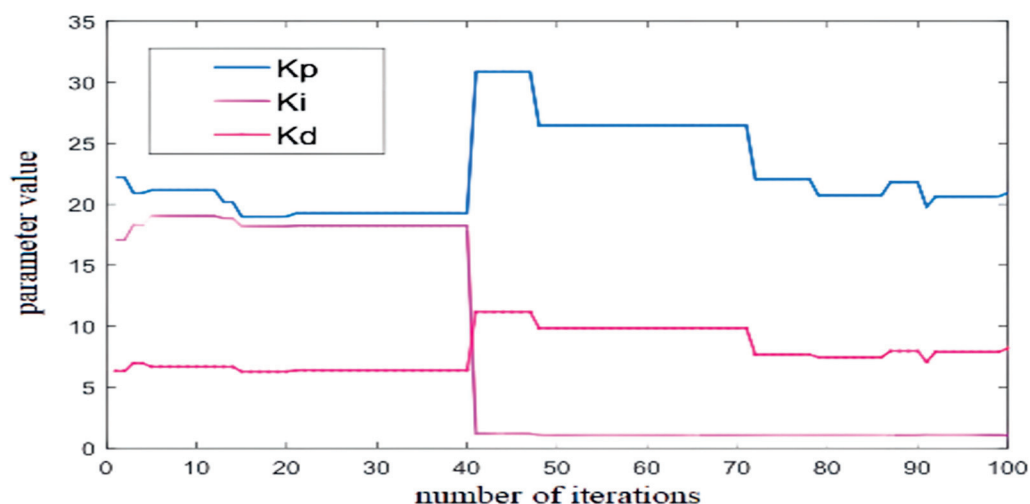


Figure 5. PSO-PID parameter optimization curve.

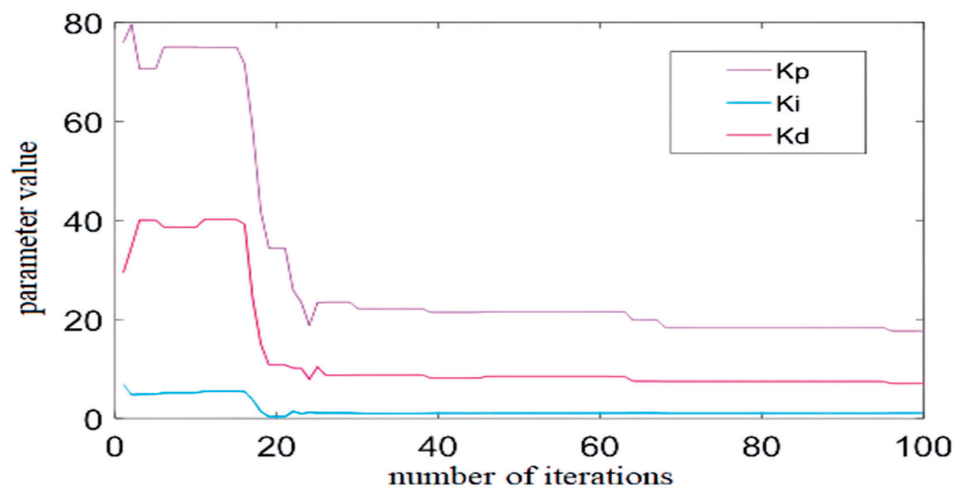


Figure 6. BSO-PID parameter optimization curve.

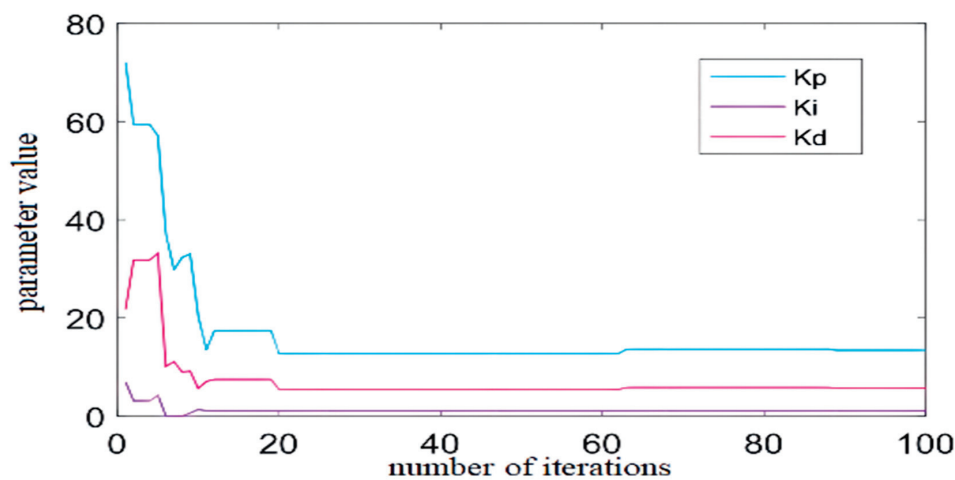


Figure 7. CBSO-PID parameter optimization curve.

4.1. Optimization Curve

Starting from the top and moving to the bottom of the figures, the curves represent the optimization progress of the respective algorithms. Here is a brief explanation of each algorithm's curve:

1. **PSO-PID Algorithm:** The topmost curve in Figure 4 represents the PID parameter optimization curve of the PSO-PID algorithm. This curve showcases the progress and convergence behavior of the PSO-PID algorithm in optimizing the PID controller parameters for the drip irrigation control system.
2. **GA-PID Algorithm:** The next curve in Figure 5 corresponds to the PID parameter optimization curve of the GA-PID algorithm. It illustrates the optimization process and convergence characteristics of the GA-PID algorithm in finding the optimal PID controller parameters.
3. **BSO-PID Algorithm:** The third curve in Figure 6 represents the PID parameter optimization curve of the BSO-PID algorithm. This curve demonstrates the optimization behavior and convergence performance of the BSO-PID algorithm in the context of the drip irrigation control system.
4. **CBSO-PID Algorithm:** Finally, the bottom curve in Figure 6 exhibits the PID parameter optimization curve of the CBSO-PID algorithm. This curve showcases the optimization progress and convergence properties of the CBSO-PID algorithm, which is the algorithm proposed in this research.

By comparing these curves, the researchers were able to analyze and evaluate the performance of each algorithm in terms of convergence speed, stability, and optimization effectiveness. The purpose of this comparison is to demonstrate the superiority of the CBSO-PID algorithm over the other algorithms in optimizing the PID controller parameters for the drip irrigation control system. The figures presented in the research show the PID parameter optimization curves for the PSO-PID, GA-PID, BSO-PID, and CBSO-PID algorithms. These curves provide a visual representation of the optimization progress and convergence behavior of each algorithm, facilitating a comparative analysis of their performance.

4.2. Control Performance and System Response

Based on the information provided, Figures 5–7 demonstrate that among the four algorithms (CBSO-PID, PSO-PID, GA-PID, and BSO-PID), the CBSO-PID algorithm has the most efficient performance in terms of PID parameter optimization. It achieves the best effect in significantly fewer iterations, specifically within 20 iterations.

On the other hand, the GA-PID algorithm performs poorly compared to the other algorithms, including PSO-PID and BSO-PID. This suggests that the genetic algorithm (GA) is less effective in optimizing the PID controller parameters for the drip irrigation control system in this particular study. The PSO-PID algorithm also exhibits suboptimal performance, although it is relatively better than the GA-PID algorithm. It implies that the particle swarm optimization (PSO) algorithm has limitations in achieving satisfactory results within the given optimization constraints. The comparison presented in Figures 4–6 highlights the superior performance of the CBSO-PID algorithm in terms of efficiency and effectiveness. It converges quickly within a small number of iterations, leading to optimal PID parameter values for the drip irrigation control system. Conversely, the GA-PID algorithm performs poorly, and the PSO-PID algorithm shows relatively better but still suboptimal results compared to the CBSO-PID algorithm.

To further verify the optimization effect of CBSO-PID, the control curve of the fitness function, the output curve of the system step response, and the output error curve of the system step response of the above four algorithms were plotted, respectively, as shown in Figures 8–10.

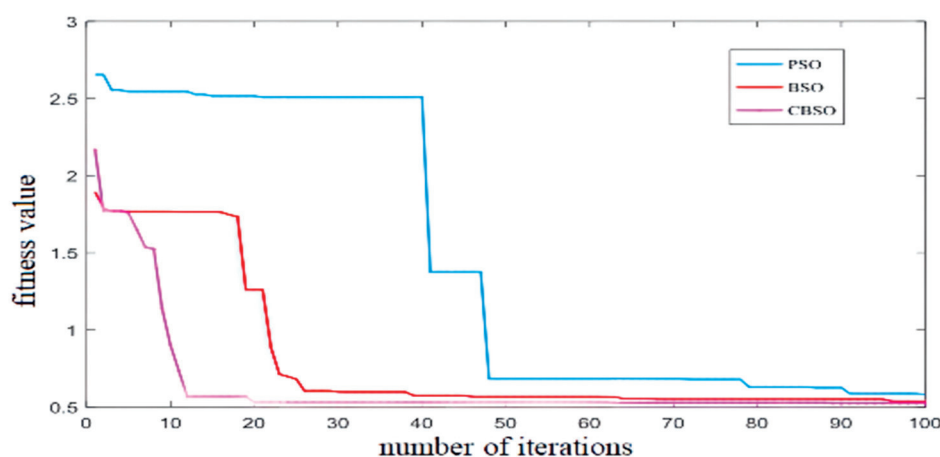


Figure 8. Different algorithms optimize the control curve of the fitness function.

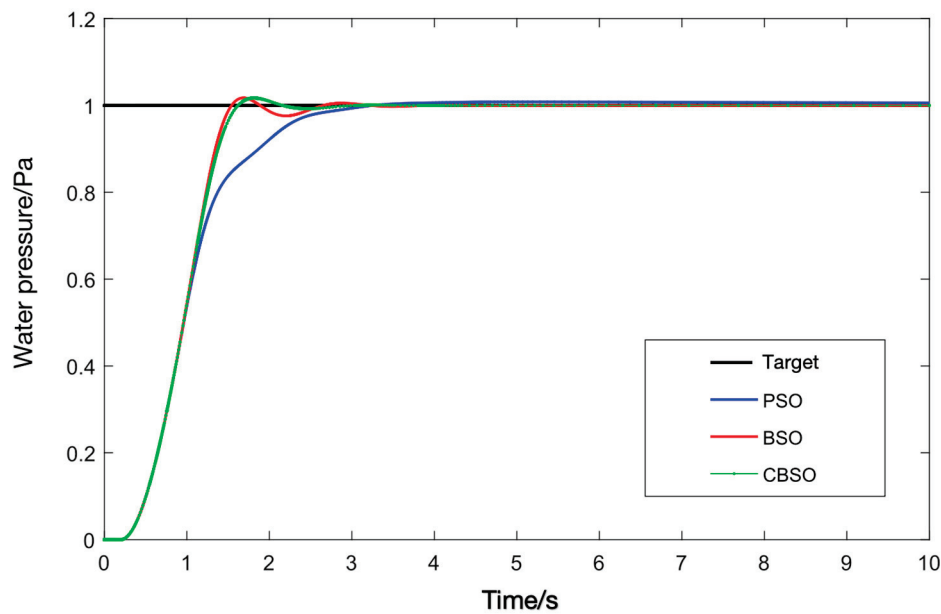


Figure 9. Output curve of system step response controlled by the different algorithms.

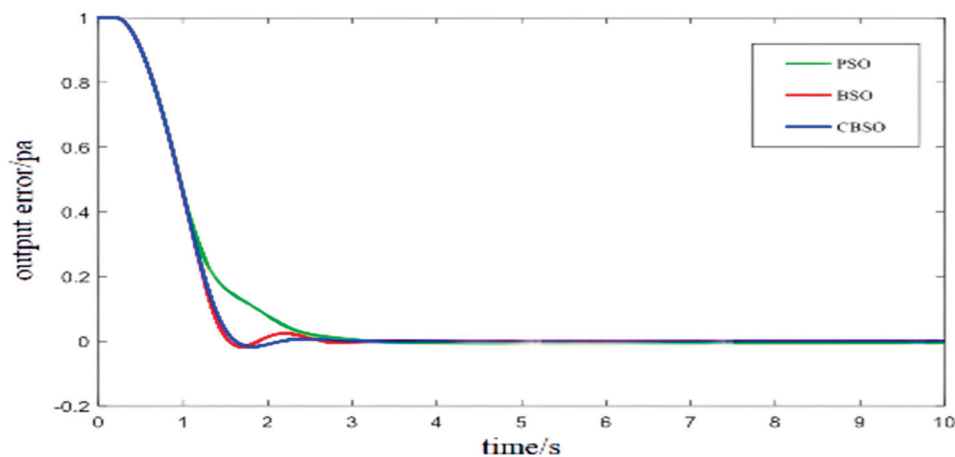


Figure 10. Step response output error curve of the different algorithms.

Based on the information provided, Figure 8 illustrates the performance of the four optimization algorithms (CBSO, BSO, PSO, and GA) in finding the optimal fitness value of the fitness function. The results indicate the following observations:

1. CBSO Algorithm: The CBSO algorithm is the fastest among the four algorithms in finding the optimal fitness value. It achieves this within only 18 iterations, indicating its efficiency in converging towards the optimal solution.
2. BSO Algorithm: The BSO algorithm is the second fastest, taking 26 iterations to find the optimal fitness value. Although slightly slower than the CBSO algorithm, it still demonstrates a relatively efficient performance.
3. PSO Algorithm: The PSO algorithm requires 47 iterations to find the optimal fitness value. It is slower compared to the CBSO and BSO algorithms but still manages to converge towards the optimal solution.
4. GA Algorithm: The GA algorithm does not find the optimal fitness value within a finite number of iterations. It falls into a local optimum and is unable to achieve the desired optimal solution. This indicates that the GA algorithm performs poorly in this particular optimization task.

In terms of stability, the CBSO and BSO algorithms are described as more stable in determining the optimal value of the fitness function. This implies that they consistently

converge towards the optimal solution across different runs or iterations [35]. On the other hand, the GA and PSO algorithms are characterized as slower and less stable. This suggests that they may exhibit more variability in their convergence behavior and require a larger number of iterations to reach the optimal fitness value reliably. Based on the findings from Figure 8, the CBSO and BSO optimization algorithms demonstrate faster convergence and greater stability in determining the optimal value of the fitness function. Meanwhile, the GA and PSO algorithms are slower and exhibit lower stability in achieving the desired optimization outcome [36].

Based on the information provided, Figures 9 and 10 provide additional insights into the performance and characteristics of the CBSO-PID algorithm compared to the other algorithms (PSO, BSO, and GA) in terms of stability, overshoot, control accuracy, and robustness. Figure 9:

1. **CBSO Algorithm:** The CBSO algorithm reaches stability in 2.72 s and exhibits a maximum overshoot of less than 0.3%. It demonstrates fast convergence and high control accuracy.
2. **PSO and BSO Algorithms:** Both the PSO and BSO algorithms take more than 3.50 s to reach stability. They also have a maximum overshoot greater than 0.5%. The PSO algorithm shows an additional increase in rise time (0.14 s) compared to the CBSO algorithm.
3. **GA Algorithm:** The GA algorithm requires a long time for both rise and convergence. It exhibits a large overshoot and significant fluctuations in the step signal within a finite number of iterations.

The CBSO algorithm stands out among the four algorithms due to its fast convergence, high control accuracy, and relatively low overshoot. In contrast, the PSO and BSO algorithms show slower convergence, higher overshoot, and the PSO algorithm introduces additional rise time compared to the CBSO algorithm. The GA algorithm performs poorly in terms of both convergence time and control accuracy. The CBSO-PID intelligent irrigation control system, as depicted in Figure 10, exhibits better control effectiveness and robustness compared to the other algorithms. The maximum errors of the GA and PSO algorithms are 0.18 Pa and 0.12 Pa, respectively. In contrast, the maximum errors of the CBSO and BSO algorithms are less than 0.02 Pa, indicating higher control accuracy and smaller deviations from the desired values. Both Figures 9 and 10 further support the superiority of the CBSO-PID algorithm over the PSO, BSO, and GA algorithms in terms of fast convergence, high control accuracy, and robustness. The CBSO algorithm demonstrates faster convergence, lower overshoot, and smaller errors, highlighting its effectiveness in intelligent irrigation control systems.

4.3. Discussion about Economical Management

Based on the results obtained from the comparison of the CBSO-PID algorithm with the PSO-PID, BSO-PID, and GA-PID algorithms, there are implications for the economical management of systems or processes.

1. **Efficiency:** The CBSO-PID algorithm consistently demonstrates fast convergence and efficient optimization compared to the other algorithms. This indicates that implementing the CBSO-PID algorithm can potentially lead to improved efficiency in various systems and processes. Faster convergence means quicker attainment of optimal parameter values, which can translate to reduced operation time and enhanced resource utilization.
2. **Control Accuracy:** The CBSO-PID algorithm exhibits high control accuracy with minimal overshoot and low error rates compared to the other algorithms. This implies that by adopting the CBSO-PID algorithm, one can achieve precise control and maintain stability in various applications. Improved control accuracy is crucial for minimizing waste, optimizing resource usage, and reducing production costs.
3. **Robustness:** The CBSO-PID algorithm demonstrates robust performance, as evidenced by its consistent and reliable results across different iterations. Robustness is essential

for ensuring consistent and stable operation, which can contribute to minimizing operational disruptions and associated economic losses.

4. **Cost Savings:** The superior performance of the CBSO-PID algorithm, characterized by faster convergence, high control accuracy, and robustness, can potentially lead to cost savings in terms of energy consumption, material utilization, and maintenance. Optimized control parameters obtained through the CBSO-PID algorithm can result in improved system efficiency, reduced resource waste, and enhanced overall productivity, all of which can contribute to cost reduction.
5. **System Optimization:** The CBSO-PID algorithm's ability to optimize PID controller parameters efficiently can have broader implications for system optimization in various industries. By fine-tuning control parameters, system performance can be enhanced, leading to increased productivity, improved product quality, and better overall operational efficiency.

The results obtained from the comparison of the CBSO-PID algorithm with other optimization algorithms highlight its potential for economical management. Implementing the CBSO-PID algorithm can contribute to improved efficiency, control accuracy, robustness, cost savings, and system optimization, thereby positively impacting economic factors in different domains.

5. Conclusions

The implementation of CBSO-PID control within the water supply management system of intelligent drip irrigation demonstrates remarkable efficacy, characterized by swift iteration, heightened control precision, minimized control duration, and enhanced robustness. In summary, the integration of CBSO within the PID control strategy presents a compelling solution for water supply management in intelligent drip irrigation systems. The demonstrated improvements in control precision, operational speed, and system stability underscore its potential for enhancing agricultural irrigation practices, signifying a substantial step towards intelligent and efficient water resource management in agriculture.

1. Within the drip irrigation framework, PID control employing the CBSO algorithm exhibits notable advantages, showcasing reduced regulation time and minimal overshoot. These attributes signify the realization of an optimal control strategy, amplifying the efficiency of the irrigation system compared with GA/PSO.
2. Throughout the CBSO algorithm's optimization process, the adjustments in step size and attenuation factor significantly enhance the practical numerical optimization of PID. This optimization mitigates traditional PID control challenges, including nonlinearity, time-varying behavior, and hysteresis, thereby improving its efficacy in real-world applications.
3. Empirical results from simulations affirm the stability and dynamic performance of CBSO-PID control. Its demonstrated stability aligns with the requisites of automatic control in agricultural irrigation systems, thereby contributing to the system's overall intelligence and efficiency.

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Review

Integration of Carbon Dioxide Removal (CDR) Technology and Artificial Intelligence (AI) in Energy System Optimization

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Abstract: In response to the urgent need to address climate change and reduce carbon emissions, there has been a growing interest in innovative approaches that integrate AI and CDR technology. This article provides a comprehensive review of the current state of research in this field and aims to highlight its potential implications with a clear focus on the integration of AI and CDR. Specifically, this paper outlines four main approaches for integrating AI and CDR: accurate carbon emissions assessment, optimized energy system configuration, real-time monitoring and scheduling of CDR facilities, and mutual benefits with mechanisms. By leveraging AI, researchers can demonstrate the positive impact of AI and CDR integration on the environment, economy, and energy efficiency. This paper also offers insights into future research directions and areas of focus to improve efficiency, reduce environmental impact, and enhance economic viability in the integration of AI and CDR technology. It suggests improving modeling and optimization techniques, enhancing data collection and integration capabilities, enabling robust decision-making and risk assessment, fostering interdisciplinary collaboration for appropriate policy and governance frameworks, and identifying promising opportunities for energy system optimization. Additionally, this paper explores further advancements in this field and discusses how they can pave the way for practical applications of AI and CDR technology in real-world scenarios.

Keywords: climate change; low carbon; sustainable development; AI-CDR; 3E analysis

1. Introduction

1.1. Research Background

Carbon Dioxide Removal (CDR) technology and Artificial Intelligence (AI) are two prominent fields that have gained significant attention in recent years [1–3]. CDR technology focuses on the removal of carbon dioxide from the atmosphere [4], while AI encompasses the development of intelligent systems capable of performing tasks that typically require human intelligence [5,6]. The integration of CDR technology and AI presents a compelling opportunity to optimize energy systems and address the challenges of climate change. CDR technology aims to mitigate climate change by actively removing carbon dioxide from the atmosphere or capturing it from emission sources [7]. Various CDR methods have been proposed and developed including Direct Air Capture (DAC) [8], which extracts CO₂ directly from ambient air, and Bioenergy Carbon Capture and Storage (BECCS), which

combines biomass energy production with carbon capture and storage [9,10]. These technologies offer the potential to reduce carbon emissions and contribute to a more sustainable future. Figure 1 shows the important role of AI in CO₂ emission reduction. The left scheme corresponds to an AI-based GHG sequestrating cycle. The right scheme describes the role of AI software in this scheme.

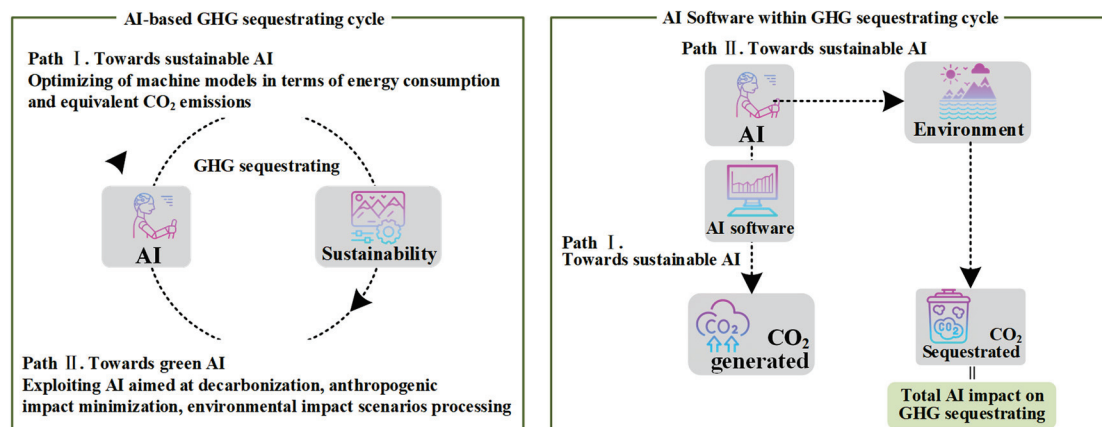


Figure 1. High-level schemes of AI-based GHG sequestrating.

Additionally, AI has demonstrated remarkable capabilities in data analysis, pattern recognition, and optimization [11]. By harnessing the power of AI, energy systems can be optimized to achieve greater efficiency, reduce the carbon footprint, and improve overall performance. The integration of CDR technology and AI holds significant promise for energy system optimization. AI techniques can enhance CDR technologies in several ways including accurate assessment and monitoring of carbon emissions, optimization of deployment and operation of CDR facilities, and real-time monitoring and adaptive control based on changing conditions [12].

The motivation behind integrating CDR technology and AI lies in the urgent need to address climate change and transition to a sustainable energy future. The rising levels of carbon dioxide in the atmosphere and the associated environmental consequences necessitate effective strategies to reduce emissions and remove existing carbon [13]. By combining CDR technology and AI, we can enhance the efficiency and effectiveness of carbon removal processes, optimize energy systems, and accelerate the transition to a low-carbon economy. The integration of CDR technology and AI presents a unique opportunity to optimize energy systems and mitigate climate change. By combining the capabilities of CDR technology in carbon removal and AI in data analysis and optimization, we can achieve more efficient and sustainable energy systems. The following sections of this review will delve deeper into the applications, advantages, challenges, and future prospects of this integration.

1.2. Overview of CDR Technology

Carbon Dioxide Removal (CDR) technology encompasses various methods and approaches aimed at removing carbon dioxide from the atmosphere or capturing it from emission sources. Here are some common CDR technologies.

- Direct Air Capture (DAC)

Principle: DAC technology directly extracts carbon dioxide from ambient air using chemical sorbents or membranes [14]. **Application Scope:** DAC can be deployed in various locations including industrial sites, power plants, or even directly in the atmosphere. **Potential Challenges:** DAC technologies face challenges related to energy consumption, cost-effectiveness, and scalability. Developing efficient and cost-competitive sorbents and optimizing the capture process are ongoing areas of research. Figure 2 shows the leveled cost projections for CO₂ direct air capture in 2050.

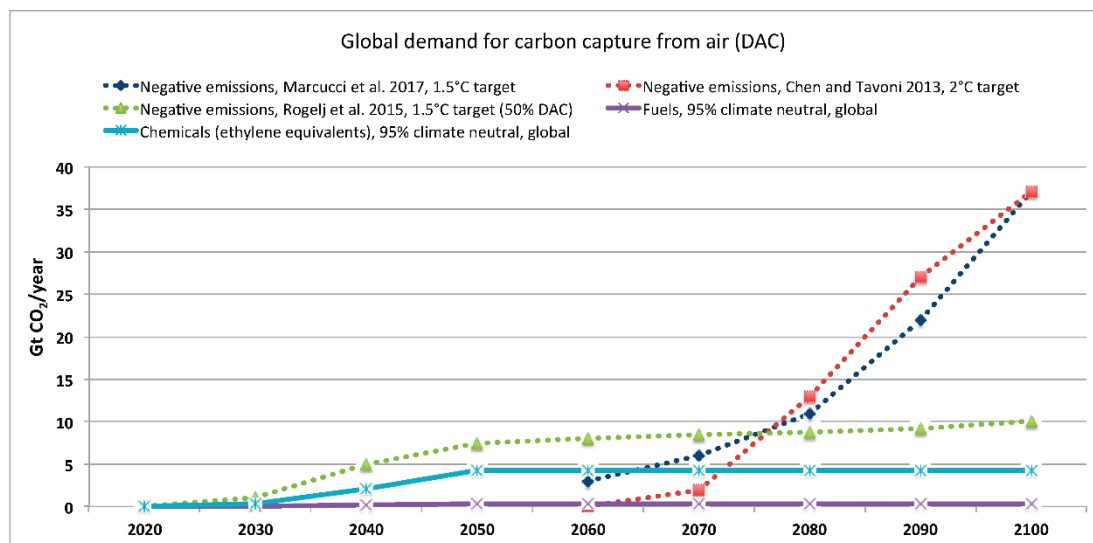


Figure 2. Global Direct Air Capture (DAC) demand for achieving negative emissions from 2060 in comparison with globally required climate-neutral CO₂ for Power-to-Liquids and Power-to-Chemicals in Gt CO₂/year [15–18].

- Bioenergy Carbon Capture and Storage (BECCS)

Principle: BECCS combines biomass energy production with carbon capture and storage. The process flow diagram in Figure 3 depicts the operations during the harvest season, which involves steam extraction for industrial processes and includes CCS. Biomass plants capture CO₂ emissions generated during energy production and store them underground [19]. Application Scope: BECCS can be implemented in power plants, industrial facilities, or dedicated biomass production facilities. Potential Challenges: Challenges include ensuring sustainable biomass feedstock supply, optimizing the energy balance of the process, and addressing potential environmental impacts associated with large-scale biomass cultivation.

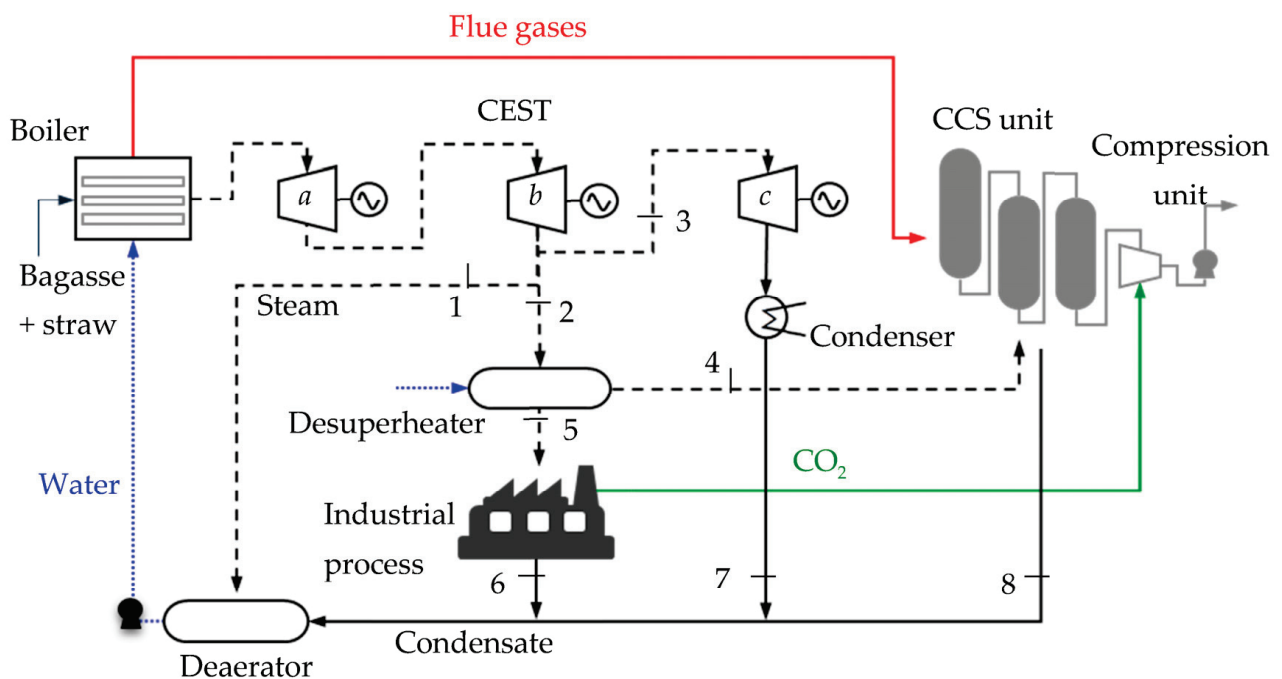


Figure 3. BECCS process flow diagram (harvest season) [20].

- Carbon Sequestration

Principle: Carbon sequestration involves capturing and storing carbon dioxide emissions in geological formations, such as depleted oil and gas reservoirs or deep saline aquifers [21]. **Application Scope:** Carbon sequestration can be applied to various emission sources including power plants and industrial facilities. **Potential Challenges:** Challenges include selecting suitable storage sites, ensuring the long-term integrity of the storage reservoirs, and addressing public perception and regulatory concerns surrounding the safety and permanence of storage.

- Enhanced Weathering

Principle: Enhanced weathering involves accelerating natural weathering processes to capture and store carbon dioxide [22]. It typically involves the application of minerals or rocks that react with CO_2 and permanently sequester it. Figure 4 illustrates a conceptual diagram that presents the strategies of CCS through mineral carbonation. **Application Scope:** Enhanced weathering can be applied to agricultural lands, coastal areas, or specific carbon capture facilities. **Potential Challenges:** Challenges include identifying suitable mineral sources, assessing the environmental impact of large-scale mineral deployment, and understanding the long-term stability of carbon storage.

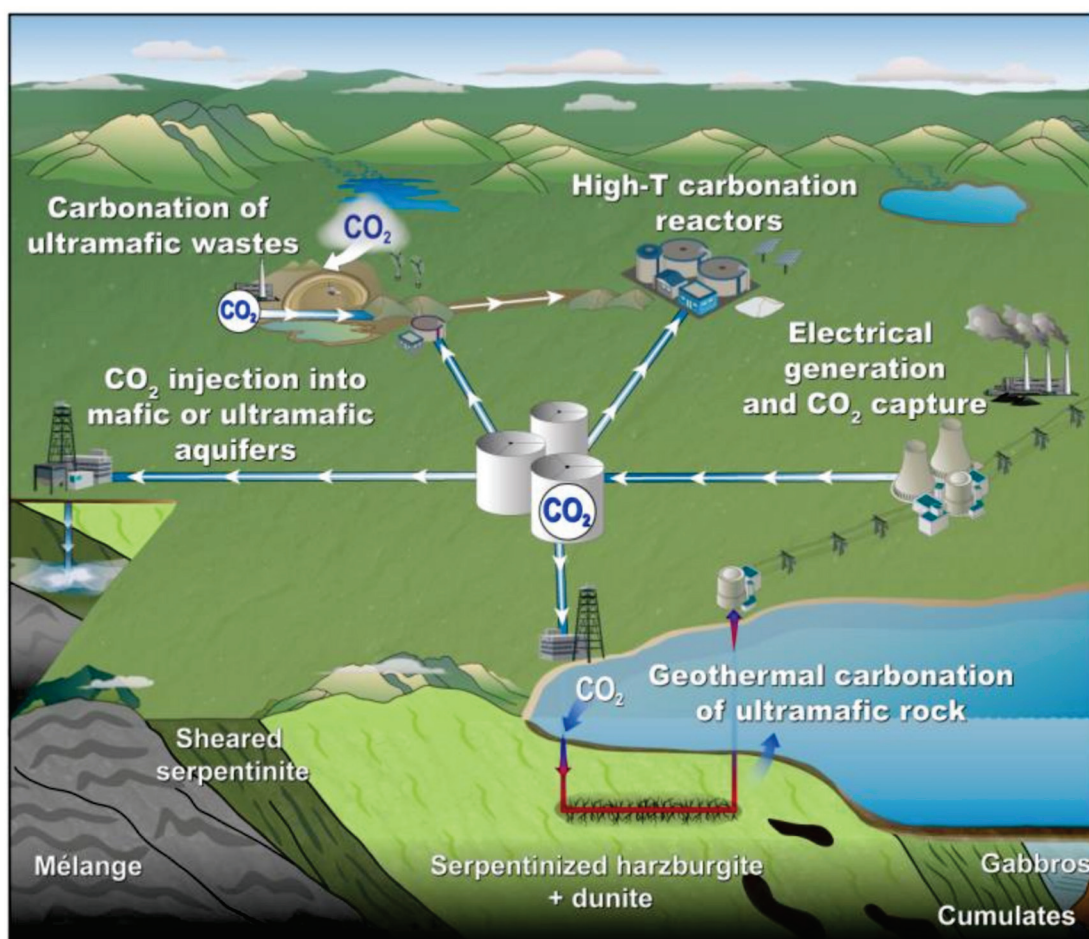


Figure 4. Visual graphics of enhanced weathering processes [23].

Each CDR technology has its own set of principles, application scopes, and challenges. It is crucial to evaluate these factors to determine the most suitable CDR technology for a given context. The advantages and disadvantages of each technology are compared as shown in Table 1.

Table 1. Comparison of advantages and disadvantages of the four technologies.

Technologies	Advantages	Disadvantages
DAC	1. It can capture carbon dioxide from the air at any location. 2. Potential for large-scale carbon capture and storage.	1. It requires significant amounts of electricity and energy. 2. Relatively high cost compared to traditional methods.
BECCS	1. It utilizes biomass feedstocks, which can be renewable and sustainable. 2. It can be integrated with existing power plants or industrial facilities.	1. It requires large areas of land to cultivate biomass feedstocks. 2. It competes with land use for food production and conservation efforts.
Carbon Sequestration	1. It enhances soil fertility and promotes sustainable land management practices 2. It can contribute to the development of carbon offset projects	1. Limited capacity to sequester large amounts of carbon dioxide 2. High costs associated with implementation and maintenance
Enhanced Weathering	1. It has the potential to improve soil fertility and agricultural productivity 2. It does not require complex infrastructure for implementation	1. High costs associated with large-scale implementation and transportation of materials 2. Potential challenges related to land use and ecosystem disruption

1.3. Research Gap of Past Reviews

While there have been previous literature reviews on Carbon Dioxide Removal (CDR) technology and Artificial Intelligence (AI) individually, there is a research gap when it comes to exploring their integration specifically for energy system optimization [24]. Previous reviews have predominantly emphasized either CDR technologies or AI applications in energy systems with limited consideration of their combined potential. This review aims to address this gap by examining the integration of CDR technology and AI, highlighting their synergistic effects and advantages for energy system optimization.

By integrating CDR technology and AI, we can optimize energy systems and tackle climate change challenges more effectively. While there have been studies on optimizing energy systems using AI techniques, there is a lack of research specifically focused on integrating CDR technology into these optimization strategies. This review aims to fill this gap by exploring how AI can optimize the deployment, operation, and performance of CDR technologies within energy systems.

Real-time monitoring and adaptive control are essential when integrating CDR technology and AI. AI enables the real-time monitoring of CDR facilities, allowing for adaptive control and optimization based on changing conditions and demands. This capability enhances the efficiency and effectiveness of CDR technology in addressing carbon emissions. The integration of CDR technology and AI has significant implications for sustainable energy development. It contributes to carbon emission reduction, improved energy system efficiency, and the development of new technologies, supporting the transition to a sustainable energy future.

In summary, this review provides a comprehensive analysis of the integration of CDR technology and AI. It covers the fundamental concepts and principles of CDR technology and AI, explores integration methods and potential advantages, and discusses practical challenges, feasibility, and environmental management aspects. By focusing on a specific gap in research and highlighting the advantages of this review, we aim to provide valuable insights for researchers, policymakers, and practitioners in the field of energy system optimization and sustainable development.

2. Integration of “CDR + AI”

The integration of CDR Technology and Artificial Intelligence (AI) offers several potential advantages, including four parts as follows:

2.1. Accurate Carbon Emissions Assessment

By combining CDR technology and AI, it becomes possible to accurately assess and quantify carbon emissions. Figure 5 shows an overview of the thematic dimensions included in the technical feasibility assessment of CDR removal. AI algorithms can analyze large amounts of data from various sources, including CDR facilities, industrial processes, and energy consumption patterns, to provide more precise estimations of carbon emissions. This can help in identifying high-emission areas, tracking progress towards emission reduction goals, and informing policy decisions [25].

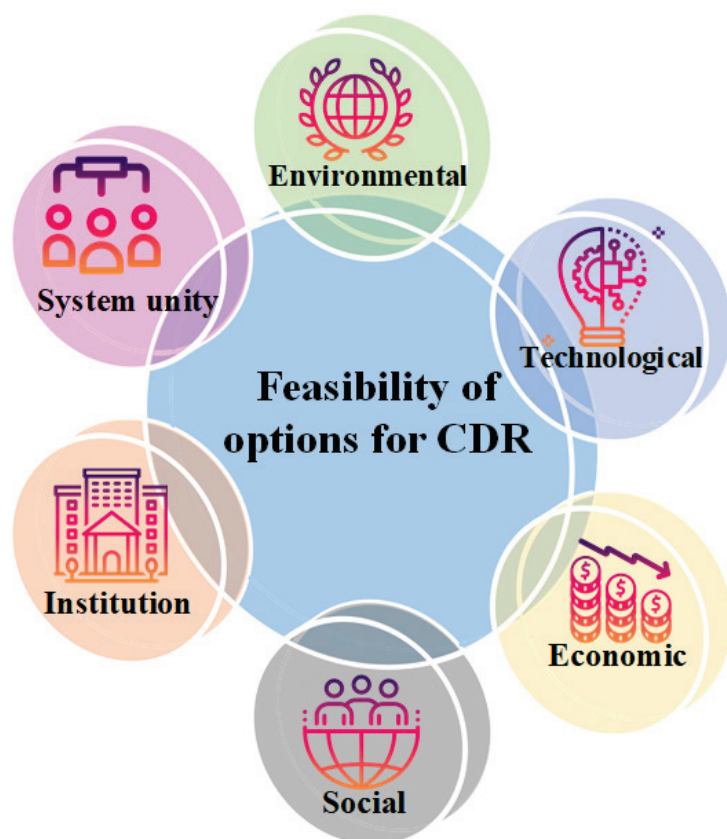


Figure 5. Overview of thematic dimensions included in the feasibility assessment framework of CDR options.

AI algorithms can integrate and analyze data from multiple sources, including emissions inventories, satellite imagery, sensor networks, and industry-specific data, to gain a comprehensive understanding of emissions across different sectors and regions [26]. By analyzing emissions-related data, AI can identify the spatial and temporal patterns of emissions, such as emission hotspots or areas with significant emission fluctuations, and pinpoint the high-emission areas that may require targeted interventions [27]. Machine learning techniques enable AI models to recognize emission patterns and make predictions based on historical data [28], identifying areas with a higher likelihood of being high-emission areas [29,30].

Satellite imagery provides valuable information on greenhouse gas concentrations, land-use changes, and industrial activities [31,32], which AI algorithms can process and analyze to identify regions with higher emissions and track changes over time [33]. Integrating data from sensors and IoT devices enables real-time monitoring of emissions, facilitating the identification of areas experiencing sudden spikes or persistent high emissions [34,35]. By visualizing emissions data spatially and using geospatial analysis techniques, AI can provide intuitive representations of high-emission areas [36,37]—making it easier for policy-makers and stakeholders to identify regions that require targeted mitigation strategies [38].

By leveraging these capabilities, AI algorithms can assist in identifying high-emission areas, providing valuable insights into the sources and patterns of emissions. This information can guide policymakers in developing targeted interventions, implementing emission reduction measures, and prioritizing areas for mitigation efforts.

2.2. Optimized Energy System Configuration

AI algorithms can optimize the integration of CDR technology into energy systems by analyzing data on energy demand, renewable energy generation [39], and other factors to identify the most efficient and cost-effective ways to reduce carbon emissions and improve overall system efficiency [40,41]. By maximizing the use of renewable energy sources, AI can help reduce carbon emissions. Figure 6 is a schematic of a low-carbon energy system.

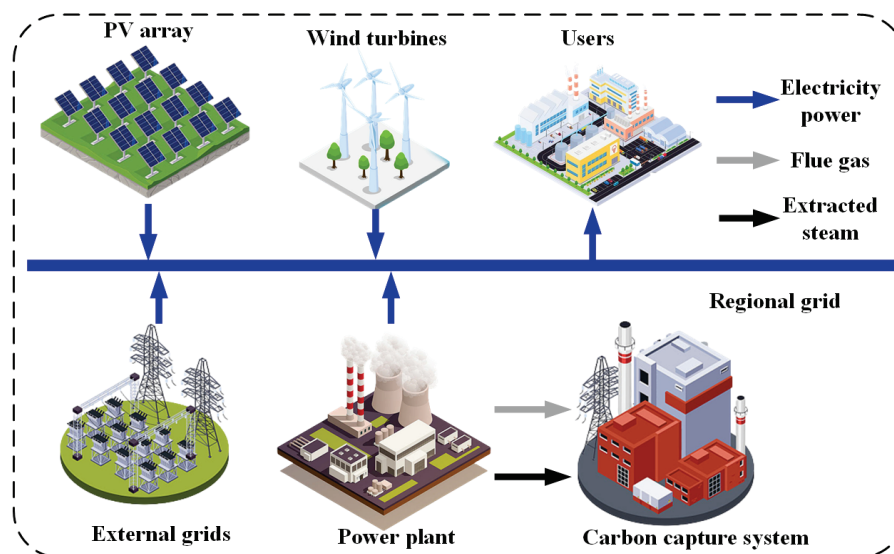


Figure 6. The schematic diagram of a low-carbon energy system.

AI algorithms can analyze extensive datasets related to energy demand, renewable energy generation, grid infrastructure, and other relevant factors [42,43]. By processing this data, AI models can build sophisticated models that capture the complexities of an energy system including the interplay between different energy sources, demand patterns, and carbon emissions [40,44]. These models enable scenario analysis and optimization to identify efficient and cost-effective configurations for integrating CDR technology [45]. Considering factors such as energy demand, renewable energy availability, storage capacities, and carbon removal targets, AI algorithms simulate and evaluate different system configurations [46,47]. This facilitates the identification of optimal solutions that maximize renewable energy use, minimize carbon emissions, and achieve specific energy and carbon removal objectives.

AI algorithms also optimize demand-side management strategies by analyzing energy demand patterns [12,48]. By leveraging machine learning techniques, AI identifies demand response opportunities, predicts peak energy demand periods, and optimizes the scheduling of energy-consuming activities [49,50]. This helps balance energy supply and demand, reduce reliance on fossil fuel-based energy generation, and increase the integration of renewable energy and CDR technologies. AI enhances the accuracy of renewable energy forecasting by analyzing historical weather data, renewable energy generation data, and other variables [51,52]. Accurate predictions of renewable energy availability enable the optimization of CDR facility scheduling and operation, aligning them with high renewable energy generation and low grid demand [53,54]. Furthermore, AI algorithms optimize energy system configurations by analyzing historical and real-time data on energy supply and demand, market prices, weather conditions, and other factors [55]. This analysis identifies opportunities for energy storage deployment, demand shifting, and smart

grid management [56], ensuring stability, accommodating intermittent renewable energy sources, and effectively integrating CDR technologies [39].

By leveraging AI capabilities, energy system operators, policymakers, and stakeholders can optimize energy system configurations to maximize CDR technology benefits. This includes minimizing carbon emissions, maximizing renewable energy use, and improving overall system efficiency and resilience.

2.3. Real-Time Monitoring and Scheduling of CDR Facilities

AI enables the real-time monitoring and adaptive control of CDR facilities. By analyzing data from sensors, AI algorithms can continuously monitor the performance and operation of CDR facilities, detecting any anomalies or inefficiencies [57]. This allows for timely adjustments and optimizations, ensuring optimal utilization of resources and maximization of the carbon removal capacity of the facilities. Figure 7 displays a map depicting the global distribution of CCUS facilities with a specific focus on Europe.

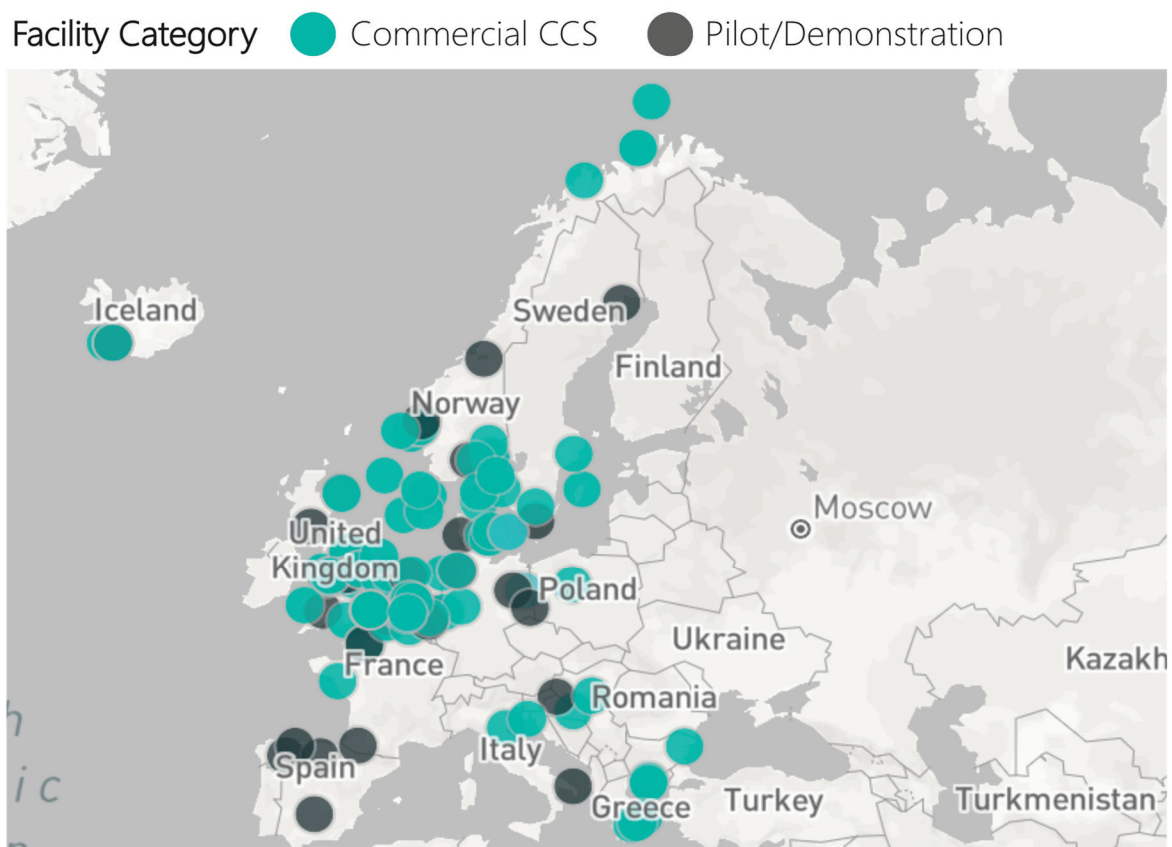


Figure 7. Worldwide distribution of CCUS facilities divided by categories, expanded in Europe [58].

AI algorithms integrate data from various sensors and monitoring devices installed in CDR facilities [59,60]. This includes parameters like temperature, pressure, flow rates, and capture efficiency. By continuously analyzing real-time data, AI monitors the performance of CDR facilities, detects anomalies or deviations from optimal conditions, and alerts operators to potential issues [61,62]. Anomaly detection techniques help identify abnormal behavior or malfunctions [63], triggering alarms or notifications by comparing real-time sensor data with historical patterns and predefined thresholds. Operators can take immediate corrective actions, minimizing disruptions in the carbon removal process. AI also predicts maintenance needs and schedules proactive maintenance activities, optimizing facility availability and reliability [64].

AI dynamically adjusts CDR facility operations based on real-time data and changing conditions. By monitoring factors like energy availability, carbon capture efficiency, and

storage capacity, AI optimizes scheduling and resource allocation. This enables adaptive control strategies that maximize carbon removal capacity, optimize energy consumption, and respond to fluctuations in renewable energy generation or demand. AI optimizes resource allocation within CDR facilities, considering real-time data on energy availability, cost, and carbon removal targets. This determines the most efficient allocation of resources for optimal carbon removal performance, minimizing costs while maximizing capacity. AI integrates with energy grid data and market signals to schedule CDR facilities. Considering electricity prices, demand peaks, and renewable energy availability, AI schedules carbon removal processes during periods of low electricity demand or high renewable energy availability. This maximizes renewable energy utilization, reduces costs, and aligns carbon removal activities with grid conditions.

2.4. Mutual Benefits and Mechanisms

The integration of CDR technology and AI can lead to mutual benefits and synergies [65]. CDR technology can provide data for AI model training and improvement, while AI optimization methods can improve the efficiency of CDR technology. The data collected from CDR facilities can be used to train AI models and enhance their accuracy and efficiency. AI algorithms can analyze complex datasets and optimize the operation and performance of CDR facilities, leading to increased carbon removal efficiency and reduced operational costs [22].

CDR facilities generate a wealth of data that can be utilized to train AI models [3]. By incorporating this data into the training process, AI algorithms can learn from real-world CDR operations and improve their accuracy and efficiency. This leads to more effective AI models that can make better decisions and optimizations in CDR technology [66].

AI algorithms can optimize the operation and performance of CDR facilities by analyzing complex datasets and identifying patterns and correlations [67]. This enables AI to make informed decisions and adjustments in real-time, enhancing the efficiency and effectiveness of CDR technology. AI algorithms can optimize various aspects of CDR technology processes, including capture, storage, and utilization of carbon dioxide, leading to cost reductions, energy savings, and increased carbon removal capacity.

AI algorithms can enable CDR systems to be adaptive and responsive to changing conditions by continuously analyzing real-time data. This adaptability allows CDR systems to optimize their performance in response to variations in energy supply, carbon emissions, and other relevant factors, ensuring effective carbon removal in real-time [68]. AI can also play a crucial role in planning the deployment and scalability of CDR technology by analyzing various factors and optimizing the allocation of resources [69].

The integration of CDR technology and AI creates a symbiotic relationship that enables improved carbon removal capabilities, cost-effectiveness, and scalability. This synergy contributes to the mitigation of climate change by offering accurate carbon emissions assessments, optimized energy system configurations, and real-time monitoring and scheduling of CDR facilities. The mutual benefits between CDR technology and AI can drive advancements in both fields, leading to more efficient and effective carbon removal solutions.

3. E Performance Improvement for Energy System

The integration of CDR technology and AI can indeed result in performance improvements in terms of efficiency, environmental impact, and economic viability [70]. The integration of CDR technology and AI can bring about significant performance improvements in terms of efficiency, environmental impact reduction, and economic viability [71]. These improvements contribute to the advancement and adoption of CDR technology as a crucial tool in addressing climate change and achieving sustainable carbon mitigation goals.

3.1. Efficiency Improvements

AI algorithms can optimize the operation and processes of CDR facilities, leading to increased efficiency. By analyzing large volumes of data, AI models can identify patterns,

correlations, and optimal operating conditions. This optimization can improve the overall efficiency of carbon removal processes, such as capture, storage, and utilization, reducing energy consumption and resource wastage [72]. Enhanced efficiency translates to higher carbon removal rates per unit of energy or resources utilized. Figure 8 shows how compression energy consumption varied with cooling temperature and compressor discharge pressure for three CO₂ capture scenarios.

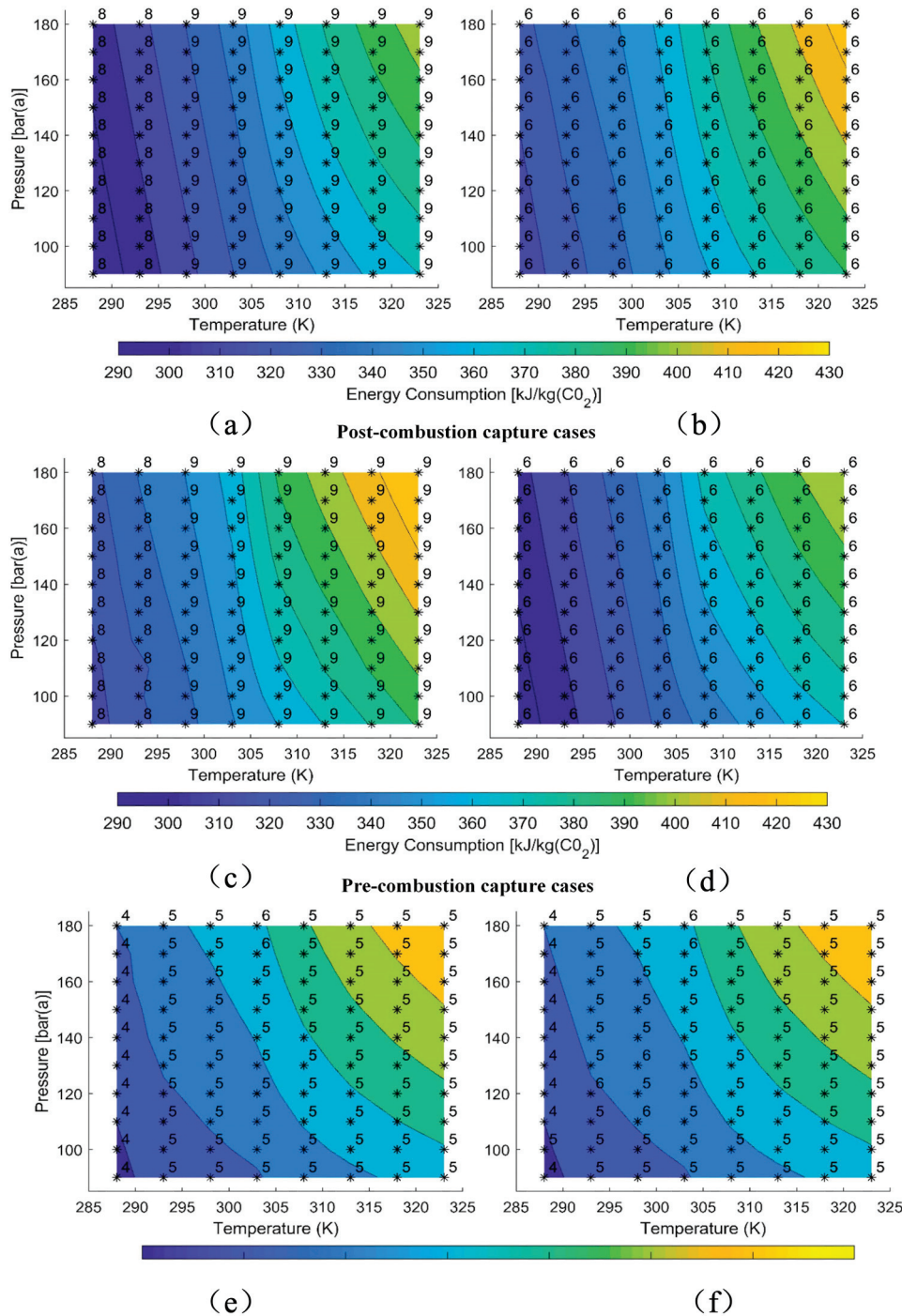


Figure 8. Three cases of optimized compression energy consumption and number of stages. (a,b) Post-combustion capture cases; (c,d) Pre-combustion capture cases; (e,f) Oxyfuel cases [73].

AI algorithms analyze data generated by CDR systems including sensor readings, operational parameters, and historical performance data. By processing this data, AI models identify patterns, correlations, and optimal operating conditions that maximize carbon

removal efficiency [74]. For example, AI determines the optimal flow rates, temperature, pressure, and solvent concentrations for carbon capture processes, minimizing energy consumption and improving capture efficiency. AI enables real-time monitoring and adaptive control of CDR facilities, detecting deviations from optimal conditions and making necessary adjustments [75].

AI optimizes energy consumption within CDR facilities by analyzing energy usage patterns and considering factors like costs and availability. This includes strategies such as load balancing, scheduling energy-intensive operations during low-demand periods, and integrating renewable energy sources [76]. AI also optimizes resource allocation and utilization within CDR facilities by analyzing data on availability, costs, and carbon removal targets. This minimizes waste, reduces costs, and maximizes the facility's carbon removal capacity. AI aids in the early detection of equipment faults or maintenance needs within CDR systems [77]. By continuously monitoring sensor data and performance metrics, AI identifies anomalies or deviations that may indicate impending failures. This enables proactive maintenance planning and reduces downtime, ensuring efficient and continuous facility operation. AI continuously learns and adapts based on feedback and performance data, identifying areas for improvement and refining optimization strategies over time [78]. This ongoing learning process leads to efficiency improvements and the better performance of CDR systems.

By leveraging AI algorithms to optimize operations, control parameters, and allocate resources, CDR facilities achieve higher efficiency, reducing energy consumption and resource wastage while maximizing carbon removal rates. These improvements contribute to the effectiveness of CDR technology in mitigating carbon emissions and combating climate change.

3.2. Environmental Impact Reduction

AI optimization methods can significantly reduce the environmental impact of CDR technology by improving the efficiency of carbon removal processes and minimizing energy requirements and associated greenhouse gas emissions [79,80]. Additionally, AI algorithms can identify opportunities for utilizing captured carbon dioxide in industrial processes or carbon utilization technologies, further reducing emissions and environmental impact [81].

By optimizing the energy consumption of CDR processes, AI algorithms can minimize energy usage without compromising carbon removal efficiency, thus reducing the carbon footprint of CDR facilities. AI can also optimize various carbon removal processes, such as capture, storage, and utilization, leading to more efficient and environmentally friendly operations [3,82]. For instance, AI algorithms can determine optimal operating conditions for carbon capture technologies, such as solvent selection, temperature, and pressure, to maximize efficiency and minimize energy consumption, thereby reducing the environmental impact of carbon removal.

Furthermore, AI algorithms can help identify opportunities for utilizing captured carbon dioxide, such as in enhanced oil recovery, carbon-based materials production, or carbon mineralization, thereby further reducing the environmental impact of CDR [83]. AI can also facilitate comprehensive life cycle assessments to evaluate the environmental impact of CDR processes comprehensively, ensuring that environmental considerations are taken into account throughout the CDR system's life cycle. Additionally, AI can assist in environmental monitoring and compliance in CDR facilities by detecting deviations from regulatory standards or environmental thresholds, enabling timely corrective actions to mitigate potential environmental impacts and ensure compliance with environmental regulations [63,84].

In summary, the integration of CDR technology with AI can lead to a substantial reduction in environmental impact through energy optimization, process efficiency improvements, identification of carbon utilization opportunities, comprehensive life cycle assessments, environmental monitoring, and climate change mitigation. These environ-

mental benefits highlight the potential of CDR technology integrated with AI in addressing climate change and promoting a sustainable future.

3.3. Economic Feasibility

The integration of AI can enhance the economic viability of CDR technology by identifying cost-effective strategies and optimizing resource allocation, energy management, and process efficiency [85]. This optimization leads to reduced operational costs, making CDR technology more economically feasible and attractive for implementation, fostering its adoption and scalability [86].

AI algorithms can optimize the allocation of resources and energy consumption within CDR facilities, leading to cost savings [87]. They can also assist in the scalability and deployment planning of CDR technology and provide decision support for stakeholders considering investments in CDR technology [88]. By optimizing costs, resource allocation, energy management, and process efficiency, AI integration enhances the economic viability of CDR technology [89], making it more attractive for implementation, fostering its adoption and scalability, and facilitating its role in addressing climate change and achieving sustainable carbon mitigation goals. Figure 9 shows the relationship between the net present value of negative CO₂ and the cost of biomass (fuel) in both scenarios.

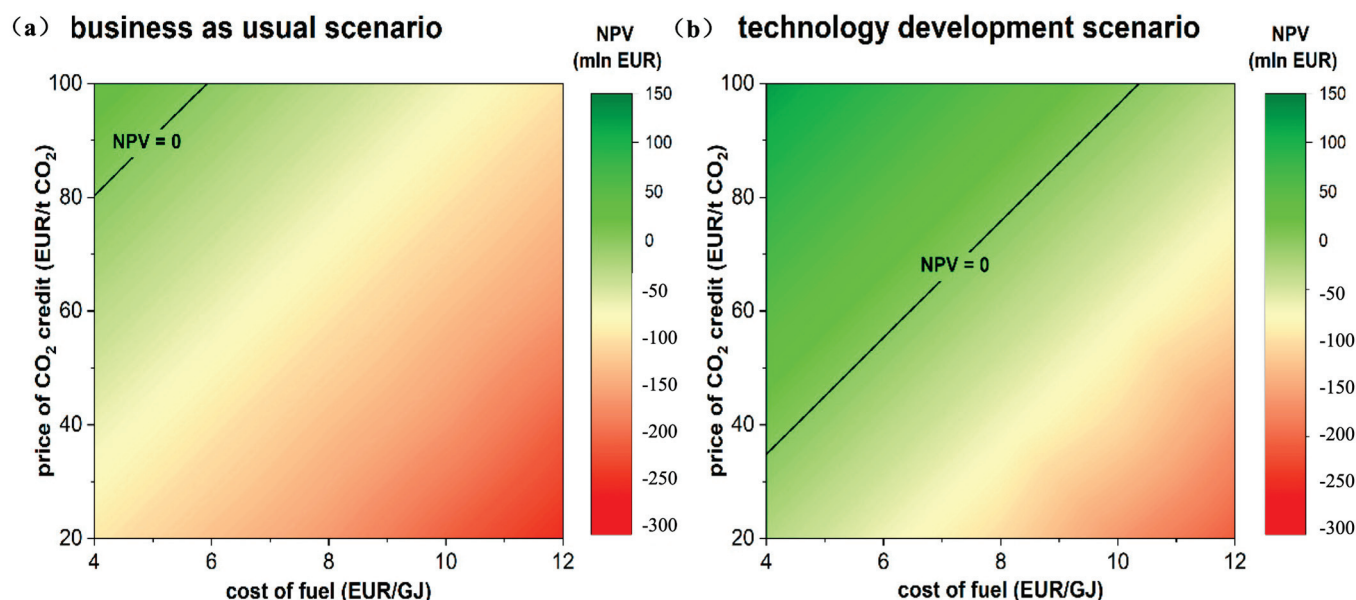


Figure 9. NPV as a function of negative CO₂ emission credits and the cost of fuel in (a) the business-as-usual scenario and (b) the technological development scenario [90].

4. Perspectives and Challenges

The success of AI algorithms depends on the availability and quality of data. Ensuring data accuracy, consistency, and reliability is crucial for accurate modeling and optimization. AI models used in CDR optimization may have inherent uncertainties due to the complex and dynamic nature of environmental conditions. Addressing data quality issues and accounting for model uncertainty is essential for reliable decision-making in CDR technology, as shown in Figure 10. Evaluating the scalability and applicability of AI algorithms in different CDR processes and system configurations is necessary to ensure technological feasibility. Legal and regulatory challenges, as well as public perception and acceptance, also need to be addressed for successful integration and adoption.

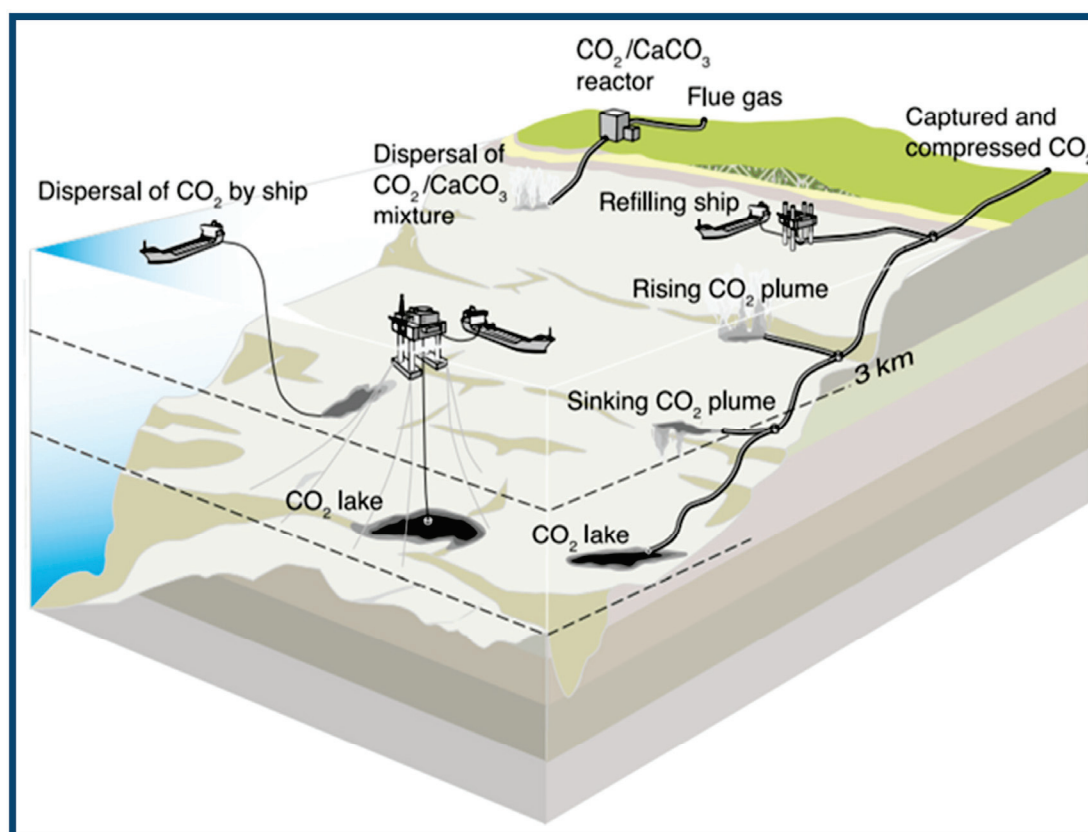


Figure 10. Schematic of several ocean storage strategies. IPCC Special Report on Carbon Dioxide Capture and Storage [91].

Future Research Directions and Key Focus Areas: Future research should focus on developing advanced AI models and optimization algorithms specifically tailored for CDR technology, including addressing model uncertainties and improving data collection methods. Developing decision support tools that account for uncertainties and risks associated with CDR technology and AI integration is essential. Collaboration between researchers, engineers, policymakers, and stakeholders is crucial for addressing technical, economic, regulatory, and social challenges. Research should also explore the development of policy and governance frameworks that support the integration of CDR technology and AI and conduct large-scale demonstrations and field trials of integrated CDR technology and AI systems.

By addressing challenges related to data quality, model uncertainty, technological feasibility, policy and regulatory environments, and public acceptance and focusing on key research areas, the integration of CDR technology and AI can advance energy system optimization for carbon removal, contributing to the practical implementation and widespread adoption of CDR technology to mitigate climate change and achieve sustainable carbon mitigation goals.

5. Conclusions

Through this review, we have gained a comprehensive understanding of the applications and potentials of integrating CDR technology and AI in energy system optimization. This integration offers new solutions for sustainable energy development, contributing to carbon emission reduction, improved energy system efficiency, and the development of new technologies.

1. This paper provides a comprehensive summary of the integration of AI and CDR technology in energy system optimization. AI optimization algorithms identify cost-effective strategies, such as optimal resource allocation, energy management, and process

optimization, reducing operational costs and promoting the adoption and scalability of CDR technology.

2. This review outlines four approaches to integrating CDR technology and AI including using AI optimization algorithms for resource allocation, energy management, process efficiency, and decision support. These approaches enhance the efficiency and effectiveness of CDR technology in carbon reduction, contributing to sustainable energy system optimization.

3. The integration of AI and CDR technology positively impacts three aspects of energy systems: environment, economy, and energy. AI optimization algorithms reduce energy consumption and carbon emissions, mitigating environmental effects. By optimizing costs, CDR technology becomes more economically feasible, reducing operational expenses. AI optimization algorithms also improve energy utilization efficiency, promoting sustainable energy development.

4. This paper suggests future research directions and areas of focus, such as improving modeling and optimization techniques, enhancing data collection and integration capabilities, enabling robust decision-making and risk assessment, fostering interdisciplinary collaboration, and developing appropriate policy and governance frameworks. Large-scale demonstrations and field trials are crucial for validating the effectiveness, feasibility, and scalability of integrated CDR technology and AI systems.

By addressing these aspects and focusing on future research directions, the integration of AI and CDR technology can significantly contribute to mitigating climate change, reducing greenhouse gas emissions, and building a sustainable future. Advanced technology and innovative approaches will play a crucial role in achieving carbon reduction targets and creating a more environmentally friendly world.

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Article

An Integrated Risk Assessment Methodology of In-Service Hydrogen Storage Tanks Based on Connection Coefficient Algorithms and Quintuple Subtraction Set Pair Potential

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Abstract: At present, there have been a number of hydrogen storage tank explosions in hydrogen filling stations, causing casualties and property losses, and having a bad social impact. This has made people realize that the risk assessment and preventive maintenance of hydrogen storage tanks are crucial. Therefore, this paper innovatively proposes a comprehensive risk assessment model based on connection coefficient algorithms and quintuple subtractive set pair potential. First of all, the constructed index system contains five aspects of corrosion factors, material factors, environmental factors, institutional factors and human factors. Secondly, a combined weighting analysis method based on FAHP and CRITIC is proposed to determine the weight of each indicator. The basic indicators influencing hydrogen storage tanks are analyzed via the quintuple subtraction set pair potential and full partial connection coefficient. Finally, the risk level and development trend of hydrogen storage tanks in hydrogen filling stations are determined by a combination of the three-category connection coefficient algorithms and the risk level eigenvalue method. The results of our case analysis show that the proposed risk assessment model can identify the main weak indicators affecting the safety of hydrogen storage tanks, including installation quality, misoperation and material quality. At the same time, it is found that the risk of high-pressure hydrogen storage tanks is at the basic safety level, and the development trend of safety conditions holds a critical value. The evaluation results can help establish targeted countermeasures for the prevention and maintenance of hydrogen storage tanks.

Keywords: connection coefficient; hydrogen storage tank; quintuple subtraction set pair potential; risk assessment; risk level eigenvalue

1. Introduction

According to statistical data of H₂ stations, the number and scale of global hydrogen filling stations will continue to grow, and it is expected that the number of global hydrogen filling stations will exceed 2000 by 2026, as shown in Figure 1 [1]. At the same time, China has also released a series of hydrogen filling station policies in recent years [2]. In particular, in March 2022, the Development and Reform Commission had clearly proposed that a large number of hydrogen filling stations will be deployed before 2025 [3].

The rapid construction and operation of hydrogen filling stations will inevitably produce a series of problems, the most important of which is safety risk. Gaseous hydrogen filling stations are built in large quantities in China. They usually consist of seven systems, among which high-pressure key facilities such as the pressurization system, hydrogen storage system and hydrogen filling system have complicated structures [4,5].

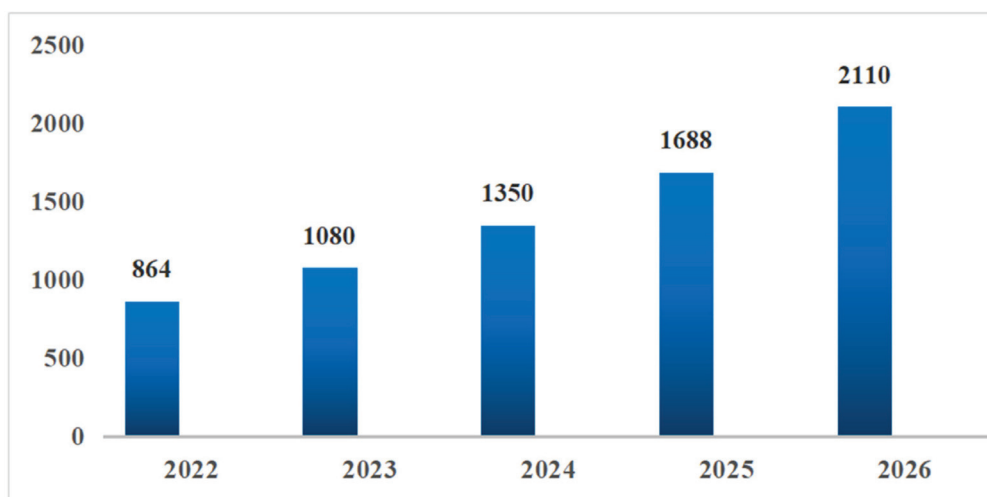


Figure 1. Forecast number of hydrogen filling stations deployed in the world from 2022 to 2026.

According to the statistics of 48 accident cases in hydrogen filling stations and joint construction stations, the accident causes include operation errors or improper maintenance, sealing problems, design problems, etc., as shown in Figure 2 [6].

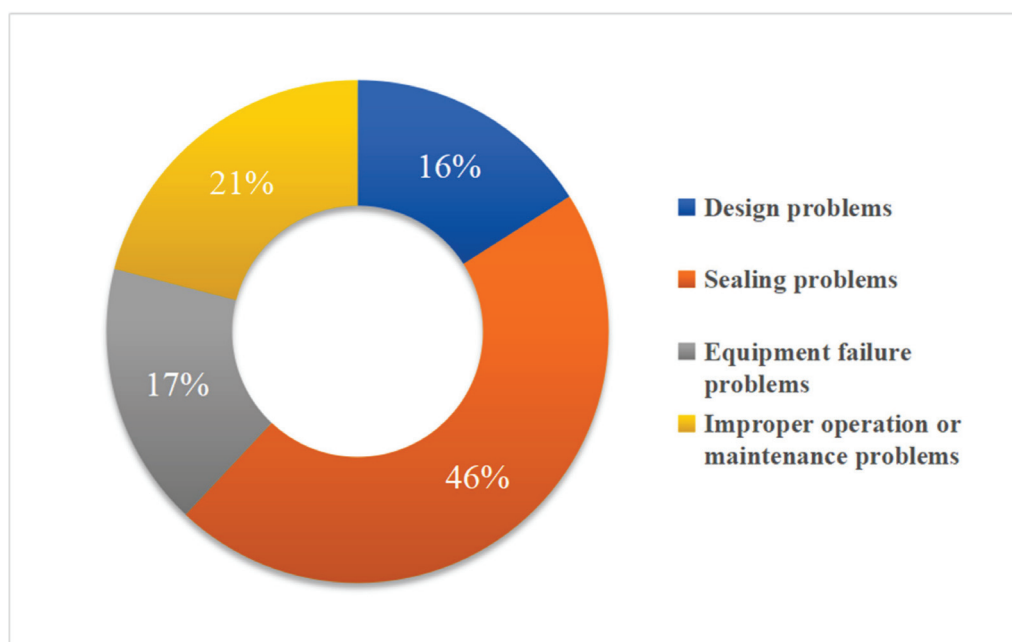


Figure 2. Accident cause statistics of hydrogen filling stations.

The safety of high-pressure hydrogen storage tanks cannot be ignored. If leakage occurs, the amount of leakage will be large, which will lead to more serious consequences than with other equipment [7,8]. In the last five years, the U.S., Norway and South Korea have successively experienced a number of hydrogen explosion accidents, most of which were caused by the failure of high-pressure hydrogen storage devices; the details of the accidents are shown in Table 1 [9–11]. It can be seen that high-pressure hydrogen storage device accidents occur frequently, so it is urgent to conduct hazard identification and risk assessment for high-pressure hydrogen storage devices so as to provide safe technical support for the hydrogen storage device.

Table 1. Typical hydrogen explosion accidents.

Date	Accidents	Cause of Accidents
10 June 2019	Norwegian joint venture hydrogen filling station explosion.	A mistake in the installation of a special structure in the end part of the high-pressure hydrogen storage tank led to a leak of hydrogen gas. It went from a minor leak to a concentrated rapid leak, which in turn led to a fire and explosion in a relatively small space.
1 June 2019	Hydrogen tanker fire in Silicon Valley, USA	As a result of the fire, there was a gas leak from about 5 to 10 hydrogen tanks, which in turn led to an explosion.
23 May 2019	Hydrogen fuel storage tank explosion in South Korea	In the course of performing a hydrogen test by water electrolysis, an operational error caused a massive explosion in a hydrogen tank with a capacity of 400 L.

At present, more and more scholars are focusing on the safety of hydrogen filling stations. Li et al. studied the hazard impact distance of major accidents in hydrogen filling stations [12]. Various types of accident consequences were assumed, including flash fire, jet fire, and cloud explosions in confined spaces. Zhao Wenqing conducted a comparative study of hydrogen filling stations in Asia, Europe, North America and other regions, and developed a risk-based algorithm to determine safe spacing, providing a basis for the scientific and reasonable formulation and revision of the safety spacing [13]. Kikukawa et al. conducted a risk assessment of a 70 MPa hydrogen filling station in Japan, identifying 721 accident scenarios and calculating the consequences such as explosion pressure and jet fire, and the results show that a safety spacing of 6 m is sufficient [14]. In addition, the international standard for risk management in hydrogen storage facilities is ISO 19880 “Risk Assessment and Management of Hydrogen Energy Infrastructure” [15]. ISO 19880 specifies safety recommendations for the risk management of hydrogen refueling stations, mitigation measures to enhance system safety, safe distances for hydrogen exhaust ports and protection measures against non-hydrogen hazards. It defines minimum design, installation, commissioning, operation, inspection and maintenance requirements for the safety of hydrogen refueling stations. It can be seen that this standard is a relevant requirement from the design stage, so it is difficult to grasp the risk status of key facilities in the hydrogen filling station during operation, and it is difficult to put forward targeted risk management and control strategies.

Most of the above studies focus on safe design during the building period, but safety evaluation during the operation period is equally important [16,17]. The development of risk assessment technology for key facilities of hydrogen filling stations in China is still at a preliminary stage, and various risk analysis methods are not systematic enough. To this end, it is necessary to further develop a comprehensive risk assessment methodology and conduct detailed assessments of key facilities, so as to prevent the occurrence of uncontrolled risk factors.

In this study, by taking advantage of the connection coefficient algorithms and quintuple subtraction set pair potential, a comprehensive risk assessment methodology is proposed. Detailed procedures of the proposed methodology and related algorithms are shown in Section 2. In Section 3, a practical application of the proposed integrated risk evaluation methodology for hydrogen filling station is presented. Section 4 presents the conclusions and recommendations of the study.

2. Procedures

The structure of the proposed methodology is shown in Figure 3. The structure includes the construction of the failure risk indicator system, the determination of indicator weights based on the FAHP and CRITIC methods, the analysis of vulnerability and development trends of key risk indicators, and a final risk level eigenvalue judgement.

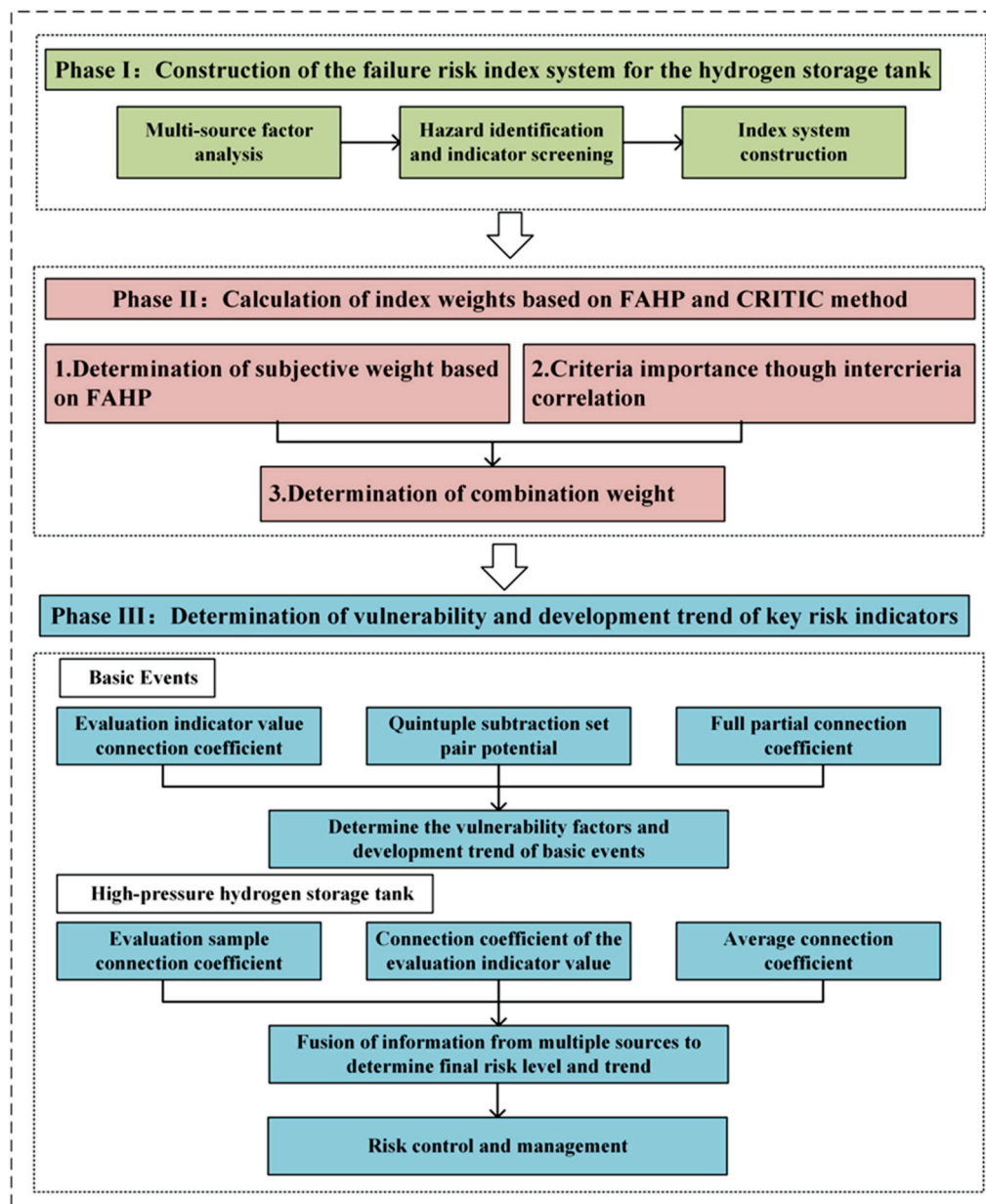


Figure 3. The risk assessment framework based on connection coefficient algorithms and quintuple subtraction set pair potential.

Among them, the failure indicator system is based on the comprehensive analysis of multi-source information factors, hazard identification and indicator screening. The FAHP–CRITIC combined weighting method can comprehensively consider the importance of expert experience and data factors. The quintuple subtraction set pair potential can diagnose the vulnerability indicators in basic events. The full partial connection coefficient can be used to identify trends in each indicator.

The overall risk status of high-pressure hydrogen storage tanks is determined by comprehensively analyzing the risk level eigenvalues and trends of the three types of connection coefficient algorithms for high-pressure hydrogen storage tanks.

2.1. Determination of Index Weight

2.1.1. FAHP

FAHP is a subjective weighting method based on the traditional AHP and fuzzy mathematics theory [18–20]. Different from the traditional AHP method, FAHP needs to

build a fuzzy complementary judgment matrix, obtain a fuzzy consistent matrix through mathematical transformation, and obtain the indicator weight using the row sum normalization method. The n indicator factors $u_1, u_2, u_3, \dots, u_n$ with the same affiliation at the same level are compared, and the importance scale is expressed by 1~9. The judgment matrix established is:

$$X_{n \times n} = (x_{ij})_{n \times n} \quad (1)$$

where x_{ij} is the AHP importance scale of u_i and u_j relative to the upper layer factor, and $x_{ii} = 0.5, x_{ij} = 1 - x_{ji}$.

The elements in the fuzzy complementary judgment matrix are summed by rows, as follows:

$$y_i = \sum_{k=1}^n x_{ik} \quad (2)$$

The fuzzy consistent matrix $Y = (y_{ij})_{n \times n}$ is obtained by mathematical transformation, and the calculation formula is as follows:

$$y_{ij} = \frac{y_i - y_j}{2(n-1)} + 0.5 \quad (3)$$

The elements in the fuzzy consistent matrix are summed by rows and normalized, and the index weight is as follows:

$$W_i = \frac{\sum_{j=1}^n y_{ij}}{\sum_{i=1}^n \sum_{j=1}^n y_{ij}} = \frac{\sum_{j=1}^n x_{ij} + \frac{n}{2} - 1}{n(n-1)} \quad (4)$$

where $i, j = 1, 2, \dots, n$.

The n -order eigenvalue matrix W^* is constructed using the weight vector, and the consistency indicator of the fuzzy judgment matrix and its eigenvalue matrix is used to test its consistency. The conditions to satisfy the consistency test are as follows:

$$W^* = \frac{W_i}{W_i + W_j} \quad (5)$$

$$I(A, W^*) = \frac{\sum_{i=1}^n \sum_{j=1}^n |x_{ij} + W_{ij}^* - 1|}{n^2} \leq \alpha \quad (6)$$

where, when $I(A, W) \leq 1$, the judgment matrix has consistency, or else it needs to be reconstructed.

2.1.2. FAHP

CRITIC is an objective weighting method that uses the objective properties of the data for scientific evaluation [21,22]. It is a better method than the entropy weight method [23,24]. At present, the CRITIC method is widely used in risk assessment, and the method has certain advantages over the objective weighting method. The specific calculation steps are as follows.

Step 1: Contrast strength.

The contrast strength is expressed as the difference between samples within an indicator. The greater the contrast strength, the greater the corresponding weights. The contrast strength formula of the indicator is:

$$S_j = \sqrt{\frac{\sum_{i=1}^p \left(x_{ij} - \frac{1}{n} \sum_{i=1}^n x_{ij} \right)^2}{n-1}} \quad (7)$$

where x_{ij} is data after standardization, S_j represents the contrast strength of the j th index, n is the number of samples, and p is total number of indicators.

Step 2: Relevance.

The stronger the relevance between an indicator and other indicators, the smaller the conflict and the more the information is repeated. The formula for the relevance coefficient is:

$$R_j = \sum_{i=1}^p (1 - r_{ij}) \quad (8)$$

where R_j is the relevance coefficient between the j th indicator and other indicators, and r_{ij} represents the relevance coefficient between the i th indicator and the j th indicator.

Step 3: Objective weight determination.

The objective weight formula is:

$$W_{2j} = \frac{S_j \times R_j}{\sum_{j=1}^p S_j \times R_j} \quad (9)$$

where W_{2j} is the objective weight of the j th indicator.

2.1.3. Combination Weighting Method Based on FAHP and CRITIC

The AHP and CRITIC are both widely used weight analysis methods [25]. Among them, AHP relies too much on expert experience to score, and so it is more subjective. CRITIC is free from the constraint of subjectivity, but ignores the importance of indicator factors. In order to reasonably determine the indicator weights of hydrogen storage tank failure risk evaluation, this paper invokes combination assignment thinking to determine the index weights. It combines the advantages of a subjective weight method and objective weight method, taking into account both expert experience in indicator weights and actual objective data. Compared with traditional AHP weighting methods, it can better reflect the true weight values of various indicators.

To this end, it is necessary to determine the ratio of subjective weight and objective weight, so that the comprehensive weight can better reflect the importance difference between multiple evaluation indicators. W_1 is the weight obtained according to the FAHP, and W_2 is the weight obtained according to the CRITIC. The linear combination W of the two weighting methods is:

$$W = \alpha W_1 + \beta W_2 \quad (10)$$

In the above formula, α and β represent the weight distribution coefficients. In order to find the best comprehensive weight vector, it is necessary to find the optimal weight distribution coefficient to minimize the standard deviation between W and the two groups of weight vectors, namely:

$$x_i = \alpha_i w_{1i} + \beta_i w_{2i} \quad (11)$$

$$\delta = \sqrt{\frac{\sum_{i=1}^j \left(x_i - \frac{\sum_{i=1}^j x_i}{j} \right)^2}{j}} \quad (12)$$

where $j = \max(i)$, $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$, $\alpha + \beta = 1$.

2.2. Connection Coefficient Algorithms Based on Set Pair Analysis Method

The set pair analysis method was first constructed by Zhao Keqin [26,27]. The general form of the evaluation sample connection coefficient, the evaluation indicator value connection coefficient and the average connection coefficient is:

$$u = a + bI + cJ \quad (13)$$

where a is the same parameter, b is the difference parameter, and c is the opposing parameter, $a, b, c \in [0, 1]$, and $a + b + c = 1$. I is the difference parameter coefficient, the value range of which is $[-1, 1]$; sometimes it only serves as a difference marker. J is the opposite parameter coefficient, which is defined as -1 and sometimes only serves as a sign of opposites.

2.2.1. Evaluation Sample Connection Coefficient

The evaluation sample connection coefficient is obtained according to the index number of each index value for the evaluation sample in the k-level evaluation grade [28,29]. The calculation formula of the evaluation sample connection coefficient is as follows:

$$u_{1i} = v_{1i0} + v_{1i1}I_1 + v_{1i2}I_2 + v_{1i3}I_3 + v_{1i4}J \quad (14)$$

$$v_{1i0} = \sum_{j=1}^{n_1} w_j, \quad v_{1i1} = \sum_{j=n_1+1}^{n_1+n_2} w_j, \quad v_{1i2} = \sum_{j=n_1+n_2+1}^{n_1+n_2+n_3} w_j, \quad v_{1i3} = \sum_{j=n_1+n_2+n_3+1}^{n_1+n_2+n_3+n_4} w_j, \quad v_{1i4} = \sum_{j=n_1+n_2+n_3+n_4+1}^{n_1+n_2+n_3+n_4+n_5} w_j \quad (15)$$

where u_{1i} is evaluation sample connection coefficient of sample i . I_1 , I_2 and I_3 are difference parameter coefficients. J is the opposite parameter coefficient. v_{1ik} is the connection coefficient component of u_{1ik} . w_j is the weight of the j th indicator. In addition, n_1 , n_2 , n_3 , n_4 , and n_5 are the number of indexes in which sample i falls into each evaluation level, respectively.

2.2.2. Connection Coefficient of the Evaluation Indicator Value

Based on the proximity of the sample value x_{ij} of indicator j in the evaluation sample i to the level of the evaluation criteria, the connectivity coefficient for the value of the evaluation indicator can be calculated [30].

When the positive index $s_{0j} < x_{ij} \leq s_{1j}$ or the reverse index $s_{0j} > x_{ij} \geq s_{1j}$,

$$\begin{cases} u_{2ij0} = 1 \\ u_{2ij1} = 1 - 2 \frac{(s_{1j} - x_{ij})}{(s_{1j} - s_{0j})} \\ u_{2ij2} = -1 \\ u_{2ij3} = -1 \\ u_{2ij4} = -1 \end{cases} \quad (16)$$

When the positive index $s_{1j} < x_{ij} \leq s_{2j}$ or the reverse index $s_{1j} > x_{ij} \geq s_{2j}$,

$$\begin{cases} u_{2ij0} = 1 - 2 \frac{(x_{ij} - s_{1j})}{(s_{2j} - s_{1j})} \\ u_{2ij1} = 1 \\ u_{2ij2} = 1 - 2 \frac{(s_{2j} - x_{ij})}{(s_{2j} - s_{1j})} \\ u_{2ij3} = -1 \\ u_{2ij4} = -1 \end{cases} \quad (17)$$

When the positive index $s_{2j} < x_{ij} \leq s_{3j}$ or the reverse index $s_{2j} > x_{ij} \geq s_{3j}$,

$$\begin{cases} u_{2ij0} = -1 \\ u_{2ij1} = 1 - 2 \frac{(x_{ij} - s_{2j})}{(s_{3j} - s_{2j})} \\ u_{2ij2} = 1 \\ u_{2ij3} = 1 - 2 \frac{(s_{3j} - x_{ij})}{(s_{3j} - s_{2j})} \\ u_{2ij4} = -1 \end{cases} \quad (18)$$

When the positive index $s_{3j} < x_{ij} \leq s_{4j}$ or the reverse index $s_{3j} > x_{ij} \geq s_{4j}$,

$$\begin{cases} u_{2ij0} = -1 \\ u_{2ij1} = -1 \\ u_{2ij2} = 1 - 2 \frac{(x_{ij} - s_{3j})}{(s_{4j} - s_{3j})} \\ u_{2ij3} = 1 \\ u_{2ij4} = 1 - 2 \frac{(s_{4j} - x_{ij})}{(s_{4j} - s_{3j})} \end{cases} \quad (19)$$

When the positive index $s_{4j} < x_{ij} \leq s_{5j}$ or the reverse index $s_{4j} > x_{ij} \geq s_{5j}$,

$$\begin{cases} u_{2ij0} = -1 \\ u_{2ij1} = -1 \\ u_{2ij2} = -1 \\ u_{2ij3} = 1 - 2 \frac{(x_{ij} - s_{4j})}{(s_{5j} - s_{4j})} \\ u_{2ij4} = 1 \end{cases} \quad (20)$$

In the above formula, the positive index indicates that the value of the index increases with the increase in the evaluation criterion level k and the negative index indicates that the value of the index decreases with the increase in the evaluation criterion level k . For positive indicators, $(s_{0j}, s_{1j}]$, $(s_{1j}, s_{2j}]$, $(s_{2j}, s_{3j}]$, $(s_{3j}, s_{4j}]$, and $(s_{4j}, s_{5j}]$ are thresholds of levels 0, 1, 2, 3, and 4, respectively.

The connection coefficient can be used as a means of evaluating the proximity between the sample value x_{ij} and the rating of the evaluation criteria s_{kj} . The variable fuzzy relationship is a relative difference function and the corresponding relative membership v_{2ijk}^* is:

$$v_{2ijk}^* = 0.5 + 0.5u_{2ijk} \quad (21)$$

After normalization, we can derive the connection coefficient component v_{2ijk} of the evaluation index value, as shown in the following formula:

$$v_{2ijk} = v_{2ijk}^* / \sum_{k=0}^4 v_{2ijk}^* \quad (22)$$

Then, the connection coefficient of the evaluation index value is:

$$u_{2ij} = v_{2ij0} + v_{2ij1}I_1 + v_{2ij2}I_2 + v_{2ij3}I_3 + v_{2ij4}I_4 \quad (23)$$

Therefore, the connection coefficient of the evaluation index value for hydrogen storage tank assessment sample i can be obtained, as follows:

$$u_{2i} = v_{2i0} + v_{2i1}I_1 + v_{2i2}I_2 + v_{2i3}I_3 + v_{2i4}I_4 = \sum_{j=1}^{n_j} w_j v_{2ij0} + \sum_{j=1}^{n_j} w_j v_{2ij1}I_1 + \sum_{j=1}^{n_j} w_j v_{2ij2}I_2 + \sum_{j=1}^{n_j} w_j v_{2ij3}I_3 + \sum_{j=1}^{n_j} w_j v_{2ij4}I_4 \quad (24)$$

2.2.3. Average Connection Coefficient of the Evaluation Sample

The average connection coefficient of the evaluation sample is:

$$v_{ik} = (v_{1ik}v_{2ik})^{0.5} / \sum_{k=0}^4 (v_{1ik}v_{2ik})^{0.5} \quad (25)$$

$$u_i = v_{i0} + v_{i1}I_1 + v_{i2}I_2 + v_{i3}I_3 + v_{i4}I_4 \quad (26)$$

The evaluation sample connection coefficient and the evaluation indicator value connection coefficient reflect the degree of correlation between the evaluation sample and the level of the evaluation criteria at the macro level and micro level, respectively, and the

connection coefficients obtained by the two types are consistent in terms of the overall trend and distribution [31].

The indicator value connection coefficient is obtained by fuzzy matching using the continuous proximity information between the indicator value of the evaluation sample and the level of the evaluation standard, and its distribution is more uniform than the connection coefficient of the index number based on the discrete value. In order to further optimize the reasonable distribution of connection coefficients and deeply analyze the correlation degree between evaluation samples and evaluation standard grades, the principle of minimum relative entropy is applied to couple the two kinds of connection coefficients.

2.2.4. Full Partial Connection Coefficient

The concept of a partial connectivity coefficient is based on set pair analysis [32,33]. The full partial connection coefficient $p_f(u)$ essentially describes the relatively determined development trend represented by the connection coefficient at the micro level, so it can be defined as:

$$p_f(u) = \partial u^+ - \partial u^- = \left[\frac{a}{a+b} + \frac{b}{b+c} I_1 \right] - \left[\frac{b}{a+b} + \frac{c}{b+c} I_2 \right] \quad (27)$$

where I_1 and I_2 are the difference coefficients of partially positive and partially negative connection coefficients, respectively. The value interval is $[-1, 1]$, which can be generally determined by the ratio value method.

When the full partial connection coefficient $p_f(u)$ is greater than zero, equal to zero or less than zero, the trend of the micro-level development expressed in terms of the connection coefficient can be diagnosed as positive development trend, critical trend or negative development trend, respectively. The indicator of negative development trend is the main factor causing the weakness of hydrogen storage tank.

2.3. Risk Level Eigenvalue Method

The risk level eigenvalue method can be used to calculate the risk level of the evaluation sample's connection coefficient, the evaluation indicator value's connection coefficient and the average connection coefficient [34]. The calculation formula of risk level evaluation based on the level eigenvalue method is as follows:

$$h_1(i) = \sum_{k=1}^5 v_{1ik} k \quad (28)$$

$$h_2(i) = \sum_{k=1}^5 v_{2ik} k \quad (29)$$

$$h(i) = \sum_{k=1}^5 v_{ik} k \quad (30)$$

2.4. Set Pair Potential

2.4.1. Division Set Pair Potential

The division set pair potential is calculated as follows:

$$s_{f1}(u) = a/c \quad (31)$$

When c is small, the division set pair potentials tend to be unstable [35]. For example, the connection coefficients $6 + 0.06I + 0.2J$ and $6 + 0.06I + 0.02J$ have little difference, but their division set pair potential $s_{f1}(u)$ values are 30 and 300, respectively, which contain very obvious differences [36]. Moreover, the division set pair potential undergoes a large range of changes, so it is not easy to classify. Therefore, it is necessary to carefully analyze and apply the division set pair potential.

2.4.2. Quintuple Subtraction Set Pair Potential

The calculation formula for quintuple subtraction set pair potential is as follows:

$$s_{f2}(u) = (a - c)(1 + b_1 + b_2 + b_3) + 0.5(b_1 - b_3)(b_1 + b_2 + b_3) \quad (32)$$

The above formula is obtained from the set pair potential formula of ternary subtraction through empirical correction via practical applications [37,38]. Obviously, $s_{f2}(u) \in [-1, 1]$. The numeric size between the subtraction set pair potentials can be compared directly based on the $s_{f2}(u)$, which greatly simplifies the tedious work of determining the order of the set pair potentials.

The subtraction set pair potential $s_f(u)$ is divided into five potential levels, among which the reverse potential $s_{f2}(u) \in [-1.0, -0.6]$, partial reverse potential $s_{f2}(u) \in [-0.6, -0.2]$, equipotential $s_{f2}(u) \in [-0.2, 0.2]$, partial same potential $s_{f2}(u) \in [0.2, 0.6]$, and same potential $s_{f2}(u) \in [0.6, 1]$. Similarly, when $s_{f2}(u) \in [-1.0, -0.2]$, the indicator is the main factor leading to the poor grade of the evaluation object, and so it can be identified as a vulnerability indicator. Therefore, the vulnerability indicator that can be identified for hydrogen storage tank failure should be improved.

3. Application of the Proposed Methodology in the Hydrogen Filling Station

In order to verify the practicability and accuracy of the proposed risk assessment methodology, this paper takes a hydrogen filling station in China as an example for in-depth analysis. The hydrogen filling station covers an area of 880 square meters, and the maximum storage capacity in the station is 800 kg. The distribution of the equipment in the hydrogen filling station is shown in Figure 4.

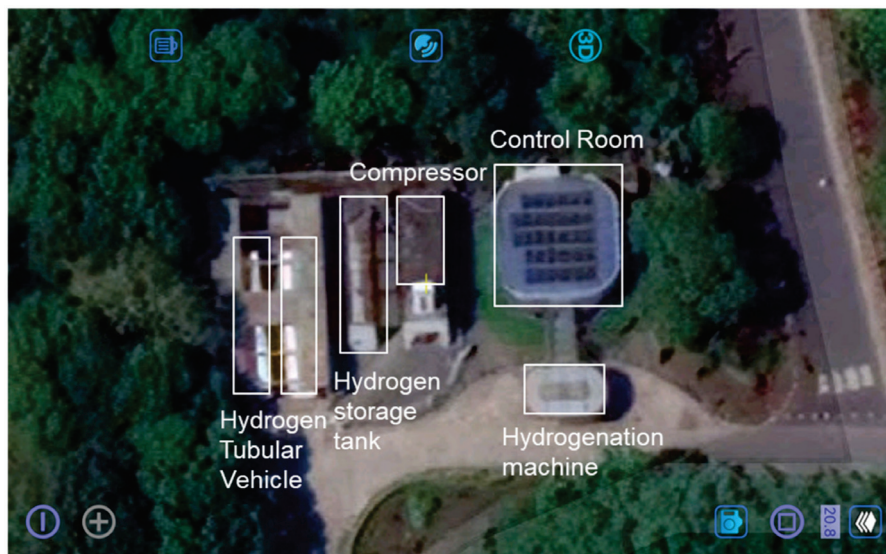


Figure 4. Equipment distribution map in the hydrogen filling station.

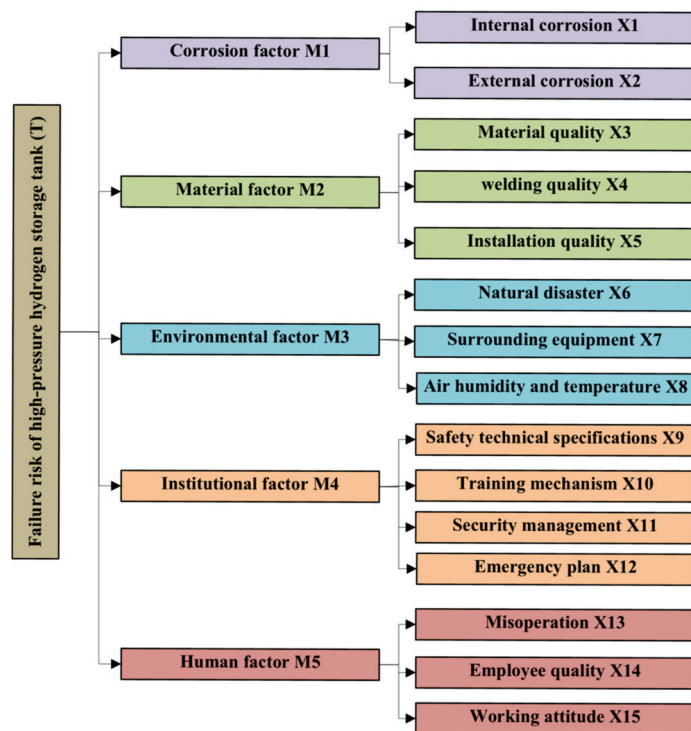
Hydrogen is transported into the station from the hydrogen source end by a hydrogen bundle truck, compressed to 45 MPa (high) pressure by a hydrogen compressor and stored in a 45 MPa hydrogen storage tank. A two-gun hydrogen filling machine at the filling island can fill hydrogen into cars and buses with a filling pressure of 35 MPa; the specific equipment details are shown in Table 2. Since the hydrogen filling station has been in safe operation for 16 years, much of its equipment may be aging, so it is necessary to carry out risk assessment on some key equipment.

Table 2. Specific equipment details.

Equipment Name	Quantity	Remarks
Hydrogen Tubular Vehicle	8	The volume is 2.3 m ³ , and the hydrogen pressure can not exceed 20 MPa.
45 MPa hydrogen storage tank	9	It consists of 9 interconnected cylindrical pressure vessels, each of which has a volume of 0.77 m ³ .
Compressor	2	There are two compressors in total, one of which is a backup.
35 MPa hydrogen double-shot hydrogenation machine	1	The maximum pressure to refill the car is 35 MPa.

3.1. Construction of the Failure Risk Index System for the Hydrogen Storage Tank in a Hydrogen Filling Station

Due to the special geographical location, natural environment and special nature of the hydrogen filling station, the index system that affects the safe operation of the hydrogen storage tank should be established first. The indicators were screened according to the principles of specificity, representativeness and practicability of the objectives. Combined with relevant accident cases, experts experience and a large number of studies, the indicators were further screened. Based on multi-source data, a safe operation index system of a high-pressure hydrogen storage tank in the hydrogen filling station has been established, with five aspects: corrosion factor, material factor, environmental factor, system factor and human factor, as shown in Figure 5.

**Figure 5.** Failure risk assessment index system of a hydrogen storage tank in a hydrogen filling station.

3.2. Calculation of Index Weights Based on FAHP and CRITIC Method

Step 1: Determination of subjective weight based on FAHP.

The secondary indicators fuzzy complementary judgment matrix is constructed as follows:

$$A = \begin{bmatrix} 0.5 & 0.1 & 0.4 & 0.3 & 0.2 \\ 0.9 & 0.5 & 0.7 & 0.7 & 0.6 \\ 0.6 & 0.3 & 0.5 & 0.4 & 0.3 \\ 0.7 & 0.3 & 0.6 & 0.5 & 0.4 \\ 0.8 & 0.4 & 0.7 & 0.6 & 0.5 \end{bmatrix}$$

The weight of the fuzzy judgment matrix A is obtained through row summation, transformation and normalization. The weight of the fuzzy judgment matrix is as follows:

$$W_1 = (0.15, \quad 0.245, \quad 0.18, \quad 0.2, \quad 0.225)^T$$

In order to test whether the weight of the fuzzy judgment matrix is reliable, a consistency test of the fuzzy judgment matrix is required. The n -order eigenvalue matrix W^* of the fuzzy judgment matrix is constructed using the weight vector, as follows:

$$W^* = \begin{bmatrix} 0.50 & 0.38 & 0.45 & 0.43 & 0.40 \\ 0.62 & 0.50 & 0.58 & 0.55 & 0.52 \\ 0.55 & 0.42 & 0.50 & 0.47 & 0.44 \\ 0.57 & 0.45 & 0.53 & 0.50 & 0.47 \\ 0.60 & 0.48 & 0.56 & 0.53 & 0.50 \end{bmatrix}$$

After the consistency check, $I(A, W) = 0.10 \leq 0.1$. This shows that the weight value meets the consistency requirement of the fuzzy judgment matrix.

Step 2: Determination of objective weight based on CRITIC

Five experts in hydrogen energy-related fields were invited to score the five secondary indicators $M_1 \sim M_5$ respectively, and MATLAB R2018b software was used to calculate the standard deviation corresponding to the contrast strength and the correlation coefficient corresponding to the correlation, so as to obtain the final objective weight. The calculation results are shown in Table 3.

Table 3. Scoring of secondary indicators by 5 experts.

Secondary Indicators	Expert A	Expert B	Expert C	Expert D	Expert E	Standard Deviation	Correlation Coefficient	Index Weight W_2
M_1	7.8	8.6	7.9	8.4	7.3	0.46	5.84	0.38
M_2	9.2	9.5	9.4	9.8	9.6	0.20	3.65	0.10
M_3	7.2	7.9	8.3	7.1	8.4	0.54	3.15	0.24
M_4	8.5	8.4	8.9	8.1	9.2	0.39	3.5	0.20
M_5	9.1	9.0	9.2	9.2	9.5	0.17	3.24	0.08

Step 3: Determination of combination weight.

The combination weighting method can better reflect the importance difference between multiple evaluation indicators. According to the calculation methods of Formula (10)–(12) and W_1 and W_2 obtained in the first two steps, the following is obtained:

$$W = \alpha W_1 + \beta W_2 \\ = (-0.23\alpha + 0.38 \quad 0.145\alpha + 0.10 \quad -0.06\alpha + 0.24 \quad 0.2 \quad 0.145\alpha + 0.08)$$

In order to obtain the minimum standard deviation of W , this paper uses the enumeration method to solve it, and obtains the minimum standard deviation when the subjective weight proportion is 0.76, as shown in Figure 6.

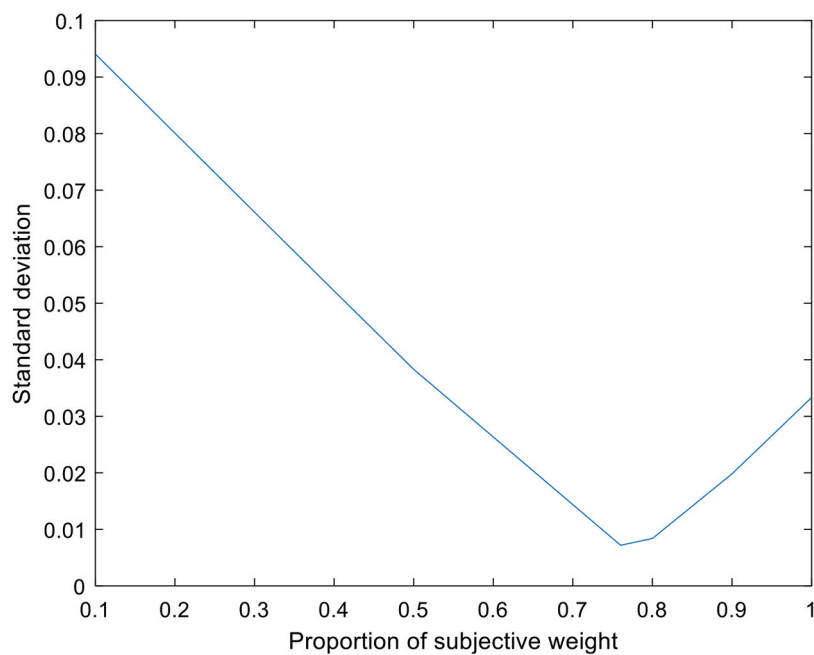


Figure 6. Enumeration calculation of the minimum standard deviation of secondary indicators.

Therefore, the comprehensive weight W is:

$$\begin{aligned}
 W &= 0.76W_1 + 0.24W_2 \\
 &= (0.21 \quad 0.21 \quad 0.19 \quad 0.20 \quad 0.19)
 \end{aligned} \tag{33}$$

The weight calculation results show that for the second-level indicators $M_1 \sim M_5$, M_1 and M_2 have the largest weights, and the weights of other indicators in descending order are M_4 , M_3 and M_5 . Similarly, according to the above method of calculating combination weights, the calculation results of basic event weights are shown in Table 4.

Table 4. Scoring of third indicators by 5 experts.

Basic Event	Subjective Weight W_1	Objective Weight W_2	Relative Comprehensive Weight W_3	Comprehensive Weight W
X1	0.4	0.31	0.4	0.15
X2	0.6	0.69	0.6	0.23
X3	0.42	0.38	0.41	0.04
X4	0.25	0.55	0.31	0.03
X5	0.33	0.07	0.28	0.03
X6	0.43	0.29	0.36	0.09
X7	0.35	0.46	0.41	0.10
X8	0.22	0.24	0.23	0.05
X9	0.3	0.19	0.29	0.06
X10	0.24	0.17	0.23	0.05
X11	0.23	0.48	0.26	0.05
X12	0.23	0.16	0.22	0.04
X13	0.47	0.11	0.38	0.03
X14	0.28	0.61	0.36	0.03
X15	0.25	0.28	0.26	0.02

3.3. Determination of Vulnerability and Development Trend of Key Risk Indicators

According to the actual situation of the site and expert experience, the evaluation indicators can be divided into five levels, namely, safe, relatively safe, basically safe, relatively dangerous and dangerous. The specific division scope of each grade is shown in Table 5.

Table 5. Risk level classification.

Risk Level	Safe	Relatively Safe	Basically Safe	Relatively Dangerous	Dangerous
Risk value	1	2	3	4	5

Five teams of professors in the fields of corrosion, materials, environment, business management and human–computer interaction were invited to score the relevant indicators. We substituted the expert evaluation data of the index into Formulae (16)–(24) to obtain the connection coefficient of the evaluation indicator value, then calculated the full partial connection coefficient from Formula (27), and finally calculated the subtraction set pair potential according to Formula (35). The specific calculation results are shown in Table 6. As shown in Table 6, the basic events X1, X3, X5, X6, X8, X9, X12 and X13 are in the opposite direction, which gives the vulnerability index of the high-pressure hydrogen storage tank in the hydrogen filling station. This is the main prevention and control object related to safety management to ensure that the risk level is controlled within an acceptable level.

Table 6. Connection coefficient of each assessment sample for basic events of hydrogen storage tank failure risk.

Basic Events	Evaluation Indicator Value Connection Coefficient	Quintuple Subtraction Set Pair Potential	Full Partial Connection Coefficient
X1	$0 + 0I_1 + 0I_2 + 0.43I_3 + 0.57J$	−0.91	−0.93
X2	$0 + 0.35I_1 + 0.5I_2 + 0.15I_3 + 0J$	0.1	0
X3	$0 + 0I_1 + 0I_2 + 0.39I_3 + 0.61J$	−0.92	−0.99
X4	$0 + 0.01I_1 + 0.5I_2 + 0.49I_3 + 0J$	−0.24	0
X5	$0 + 0I_1 + 0I_2 + 0.29I_3 + 0.71J$	−0.96	−1.13
X6	$0 + 0I_1 + 0I_2 + 0.45I_3 + 0.55J$	−0.90	−0.98
X7	$0 + 0.03I_1 + 0.5I_2 + 0.47I_3 + 0J$	−0.22	0
X8	$0 + 0I_1 + 0.19I_2 + 0.5I_3 + 0.31J$	−0.70	−0.55
X9	$0 + 0I_1 + 0I_2 + 0.4I_3 + 0.6J$	−0.92	−0.98
X10	$0 + 0I_1 + 0.31I_2 + 0.5I_3 + 0.19J$	−0.55	−0.35
X11	$0 + 0I_1 + 0.43I_2 + 0.5I_3 + 0.07J$	−0.37	−0.14
X12	$0 + 0I_1 + 0.02I_2 + 0.5I_3 + 0.48J$	−0.86	−0.80
X13	$0 + 0I_1 + 0I_2 + 0.37I_3 + 0.63J$	−0.93	−1.02
X14	$0 + 0.03I_1 + 0.5I_2 + 0.47I_3 + 0J$	−0.22	0
X15	$0 + 0.22I_1 + 0.5I_2 + 0.28I_3 + 0J$	−0.03	0

At the same time, it can be found that the full partial connection coefficient and the subtraction set pair potential of the basic event have a high degree of similarity in Figure 7. The main reason is that both can describe the uncertain state and development trend of indicators to a certain extent. Among them, the subtraction set pair potential focuses on identifying the uncertain state of each basic event, thereby identifying the vulnerable indicators. The full partial connection coefficient focuses on describing the development trend of each basic event.

Therefore, based on the identification of X1, X3, X5, X6, X8, X9, X12, and X13 vulnerability indicators, it can be found that the full partial correlation coefficients of vulnerability indicators are all less than 0, indicating a negative development trend. The sequence of negative development trends can be ranked as $X5 > X13 > X3 > X6 = X9 > X1 > X12 > X8$. Priority control should be given to installation quality, misoperation, material quality, natural disasters, internal corrosion, emergency planning, and air humidity and temperature, in order of priority.

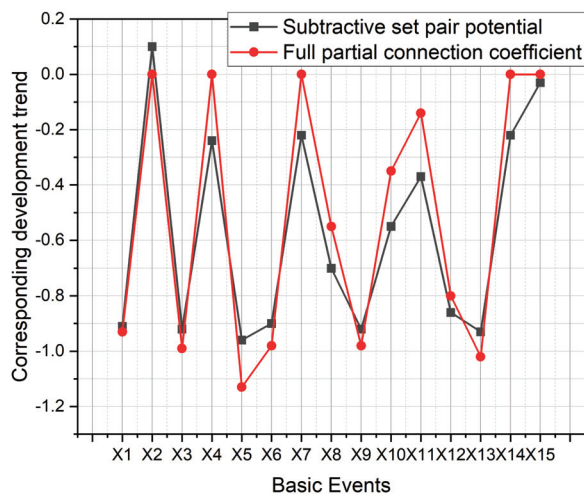


Figure 7. Subtraction set pair potential and full partial connection coefficient corresponding to each basic event.

3.4. Determination of Risk Level and Development Trend of High-Pressure Hydrogen Storage Tank

Based on the data in Table 7 and the index weights in Table 4, the final connection coefficient of the evaluation index number is obtained using Formulae (14) and (15). Then, the final connection of the evaluation index value can be obtained from Formulae (16)–(24), and we can obtain the final average connection coefficient of the evaluation sample from Formulae (25) and (26). Finally, we can determine the final risk level and development trend of a high-pressure hydrogen storage tank.

Table 7. Assessment results of failure risk for a high-pressure hydrogen storage tank.

Connection Coefficient	Connection Coefficient Value	Evaluation Grade	Subtractive Set Pair Potential	Full Partial Connection Coefficient
Evaluation sample connection coefficient	$0.4 + 0.14I_1 + 0.46I_2 + 0I_3 + 0J$	2.06	0.68	0.69
Connection coefficient of the evaluation indicator value	$0 + 0.09I_1 + 0.25I_2 + 0.38I_3 + 0.28J$	3.85	−0.59	−0.50
Average connection coefficient	$0 + 0.25I_1 + 0.75I_2 + 0I_3 + 0J$	2.75	0.13	0

According to the comprehensive analysis of the three connection coefficients, the risk level of the high-pressure hydrogen storage tank is close to Level 3, which means it is basically safe. The subtraction set pair potential approaches 0.1 and is in equilibrium, indicating that the high-pressure hydrogen storage tank has a certain safety bearing capacity. The full partial connection coefficient approaches 0, indicating that the safety situation of high-pressure hydrogen storage tanks is undergoing a critical development trend.

Based on the above analysis results, it can be seen that the high-pressure hydrogen storage tank of the hydrogen filling station is at a medium risk level, and the risk development trend is in a critical state, as shown in Table 7. It is necessary to strengthen control over weak indicators X1, X3, X5, X6, X8, X9, X12, and X13. After our investigation, we find the risk status of high-pressure hydrogen storage tanks is consistent with the actual situation on site, which confirms the effectiveness and practicality of the proposed method.

4. Conclusions

In order to establish a highly applicable risk assessment method for high-pressure hydrogen storage tanks in hydrogen filling stations, this paper proposes a comprehensive risk assessment methodology based on connection coefficient algorithms and quintuple subtraction set pair potential. The methodology mainly includes the FAHP–CRITIC combined weighting method, quintuple subtraction set pair potential, the full partial coefficient method and the risk level eigenvalue method.

The FAHP–CRITIC combined weighting method is a good method that can comprehensively consider the subjective experience and objective data, so it can effectively avoid the uncertainty caused by a single-type weighting method. In order to effectively deal with the uncertainty between evaluation indicators and evaluation criteria, a quintuple subtraction set pair potential algorithm is proposed, and it is used to identify the uncertainty state of each indicator of a high-pressure hydrogen storage tank. At the same time, the full partial connection coefficient can identify the development trend of each indicator.

The usability and validity of the methodology proposed in this study were verified through a case study on the risk encountered by high-pressure hydrogen storage tanks. The results show that the risk level of a high-pressure hydrogen storage tank in the hydrogen filling station is grade 3, the subtraction set pair potential approaches 0.1, and the full partial connection coefficient approaches 0. By comparing the result with the actual situation, we found that the result was consistent with the actual situation on site.

Compared with traditional risk assessment methods, the proposed risk assessment method not only identifies the risk level and weak indicators of the target, but also determines the development trend of each weak indicator. The risk assessment results are more accurate and specific, which can provide direction to guide site managers in risk control.

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Article

Charging and Discharging Optimization of Vehicle Battery Efficiency for Minimizing Company Expenses Considering Regular User Travel Habits

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Abstract: With the increasing popularity and development of electric vehicles, the demand for electric vehicle charging is also constantly increasing. To meet the diverse charging needs of electric vehicle users and improve the efficiency of charging infrastructure, this study proposes an optimization strategy for electric vehicle charging and discharging. This method considers both the user's travel mode and the operational efficiency of the charging pile. Firstly, a probability model based on travel spatiotemporal variables and Monte Carlo algorithm were used to simulate the travel trajectory of electric vehicles, providing a data foundation for optimizing the charging and discharging schemes of electric vehicles. Then, with the dual objective of minimizing the operating costs of charging piles and user charging costs, a linear programming model was constructed to optimize the charging and discharging strategies of electric vehicles. Finally, the model was validated using an apartment building as an example. The results indicate that, under the normal travel habits of users, with the goal of minimizing company expenses, the annual cost of the company reaches its minimum at a certain number of charging piles. When the cost of electric vehicle users dominates the objective function, they will pay more attention to battery degradation, significantly reducing their willingness to participate in discharge.

Keywords: charging and discharging strategy; enterprise electric vehicles; Monte Carlo simulation; user travel habit

1. Introduction

As the use of fossil fuels continues to rise, issues like environmental pollution and energy crises are increasingly emerging [1,2]. Against this backdrop, electric vehicles (EVs), as eco-friendly and low-carbon modes of transportation, have become significant alternatives to traditional fuel vehicles and a viable solution to alleviate the energy crisis [3–6]. EVs commonly utilize various types of batteries, including lead acid batteries, nickel hydrogen batteries, and lithium-ion batteries [7]. Additionally, the batteries in EVs can serve as distributed energy storage devices, helping to stabilize renewable energy generation, participate in electricity market auxiliary services, or manage demand-side electricity needs. Consequently, the development of the EV industry has become a global consensus for low-carbon development [8]. According to global forecasts, by 2040, the number of EVs worldwide is expected to increase from 3 million to 66 million [9]. Many EU countries use fiscal incentives to promote EVs to help cities decarbonize. At the same time, Germany has formulated some policy measures to promote EVs, for example, purchasing bonuses and tax incentives for EVs to support the replacement of traditional internal combustion engine vehicles [10,11].

However, with the widespread adoption of EVs, the inadequacy of public charging infrastructure and the uneven distribution of charging piles have become new challenges. Particularly for companies, communities, and schools, establishing a parking lot capable of powering EVs not only meets the changing needs of EV users but also leverages the energy storage potential of EV fleets during prolonged parking. With the support of bi-directional charging technology and in the context of real-time electricity pricing markets, the flexible load characteristics of EV charging and discharging can help operators in the electric grid to shave peak and fill valley demands, while also economically benefiting both operators and EV users. However, as a novel type of load, EV charging behavior is characterized by its randomness and intermittency. The large-scale integration of EVs into the grid presents significant load challenges. Disorganized charging of EVs can result in reduced charging efficiency and underutilization of charging piles, thereby compromising the safety, efficiency, and overall charging experience for EV users. Consequently, the pressing challenge lies in devising an effective scheduling approach for EV charging within the charging piles.

Many scholars have also conducted extensive research on the simulation of EV travel. These simulation methods include Monte Carlo simulation, Markov chain simulation, multi-agent reinforcement learning, etc. Liu and Lin [12] analyzed the uncertainty of market penetration of EVs by integrating nested polynomial logit and Monte Carlo simulation. Wang and Infield [13] simulated the usage patterns of EVs based on Markov chain Monte Carlo simulation, and analyzed the impact of EV charging on the power grid based on the usage patterns. This method can model the travel patterns of EVs based on uncertain travel data, while generating accurate travel patterns. Afshar et al. [14] simulated EV charging based on traffic flow analysis and Monte Carlo methods. The model can accurately calculate the charging needs of EVs in different time and space. Fu et al. [15] introduced a charging scheduling control strategy for EVs, leveraging multi-agent reinforcement learning. This method can improve the charging efficiency of EV charging piles while reducing the cost of EV charging. However, multi-agent reinforcement learning methods can simultaneously consider multiple objectives and avoid extreme biases on certain objectives. Simultaneously, it can handle intricate constraints while dynamically adjusting strategies based on diverse goals and limitations. However, in multi-agent systems, due to the constantly updating strategies of each agent, the environment in which each agent operates is unstable. This undermines the conditions for modeling the system as a Markov process, making it difficult for the method of independently training each agent to converge in complex scenarios [16]. Monte Carlo simulation can handle various complex mathematical models and uncertainty factors. This method is based on many random samplings, and through multiple simulation experiments, the probability distribution of EV travel and charging can be obtained, which can provide reliable results. The Monte Carlo method can improve computational efficiency through techniques such as parallel computing, making the simulation of EV travel and charging faster and more efficient. The advantages of the Monte Carlo method in simulating EV travel and charging mainly lie in its flexibility, reliability, and efficiency. These advantages give Monte Carlo methods broad application prospects in the field of EVs.

In the field of EV charging optimization, scholars have engaged in comprehensive research. For example, Wu et al. [17] developed a charging schedule strategy for EVs based on time-of-use electricity pricing, with the primary goal of minimizing user charging costs, constrained by the number of charging piles and the instantaneous power capacity of charging piles. Zhang et al. [18] introduced a strategy for orderly real-time charging that seeks to maximize the use of renewable energy and concurrently minimize the charging costs for EV users. Wu and Pang [19] crafted an optimal strategy for the orderly charging and discharging of EVs, aiming to minimize both operational costs and peak–valley load differences under variable electricity pricing regimes. Gharibi et al. [20], considering 24-h predicted electricity prices, battery aging, and charging costs, proposed a proactive day-ahead charging and discharging strategy for EVs. Zhang et al. [21] devised a two-stage

EV charging and discharging optimization strategy using particle swarm optimization, focusing on minimizing vehicle expenses and maximizing charge volume while considering the cyclical costs of battery charging and discharging. These studies, primarily centered on the benefits to EV owners, often lack widespread applicability in real-world engineering contexts. Consequently, Fu et al. [22] expanded the scope to include the interests of both charging pile operators and EV users. They approached the issue as a non-cooperative game, aiming to optimize EV charging strategies that maximize charging pile benefits and minimize costs for EV users.

Based on the analysis, we observe that many scholars have conducted research related to operational strategies for EVs. With the growing popularity of EVs, many businesses have started to use EVs owned by their employees as mobile energy storage units, integrating them into the company's own electricity usage. As shown in Figure 1, the destinations of EVs consist of working and non-working areas. According to user travel data, users within a company have similar habits when using EVs. At present, lithium-ion batteries are the mainstream batteries for EVs, mainly composed of a positive electrode, negative electrode, electrolyte, and separator. This type of battery achieves energy storage and release through the insertion and removal of lithium ions and is widely used in EVs, smartphones, laptops, and other fields. How to consider the interrelated dynamics among businesses, operators, and EV users, and how to optimize the operation of EV charging and discharging strategies to reduce the corporate cost of purchasing electricity has become a current hot topic of research. Therefore, the main contributions of this paper are as follows:

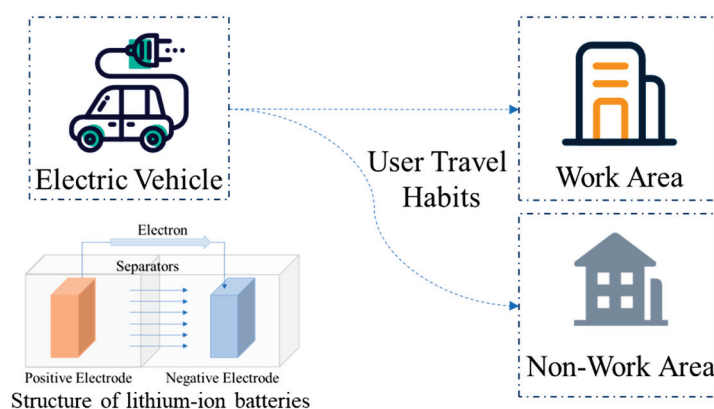


Figure 1. Electric vehicle motion path and its battery structure.

(1) The study comprehensively considers the electrical load demands of the company and the willingness of employees to engage in the scheduling of EV charging and discharging. It sets out with dual objectives: to minimize the electricity purchasing costs for the company and to reduce the charging expenses for employees who own EVs. The paper delves into how the company's and employees' annual costs fluctuate under scenarios featuring various quantities of charging piles.

(2) The research considers the diverse patterns of EV usage by employees across various typical days. It focuses on harmonizing the interplay among the quantity of charging piles, the profitability of operators, and the benefits to employees. To achieve this, it establishes an optimization model for EV charging and discharging, dedicated to refining and enhancing the strategies for their charging and discharging processes.

2. Problem Description

This paper proposes an optimization method for EV charging and discharging for companies with EV users. This method is based on EV travel data, company electricity demand, and electricity market prices to guide companies in determining the scale of EV charging piles. It further optimizes the charging and discharging scheduling strategies of these charging piles to maximize company profits while minimizing the costs for EV users.

The framework of the proposed method is shown in Figure 2, which is divided into several parts: (1) data preprocessing, (2) modeling of EV travel patterns, (3) optimization models, and (4) model solving and analysis.

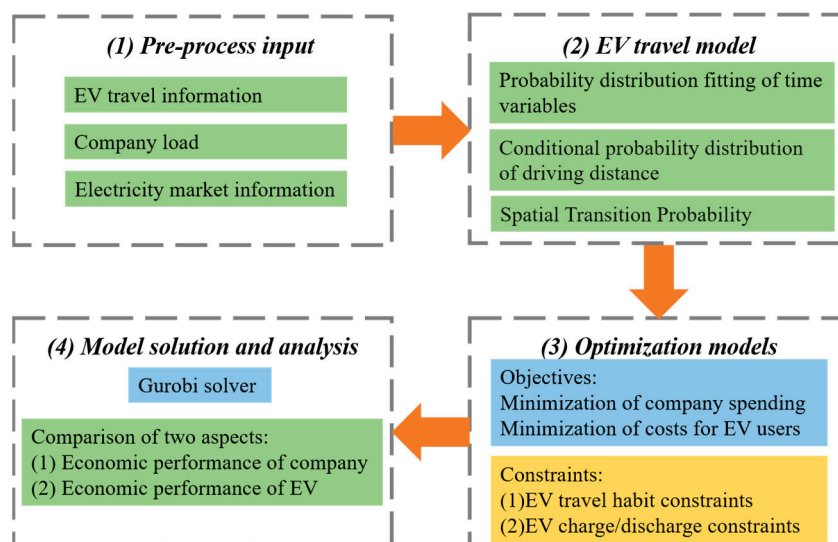


Figure 2. The framework of optimization methods for electric vehicle (EV) charging and discharging.

The first part involves filtering the required data, including people's travel data, company load data, and electricity market price data. The second part establishes a travel time variable probability distribution model, a conditional probability model for travel distance, and spatial transfer probability based on population travel data. This culminates in the development of an EV travel model for both weekdays and weekends. In the third part, considering the constraints of charging and discharging of EVs, a linear programming model is established to minimize the costs for both the company and the EV users. The stakeholders of the charging pile are categorized into two groups: companies and EV users. Distinct objective functions are proposed for each group of stakeholders. For companies, the objective function is to minimize the combined cost of electricity and investment fees. For EV users, the goal is to minimize the total cost of electricity and battery degradation. Additionally, the performance constraints of charging piles and EVs, travel-habit constraints of EV owners, and electricity prices in the electricity market are also considered. The final part uses the Gurobi solver to solve the model and compares the results from the perspectives of both company and user interests under different scenarios.

3. EV Travel Simulation Based on Improved Probability Model and Monte Carlo Algorithm

The precision of the travel mode and probability distribution model for EV users plays a crucial role in influencing the simulation and prediction of EV charging load. This paper uses the 2009 US National Household Travel Survey (NHTS) dataset as an example, and simulates the charging load of EVs based on an improved probability model and the Monte Carlo algorithm [23]. Lithium-ion batteries in EVs are a key energy component, mainly composed of positive electrode, negative electrode, separator, and electrolyte [24]. Positive electrode materials are usually transition metal oxides or polyanionic compounds with high electrode potential and structural stability. The negative electrode material is mainly carbon material, used for storing lithium ions. The diaphragm is located between the positive and negative electrodes to prevent direct contact and allow lithium ions to pass through. Electrolyte is the medium for ion transport, usually composed of organic solvents and lithium salts. During charging, lithium-ion batteries function by allowing lithium ions to migrate from the positive electrode to the negative electrode through the electrolyte, while electrons flow from the positive to the negative electrode via an external circuit, thus

storing energy. Conversely, during discharging, the ions migrate from the negative to the positive electrode, and the electrons flow in the opposite direction, releasing electrical energy. During this process, lithium ions move back and forth between the positive and negative electrodes, achieving the storage and release of electrical energy. The state of charge (SOC) of an EV refers to the ratio of the current remaining charge of a lithium-ion battery to its total capacity. SOC directly affects the range of EVs and the charging needs of users. Frequent deep discharge and charging can affect the lifespan of lithium-ion batteries. Therefore, intelligent charging strategies should adjust the charging rate and charging cutoff voltage based on SOC to extend battery life. The operating status of EVs includes driving speed, acceleration, deceleration, and road conditions. High speed driving and high-power demand can lead to an increase in battery discharge current, which in turn causes the battery temperature to rise. High temperature can accelerate the chemical reactions inside the battery, which may lead to a decrease in battery performance or even thermal runaway. The thermal management system of lithium-ion batteries should be considered in the mechanism to ensure that the battery can operate within a safe temperature range under various operating conditions. Driving behavior includes modes such as acceleration, deceleration, cruising, and parking. Frequent acceleration and deceleration can cause the battery to withstand significant charging and discharging cycles, which can increase the internal friction and aging rate of the battery. The charging speed and efficiency of lithium-ion batteries directly affect the charging time and range of EVs. Meanwhile, its lifespan determines the service life and cost of EVs. The lifespan of a battery is influenced by various factors, including charging and discharging times, charging and discharging depth, charging and discharging rate, temperature, etc. These factors may all affect the capacity and performance of batteries, thereby affecting the range and service life of EVs. Because most EVs in China run on lithium-ion batteries, we conducted a unified study on the charging and discharging behavior of EVs based on lithium-ion batteries.

3.1. Probability Distribution Model of Travel Time Variables

To enhance the accuracy of the travel variable probability distribution model, algorithms such as Weibull, Stable, Normal, Lognormal, Generalized Extreme Value (GEV), Exponential, Inverse Gaussian, Gamma, Burr Type XII, Birnbaum–Saunders, Logistic, Loglogistic, t Location-Scale (tLS), Nakagami and Rician distributions were utilized. The diverse distribution shapes of these algorithms can more accurately fit the probability distribution of various travel variables.

Each distribution model mentioned above is applied to fit a specific variable, with the objective of identifying the most effective model. The model demonstrating the optimal fit is then chosen as the definitive model for implementation. To evaluate the accuracy of the model, the coefficient of determination and the adjusted coefficient of determination are utilized, as shown in Equations (1) and (2):

$$R^2 = \frac{\sum_{i=1}^n (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (1)$$

$$R_a^2 = 1 - (1 - R^2) \times \frac{n - 1}{n - p - 1} \quad (2)$$

where y_i represents the i sample value (out of n samples) of the dataset y to be fitted; $\bar{y}$ is the mean value of the samples; $\hat{y}_i$ is the fitted value of y_i ; and p is the number of parameters in the probability distribution model used.

3.1.1. First Travel Start Time

In order to fit the probability distribution model of the first travel start time, we tried all of the distribution models mentioned above and obtained the fitting accuracy when using

different models according to the determination coefficient and adjusted determination coefficient in Equations (1) and (2). Finally, the Inverse Gaussian model is used to fit the probability distribution of the first travel start time, as shown in Figure 3, and its probability density function is shown in Equation (3):

$$f(t_{s1}|\mu, \lambda) = \sqrt{\frac{\lambda}{2\pi t_{s1}^3}} \exp\left\{-\frac{\lambda(t_{s1} - \mu)^2}{2\mu^2 t_{s1}}\right\} \quad (3)$$

where μ is the mean parameter of the distribution, λ is the shape parameter of the distribution, and t_{s1} represents the start time of the first trip.

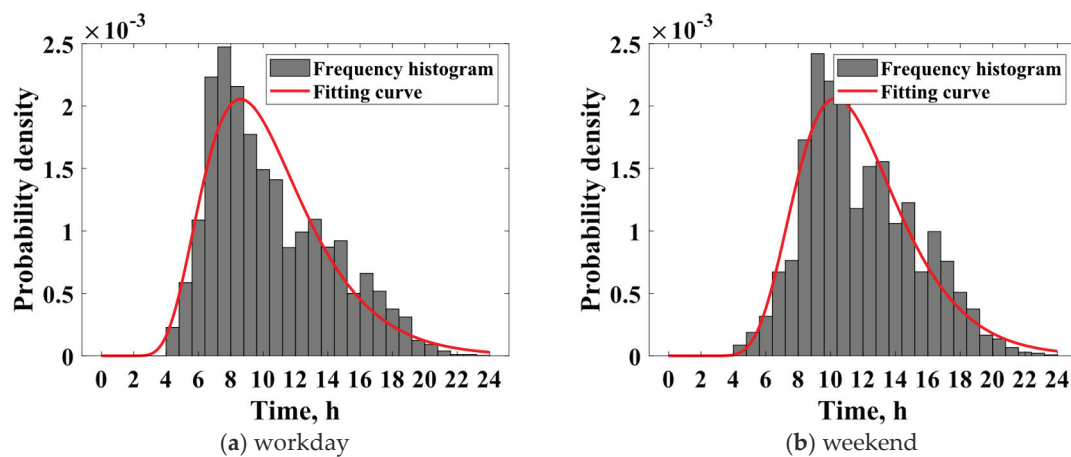


Figure 3. Probability distribution of first travel start time.

3.1.2. Driving Time of EVs

Depending on the type of place in the dataset, it can be divided into W (for working area), H (for home/residential area), and O (for other area). This paper mainly considers the vehicle track passing through the working area, so the driving type is divided into working area and non-working area (H and O areas). Based on location (two types of starting areas/two types of ending areas) and day type (workday/weekend), driving time of vehicles is classified into eight categories. The probability distribution model for eight types of driving time is shown in Table 1 and Figures 4 and 5.

Table 1. Probability distribution of driving time.

Travel Type	Day Type	
	Workday	Weekend
W to non-W	Burr	Stable
non-W to non-W	GEV	Burr
non-W to W	Burr	Stable
W to W	Burr	Logistic

W represents the working area, and non-W represents the non-working area.

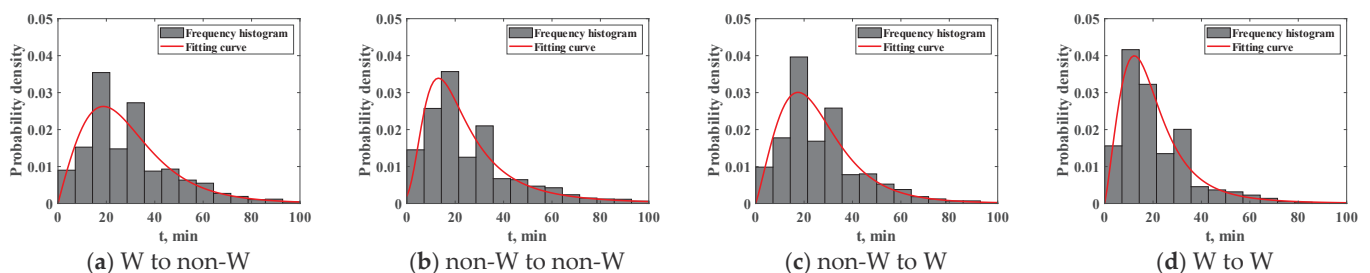


Figure 4. Probability distribution of driving time on workday.

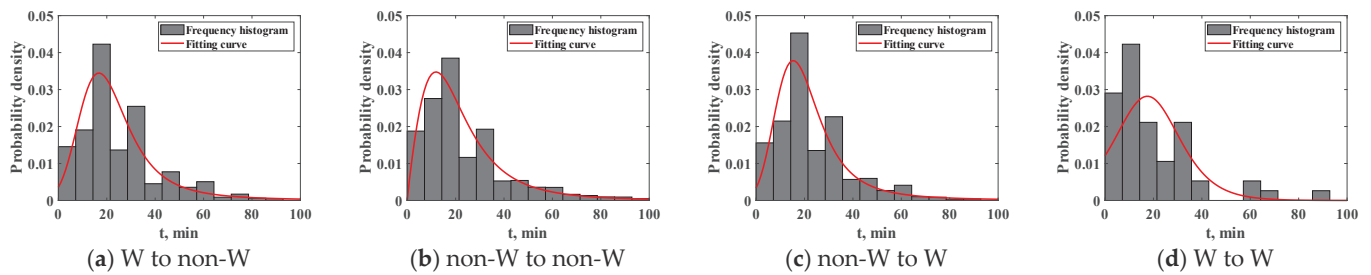


Figure 5. Probability distribution of driving time on weekend.

3.1.3. Parking Time of EVs

According to the parking location and type of day, the parking time of vehicles is classified into six categories. The probability distribution model for six types of parking time is shown in Table 2 and Figures 6 and 7.

Table 2. Probability distribution of dwell time.

Travel Type	Type of Location		
	W	O	H
workday	t Location-Scale	GEV	Gamma
weekend	Logistic	GEV	Nakagami

W represents the working area, H represents the residential area and O represents other area.

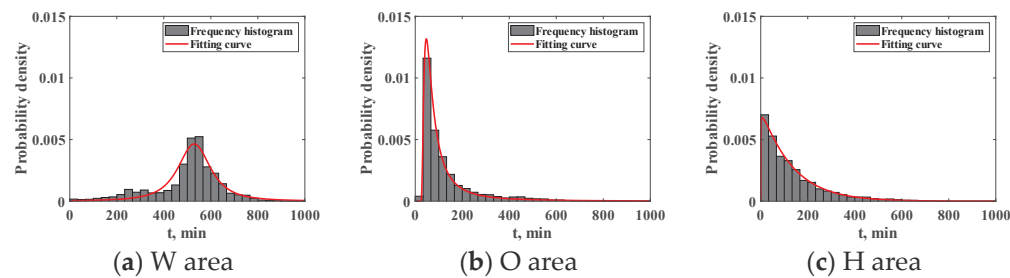


Figure 6. Probability distribution of parking time on workday.

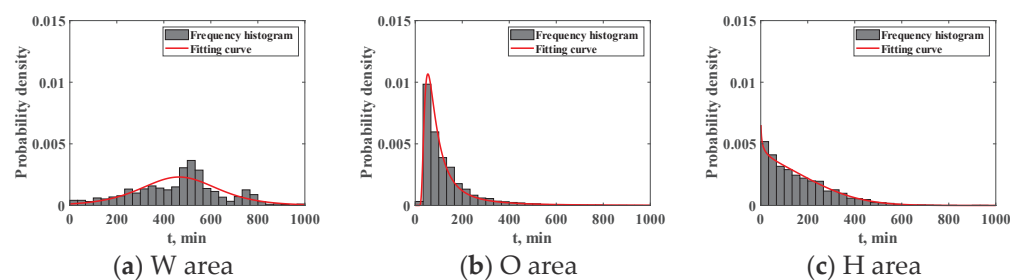


Figure 7. Probability distribution of parking time on weekend.

3.2. Probability Distribution Model for Driving Distance Conditions

Consider the driving distance d as a probability distribution that follows the condition of driving time. Driving distance and driving time are classified in the same way, and are classified into eight categories. According to the driving time, the driving distance under each type is divided into four time windows, which are 0–15 min, 15–30 min, 30–45 min, and more than 45 min. The normal distribution is used to fit the eight types of driving distances in the i time window. The probability distribution of driving distance is shown

in Table 3 and Figures 8–15. The conditional probability density function is shown in Equation (4):

$$P_d(d|\Delta t_i) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{1}{2\sigma_i^2}(d-\mu_i)^2} \quad (4)$$

where Δt_i is the i time window of the driving time; σ_i is the standard deviation of the distance traveled in the i time window; μ_i is the average distance traveled in the i time window.

Table 3. Probability distribution of driving distance.

Day Type	Travel Type	Driving Time	Driving Distance
workday	W to non-W	Burr	0–15 min
			Gamma
			15–30 min
			GEV
	non-W to non-W	GEV	30–45 min
			Nakagami
			>45 min
			GEV
	non-W to W	Burr	0–15 min
			Gamma
			15–30 min
			GEV
	W to W	Burr	30–45 min
			GEV
			>45 min
			Logistic
weekend	W to non-W	Stable	0–15 min
			Nakagami
			15–30 min
			Poisson
	non-W to non-W	Burr	30–45 min
			GEV
			>45 min
			Normal
	non-W to W	Stable	0–15 min
			Weibull
			15–30 min
			GEV
	W to W	Logistic	30–45 min
			GEV
			>45 min
			GEV

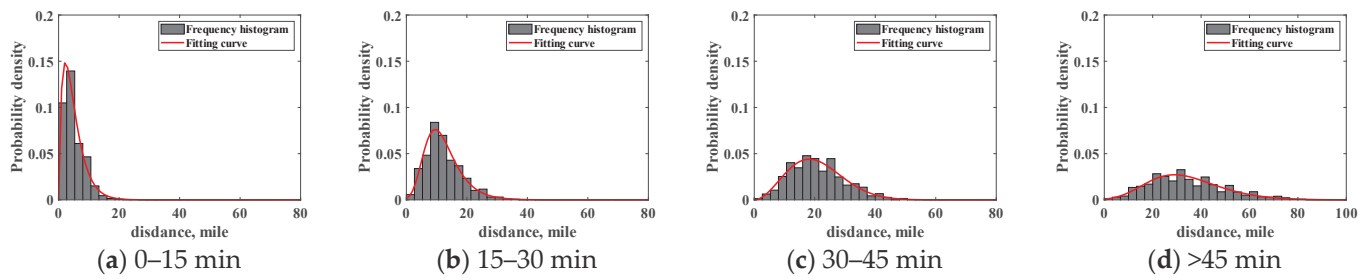


Figure 8. Probability distribution of driving distance of W to non-W travel type on workday.

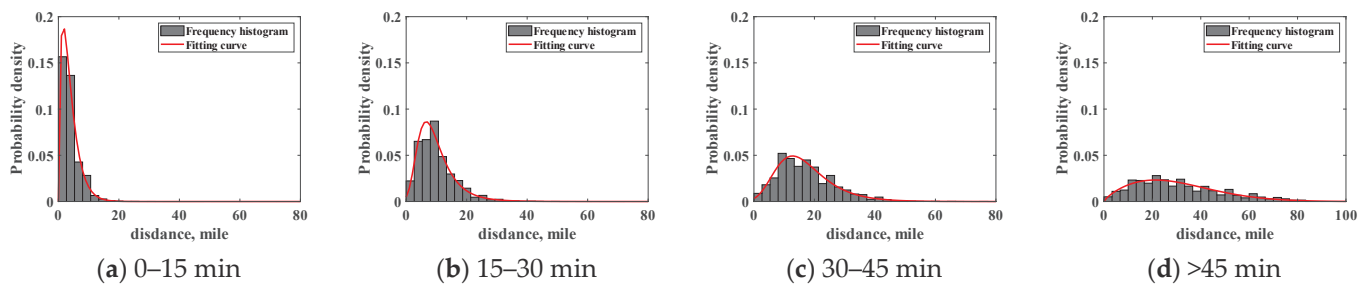


Figure 9. Probability distribution of driving distance of non-W to non-W travel type on workday.

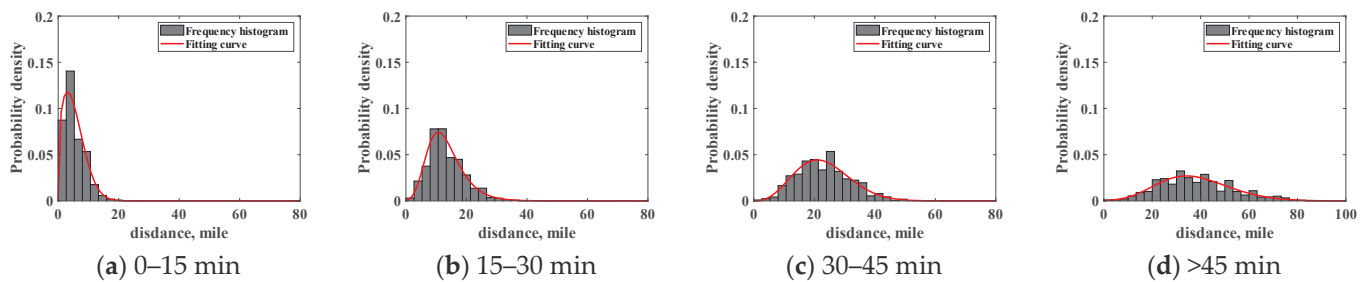


Figure 10. Probability distribution of driving distance of non-W to W travel type on workday.

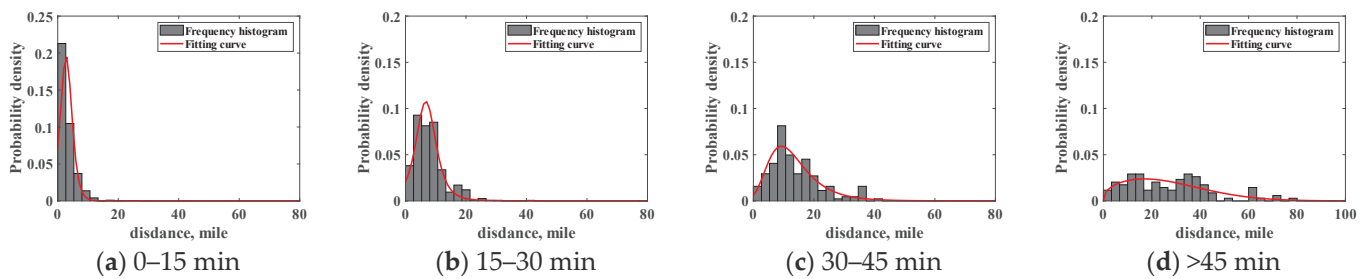


Figure 11. Probability distribution of driving distance of W to W travel type on workday.

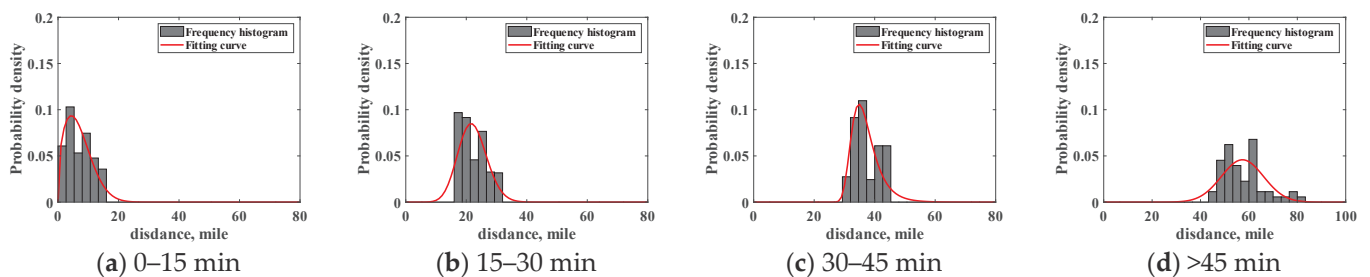


Figure 12. Probability distribution of driving distance of W to non-W travel type on weekend.

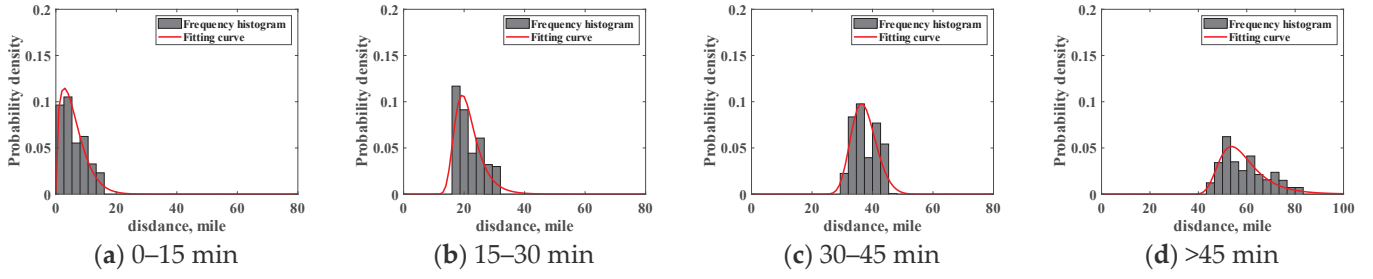


Figure 13. Probability distribution of driving distance of non-W to non-W travel type on weekend.

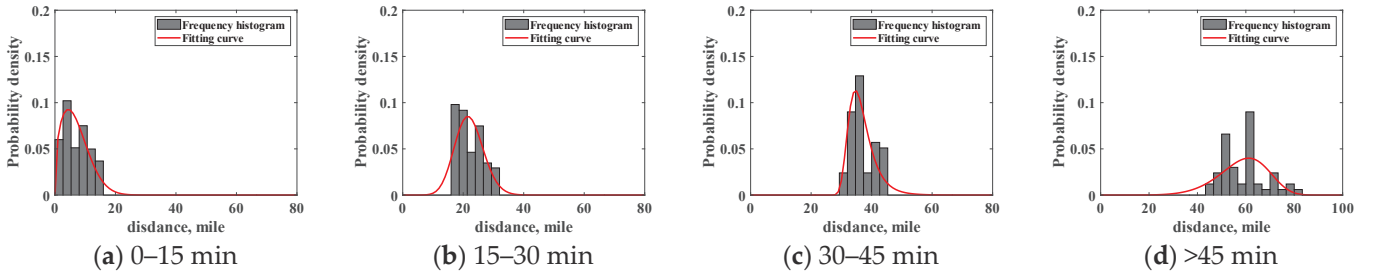


Figure 14. Probability distribution of driving distance of non-W to W travel type on weekend.

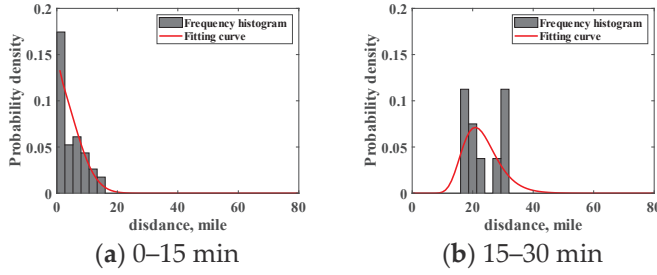


Figure 15. Probability distribution of driving distance of W to W travel type on weekend.

3.3. Space Transfer Probability

The spatial transfer probability refers to the probability of a vehicle traveling from destination D_m to the next destination D_{m+1} within a given time. If the current destination D_m is only related to the previous destination D_{m-1} and is not related to an earlier destination, the spatial transition probability is shown in Equation (5):

$$P(D_m \rightarrow D_{m+1}) = P(D_{m+1}|D_m) \quad (5)$$

By discretizing the vehicle travel start time of all time intervals, the spatial transition probability can be transformed into an $M \times N \times N$ three-dimensional matrix. M is the number of discrete time intervals; N is the number of destination types. The spatial transition probability matrix under a given time interval is an $N \times N$ two-dimensional matrix, as shown in Equation (6):

$$P_{t_i} = \begin{bmatrix} p_{t_i, D_1, D_1} & \cdots & p_{t_i, D_1, D_N} \\ \vdots & \ddots & \vdots \\ p_{t_i, D_N, D_1} & \cdots & p_{t_i, D_N, D_N} \end{bmatrix} \quad (6)$$

where p_{t_i, D_j, D_k} represents the probability of departing from the current area D_j to the next destination D_k within time interval t_i . The sum of probabilities for the same column in the matrix is 1. The diagonal element may not necessarily be 0, indicating the presence of a portion of round-trip travel.

3.4. Simulation of Electric Vehicle Travel Trajectory

Step 1:

The 2009 American Household Travel Survey (AHTS) dataset is used as input, distinguishing between day types and regional types. A probabilistic model of the user's spatio-temporal travel variables (i.e., first trip start time, trip length, stop length, and trip distance) is established.

Step 2:

Taking the above travel probability model as input, the travel habits of EV users are simulated by the Monte Carlo method. The probability model includes continuous probability distribution of spatio-temporal variables and a discrete spatial transfer probability matrix. Each variable is extracted sequentially to obtain the travel trajectory of each user for a day, and the detailed method is as follows:

- (1) Taking home as the starting area of the first trip, the departure time of the first trip is extracted according to the corresponding probability distribution.
- (2) The destinations are extracted with corresponding spatial transfer probabilities based on the obtained departure times and known starting areas.
- (3) After obtaining the destination of the trip, the driving duration is extracted based on the probability distribution corresponding to the starting point and destination. The end time of the trip is calculated based on the start time and duration of the trip.
- (4) Under the condition of the obtained driving duration, the driving distance is extracted according to the corresponding probability distribution.
- (5) The stopping duration is extracted based on the probability distribution corresponding to the stopping location. Based on the driving end time and the stopping duration, the departure time for the next leg of the trip is calculated to start the simulation of the next trip.

Step 3:

By using the exhaustion method to fix the number of charging piles, the maximum number of vehicles that can be served by the charging station at the same time can be obtained. According to the travel habits of each EV user, the vehicle travel trajectory through the working area is screened. Finally, according to the following rules, the charging station can accommodate the charging and discharging of vehicles passing through the working area to the maximum extent.

Firstly, among the vehicles passing through the working area, it is necessary to coordinate and arrange the charging of vehicles that can use the same charging pile. Secondly, vehicles that can be parked at the charging pile for a long time are arranged to increase the time they contribute to the company's peak shaving and valley filling. Finally, vehicles with a higher state of charge when parked for the first time are arranged to increase the potential of vehicles to contribute to the company's load shaving and valley filling. The charging and discharging strategies for EVs parked in the company's parking lot are optimized to minimize the company's expenses and minimize the expenses of EV users.

4. Optimization Model for Charging and Discharging Strategies of EVs

In this section, the impact of the number of charging piles on the company's annual spending was first determined. Secondly, a charging and discharging strategy is established for vehicles parked at charging piles, considering the interests of the company (charging pile builders and operators) and employees (EV users). By comparing the results of different objective functions, the optimal EV charging and discharging strategy is ultimately obtained.

4.1. Objective Function

This study compared two objective functions. The first objective function is to minimize the company's expenses, and the second objective function is to minimize the expenses of EV owners. Firstly, the charging price for EVs in the parking lot is Pr_c (CNY/kWh) and the discharge subsidy is Pr_{dc} (CNY/kWh). Pr_{ser} (CNY/kWh) is the service fee for EV

charging using the company's charging pile in the parking lot, and the electricity market has a time of use electricity price of Pr_{grid} (CNY/kWh).

$$Pr_c = Pr_{grid} + Pr_{ser} \quad (7)$$

It is worth noting that when charging an EV, the user hands over Pr_{grid} of Pr_c directly to the grid and Pr_{ser} to the company. When the EV is discharged, the company will provide all Pr_{dc} subsidies to EV users.

4.1.1. The Optimization Goal Is to Minimize Company Expenses

When a company operates and builds its own charging pile, the cost consists of three parts: (1) the company's daily load, (2) the construction cost of charging piles, and (3) providing emission subsidies for EV users. The company's revenue is the charging service fee paid for vehicle charging. When considering the annual cost of charging pile investment, the company will settle the initial one-time investment cost of charging piles in equal installments. The annual cost of investment in charging piles is shown in Equations (8)–(10):

$$P_{cp} = Pr_{cp} \cdot N_{cp} \quad (8)$$

$$Cost_{cp_ann} = P_{cp} \frac{j(1+j)^n}{(1+j)^n - 1} \quad (9)$$

$$Cost_{cp_day} = \frac{Cost_{cp_ann}}{365} \quad (10)$$

where P_{cp} is the one-time investment amount for the charging pile in CNY. Pr_{cp} is the unit price of the charging pile (including infrastructure renovation costs, installation costs, and maintenance costs, etc.) in CNY, taken as 9000 here; N_{cp} is the number of charging piles in CNY; $Cost_{cp_ann}$ is the annual investment amount for charging piles in CNY; j is the compound interest factor, which is expected to be paid multiple times in equal amounts within n years. Here, 8% compound interest is taken and settled within 10 years; $Cost_{cp_day}$ is the daily investment amount for the charging pile in CNY.

The daily expenses of the company are shown in Equation (11):

$$Cost_{com} = (P_{load} - P_{ev_dc}) \times Pr_{grid} - P_{ev_c} \times Pr_{ser} + P_{ev_dc} \times Pr_{dc} + Cost_{cp_day} \quad (11)$$

where P_{load} is the company's regular load in kWh, P_{ev_c} is the EV charging power in kWh, and P_{ev_dc} is the EV discharge power in kWh.

4.1.2. The Optimization Goal Is to Minimize Employees' Expenses

The expenses of employees using EVs are divided into two parts: (1) the charging electricity cost during car charging (Pr_c) and (2) the cost of charging and discharging losses for EV batteries. The employee's income is the subsidy obtained from the discharge of EVs (Pr_{dc}). Equation (12) represents the overall expenses of employees:

$$Cost_{ev} = P_{ev_c} \times Pr_c - P_{ev_dc} \times Pr_{dc} + Loss(P_{ev}) \quad (12)$$

$$Loss(P_{ev}(i, t)) = \frac{c}{100} |P_{ev}(i, t)| \frac{C_{change}}{E_{cap}} \quad (13)$$

where $Loss(P_{ev}(i, t))$ represents the battery loss cost of the i EV within 1 h at time t . c is a parameter taken based on the type of battery, where the vehicle battery is a lithium battery with a value of 0.0157; $P_{ev}(i, t)$ is the average charging/discharging power of the i vehicle during time t , with charging at $P_{ev}(i, t) \geq 0$ and discharging at $P_{ev}(i, t) \leq 0$. This is also equivalent to the total charging/discharging amount within 1 h at time t , in kWh; C_{change} is

the cost of battery replacement, calculated based on a battery capacity of 1000 CNY/kWh, where 40,000 CNY is taken; E_{cap} is the maximum capacity of the battery; here it is 40 kWh.

4.2. Energy Balance Constraint

The energy balance constraint requires that the output of the company's electricity within time t must be equal to the input. The power balance is shown in Equation (14). On the left side is the daily load of the company at time t , and on the right side is the sum of the electricity provided by the power grid at time t and the electricity discharged by all EVs at time t . N_{ev} represents the total number of EVs:

$$P_{load}(t) = P_{grid}(t) + \sum_{i=1}^{N_{ev}} P_{ev_dc}(i, t) \quad (14)$$

4.3. Electric Vehicle Travel Constraints

The constraint relationship mainly includes the constraints of EV battery charging and discharging parameters and the constraints of EV travel behavior. The constraint on the charging and discharging power of EV batteries is shown in Equation (15):

$$P_{dcmax} \leq P_{ev}(i, t) \leq P_{cmax} \quad (15)$$

where P_{dcmax} is the maximum discharge power of the battery. P_{cmax} is the maximum value of battery charging power. The specified discharge power is negative and the charging power is positive.

If each vehicle user travels up to three times per day, and the starting and ending points of the entire journey are home (H), then within a day, vehicle users can park at the work area (W) up to two times. If the initial state of charge (SOC) of the vehicle's battery (starting from home) is 0.8, the SOC upon first arriving at the W area is calculated based on the driving distance and the vehicle's power consumption rate. Considering that overcharging or over-discharging can lead to battery degradation, the lower limit for charging and discharging the SOC during parking is set to 0.2, and the upper limit is 0.8. Only when the vehicle leaves the company parking lot for the last time is the battery charged to a SOC greater than 0.85. Based on observations of vehicle trips passing through the work area, it is found that when vehicles park twice in the work area, the W-W trips are often short trips concentrated around the noon period. This may be due to vehicle owners going out for lunch. Therefore, when the vehicle trip includes a W-W segment, the SOC when departing from the work area should meet the power consumption requirements for the W-W trip. When returning to the W area, the vehicle's battery SOC should not be less than 0.15. The SOC, except for the first arrival at the W area, is calculated by Equation (16). Equations (17) and (18) show that vehicle i only stops in the W area once:

$$SOC(i, t) = SOC(i, t-1) + \frac{P_{ev}(i, t)}{E_{cap}} \quad (16)$$

$$0.2 \leq SOC(i, t_1) \leq 0.8 \quad (17)$$

$$SOC(i, t_{1end}) \geq 0.85 \quad (18)$$

where t_1 indicates that the vehicle only stops in the W area once a day, that is, any hour except the last hour during the time of parking in the company's parking lot. t_{1end} represents the last hour when the vehicle is parked in the company parking lot. It should be noted that SOC is a state variable. When talking about t , SOC refers to the value of SOC at the last moment of the corresponding small time at t . The SOC at 2 refers to the SOC at 02:00.

Equations (19)–(22) show the constraint of SOC when vehicle i stops in the W area twice:

$$0.2 \leq SOC(i, t_{2,1}) \leq 0.8 \quad (19)$$

$$0.15 + SOC_{W-W} \leq SOC(i, t_{2,1end}) \leq 0.8 \quad (20)$$

$$0.2 \leq SOC(i, t_{2,2}) \leq 0.8 \quad (21)$$

$$SOC(i, t_{2,2end}) \geq 0.85 \quad (22)$$

where $t_{2,1}$ indicates that the vehicle is parked in the W area twice a day, with the first time parked in the company parking lot, excluding any hour in the last hour. SOC_{W-W} represents the SOC converted based on battery capacity to support the electricity required for vehicle W-W travel; $t_{2,1end}$ represents the last hour when the vehicle first stops at the company parking lot; $t_{2,2}$ indicates that the vehicle is parked in the W area twice a day, with the second time parked in the company parking lot, excluding any hour in the last hour; $t_{2,2end}$ represents the last hour of the vehicle's second stop at the company parking lot.

5. Case Study

Firstly, this section introduces the input data of the model. Secondly, the impact of the number of charging piles on the company's annual spending is explored. Finally, the scheduling of charging and discharging for vehicles parked in the parking lot is optimized. We compare and analyze the profit differences between companies and EV users under different objective functions.

5.1. Input Data

Based on the available time-of-use electricity pricing data and the residential electricity load data (substituting for the company's power load data in this paper), the k-means clustering method is applied to obtain eight typical weekdays and four typical weekend days. The time span covers a whole year's data, resulting in different typical days, which are used for calculating annual costs. The number of vehicles passing through the W area on the selected typical days is shown in Table 4. The parameters of EVs are shown in Table 5. Table 6 shows the electricity market price information used in this paper.

Table 4. Number of typical daily vehicles.

Day Type	Number of Vehicles
Workday1	44
Workday2	35
Workday3	36
Workday4	36
Workday5	44
Workday6	37
Workday7	31
Workday8	37
Weekend1	11
Weekend2	10
Weekend3	7
Weekend4	8

Table 5. Electric vehicle parameters.

Electric Vehicle Parameters	Value
Battery capacity	40 kWh
Maximum charge power	7 kW
Maximum discharge power	0.8 kW
Consumption rate	0.18 kWh/km
Battery replacement cost	1000 CNY/kWh

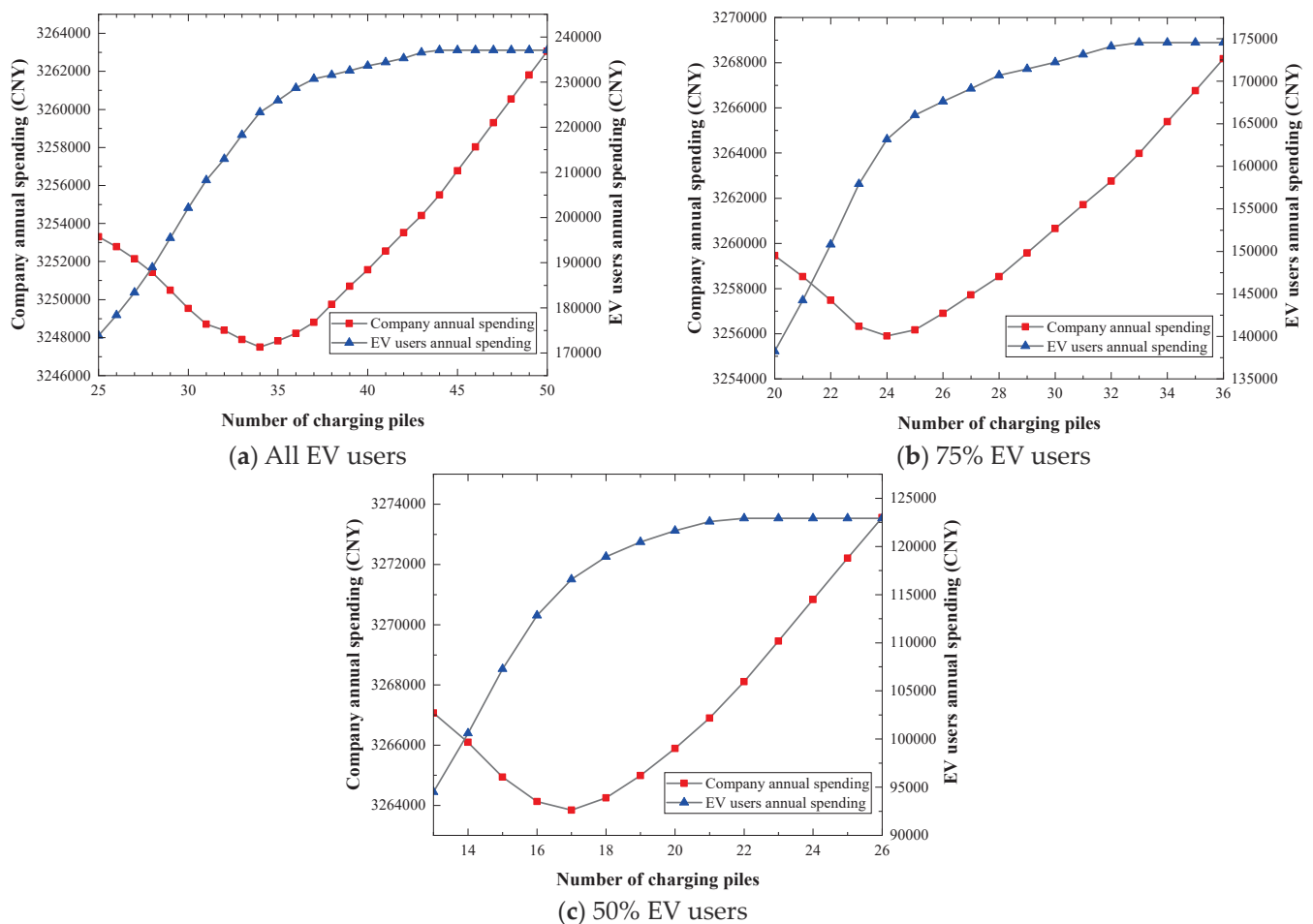
Table 6. Electricity market prices.

Time	The Company's Electricity Purchase Price (CNY/kWh)	Electric Vehicle Charging Price (CNY/kWh)	Vehicle Discharge Subsidy (CNY/kWh)
22:00~07:00	0.2399	0.3023	0.15
07:00~09:00			
15:00~17:00	0.916	1.2884	0.5
21:00~22:00			
09:00~15:00	1.0027	1.4167	0.7
17:00~21:00			

5.2. Results and Discussion

5.2.1. The Objective Function Only Considers the Economic Benefits of the Company

It is known that the expenses of the company consist of regular load electricity costs, discharge subsidies for EV users, charging service fees collected from EV users, and investment costs for charging piles. The participation of EV users can be categorized into full participation, 75% participation, and 50% participation. By minimizing the company's spending objective function, we can establish a relationship between the annual spending of the company and the number of charging piles as depicted in Figure 16.

**Figure 16.** Annual spending of the company and EV users considering only the company's benefit.

As can be seen from Figure 16a, when the quantity of charging piles reaches 34, the company's annual spending is the smallest. When the quantity of charging piles is less than 34, the more charging piles, the less the annual spending of the company. This is because, at this stage, the company's revenue comes from collecting service fees paid by EV users, as well as using the low-cost electricity emitted by EVs during peak tariff periods. When the quantity of charging piles exceeds 34, the company's annual fee increases with the quantity of charging piles. This is because the cost of investing in charging piles exceeds the charging service fees charged. As the quantity of charging piles increases, the total annual cost for EV users begins to grow rapidly and then levels off. This is because when the number of charging piles reaches a certain level, the number of vehicles that can be served increasingly approaches the total number of vehicles parked in the company's parking lot. When the quantity of charging piles is greater than or equal to 44, the total annual cost of EV users remains unchanged and no longer increases with the increase in the quantity of charging piles. This is because the maximum number of vehicles in a typical day is 44, indicating that the number of charging piles is already sufficient to meet the charging/discharging needs of all vehicles.

Figure 16b,c show the same rule. In Figure 16b,c, the number of charging piles that make the company's annual spending minimum is 24 and 17, respectively, and the number of charging piles that make the annual cost stable for EV users is 33 and 22, respectively.

5.2.2. The Objective Function Only Considers the Economic Benefits of the EV Users

The cost to EV users includes charging service fees, EV discharge subsidies issued, and the costs of battery degradation caused by charging and discharging. When the objective function considers only the minimization of EV users' costs, the annual spending of the company increases with the number of charging piles, as shown in Figure 17. This is because, under this objective, EV users are no longer keen to earn discharging subsidies and only participate in the company's scheduling plans. However, even with an increase in the number of dispatchable vehicles, the company can only earn limited charging service fees. The trend in annual total expenses for EV users is the same as the above example, but the annual spending for EV users has decreased compared to the above example. This is also the result of considering the cost of EV users in the objective function.

The charging service fees and the discharging subsidies for EVs under the two objective functions are shown in Figure 18. Here, Group A represents the results considering only the company's costs, while Group B represents the results considering only EV users' costs. From the figures, it is evident that when only user interests are considered, EVs do not frequently participate in the company's charging and discharging scheduling. It can also be observed from the EV discharging subsidies in Group B, which show no significant fluctuation with the increase in the number of charging piles. Therefore, it can be inferred that when only considering the interests of EV users, without altering the electricity market prices and the vehicle charging and discharging prices, the willingness of EV users to participate in electricity scheduling remains unchanged.

5.2.3. The Objective Function Considers Both the Interests of the Company and EV Users

The objective function is set to the sum of the company's expenses and the EV users' expenses under different weights, as shown in Equation (23):

$$Cost = \alpha \cdot Cost_{com} + \beta \cdot Cost_{ev} \quad (23)$$

where α represents the weight of company expenses, and β represents the weight of EV user expenses, $\alpha + \beta = 1$.

Figures 19 and 20 show the variation in costs for the company and EV users with the number of charging piles under objective functions with different weights. Through analysis of the figures, when the EV users' costs are dominant in the objective function, both the annual costs for the company and the annual costs for EV users exhibit the same trend and almost equal values. This is because in the scenario where EV users' costs are

predominant, the charging and discharging scheduling strategies are essentially consistent, that is, minimizing battery degradation, only undertaking necessary charging, and participating in limited discharging plans. Also, since the electricity market prices remain constant, there are no additional incentives to motivate EV users to change this behavior.

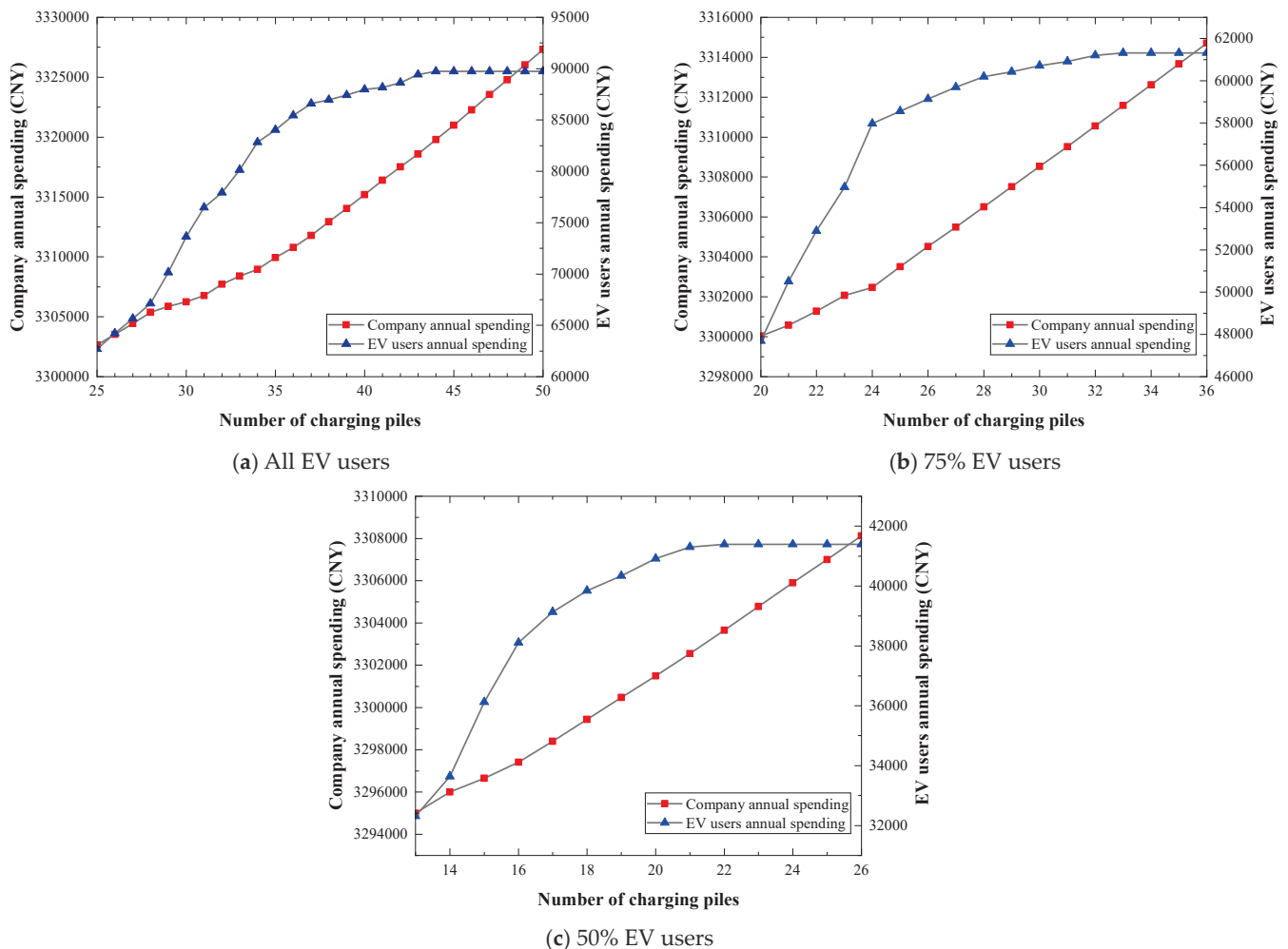


Figure 17. Annual spending of the company and EV users considering only the EV users' benefit.

In the case of not optimizing vehicle charging and discharging, that is, when the vehicle arrives at the station, it will start charging, and after charging to SOC to 0.8, the power will be transferred without affecting the subsequent travel, as shown in Figures 19 and 20 below. With the participation of all EV users, when the objective function only considers the cost of the company, it can be concluded that the company annual spending of the optimized scheme is 0.725% less than that of the non-optimized scheme. If the objective function only considers EV cost, it can be concluded that the EV annual cost of the optimized scheme is 36.443% less than that of the non-optimized scheme.

In the case of 75%EV user participation, when the objective function only considers the company's cost, it can be concluded that the company annual cost of the optimized scheme is 0.544% less than that of the non-optimized scheme. If the objective function only considers EV cost, it can be concluded that the EV annual cost of the optimized scheme is 60.793% less than that of the non-optimized scheme.

In the case of 50%EV user participation, when the objective function only considers the company's cost, it can be concluded that the company annual cost of the optimized scheme is 0.419% less than that of the non-optimized scheme. If the objective function only

considers EV cost, it can be concluded that the EV annual cost of the optimized scheme is 38.003% less than that of the non-optimized scheme.

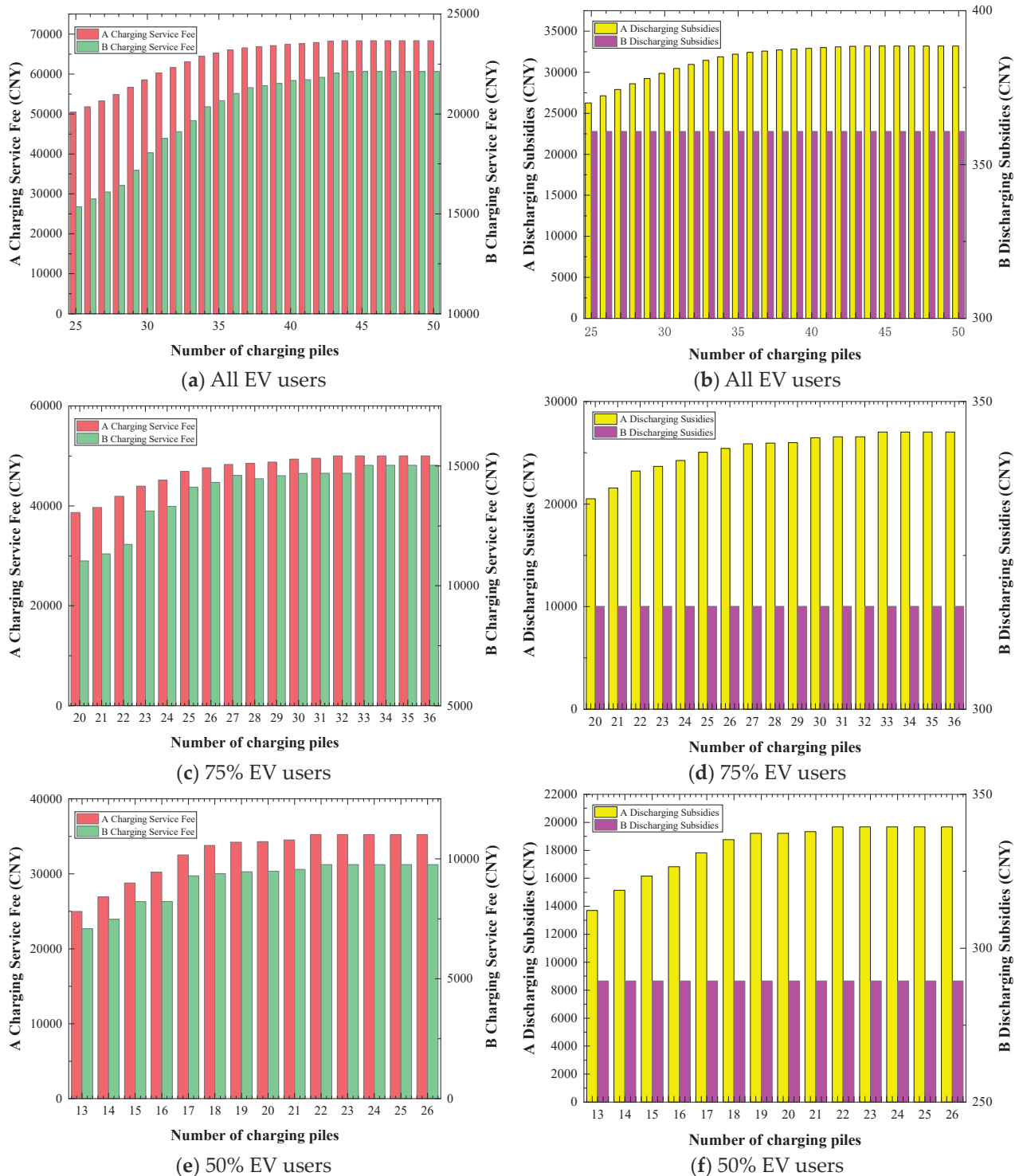


Figure 18. The charging service fees and discharging subsidies under two objective functions.

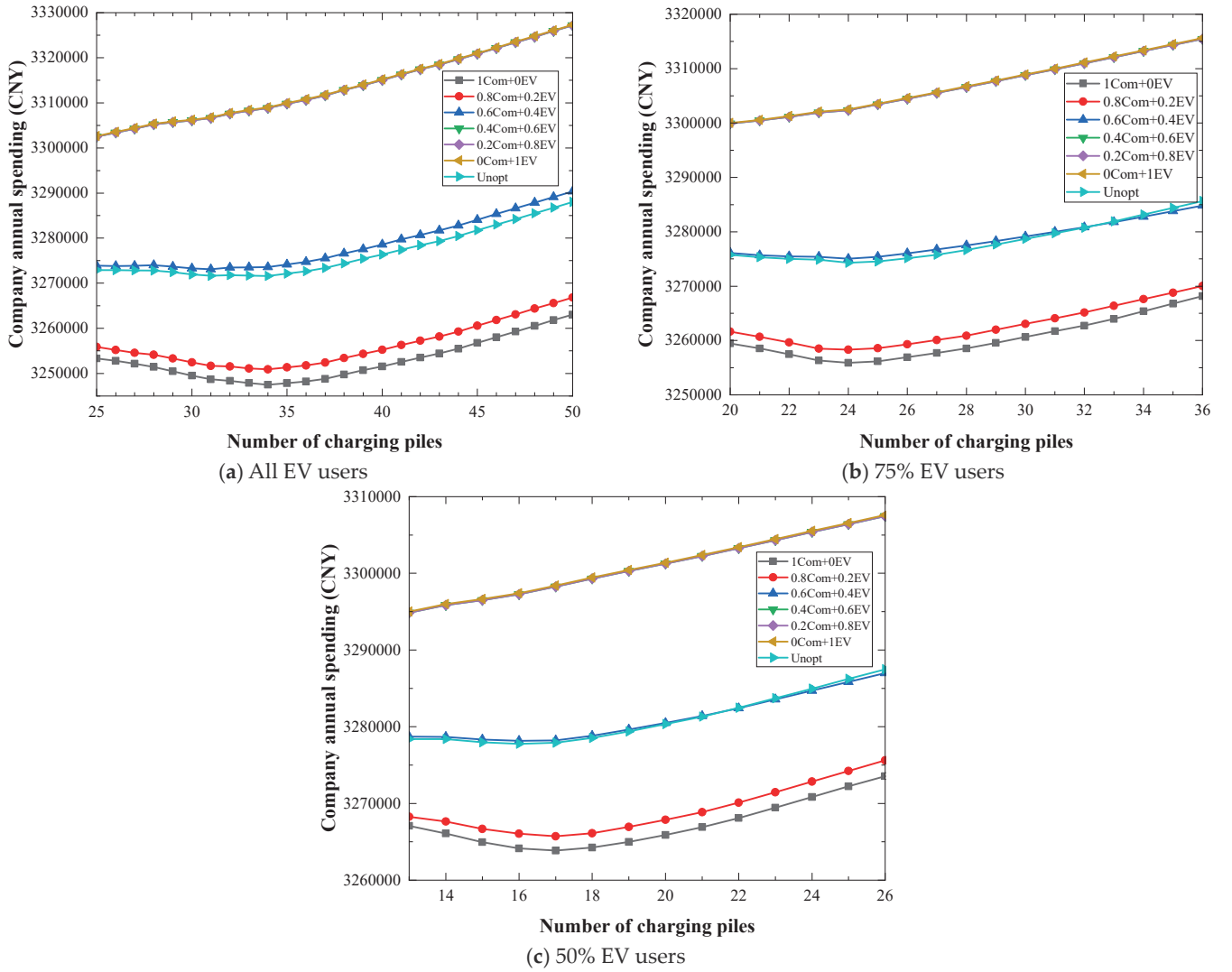


Figure 19. Annual spending of the company with different weights in the objective function.

The trends in EV battery loss, EV users' charging service fees, and EV users' discharging subsidies also clearly show that when EV users' costs dominate the objective function, users' enthusiasm for discharging significantly decreases, as shown in Figures 21–23.

Investment return rate is a way to measure the economic return that a company receives from investment activities. The return on investment for the company in charging piles is shown in Equation (24). The company's profit is the difference between the cost without installing charging piles and the cost with installing charging piles, where the cost without installing charging piles consists only of the company's regular load electricity charges. The change in the company's return on investment with the variation in the number of charging piles is shown in Figure 24. As the number of charging piles increases, the company's return on investment decreases. This indicates the need to find a balance between the company's return on investment and the annual expenditure of EV users, so that both the company and EV users can achieve good returns.

$$ROI = \frac{P_{load} \cdot Pr_{grid} - (P_{load} - P_{ev_dc}) \cdot Pr_{grid} + P_{ev_c} \cdot Pr_{ser} - P_{ev_dc} \cdot Pr_{dc} - Cost_{cp_ann}}{P_{cp}} \quad (24)$$

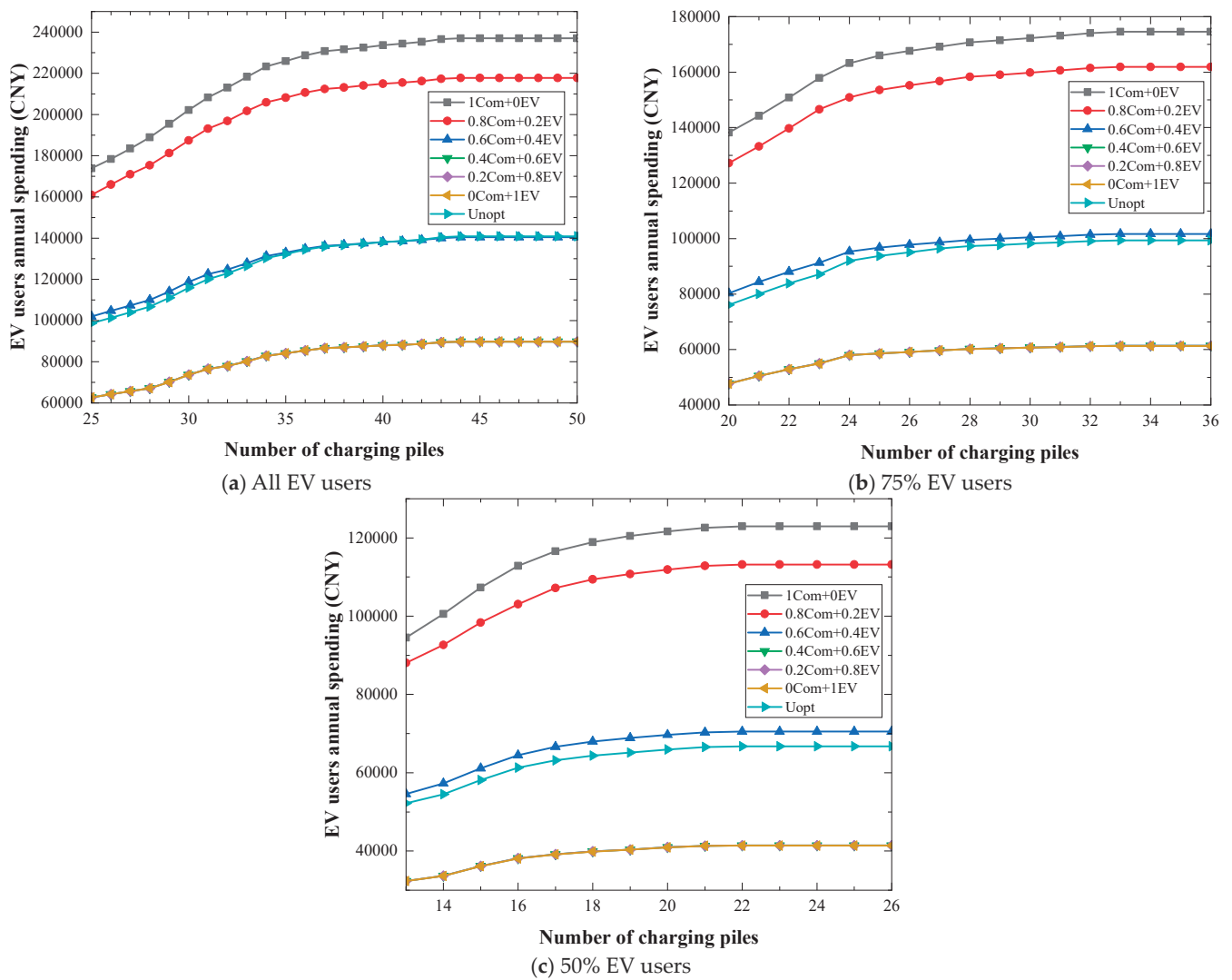


Figure 20. Annual spending of the EV users under different weights in the objective function.

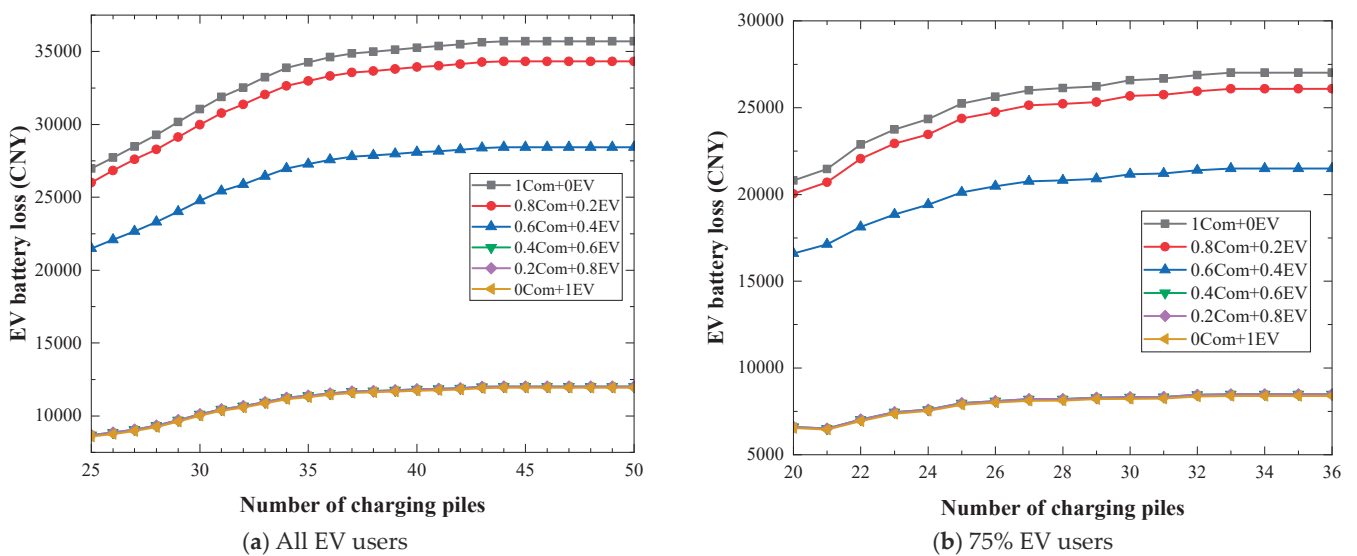


Figure 21. Cont.

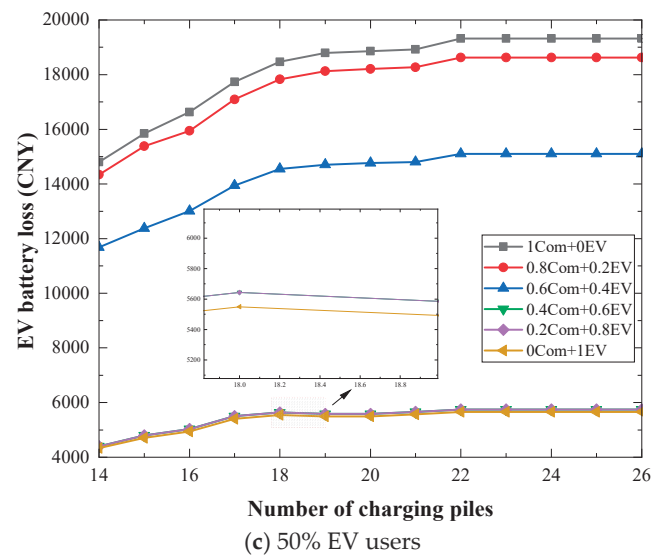


Figure 21. EV battery loss under different weights in the objective function.

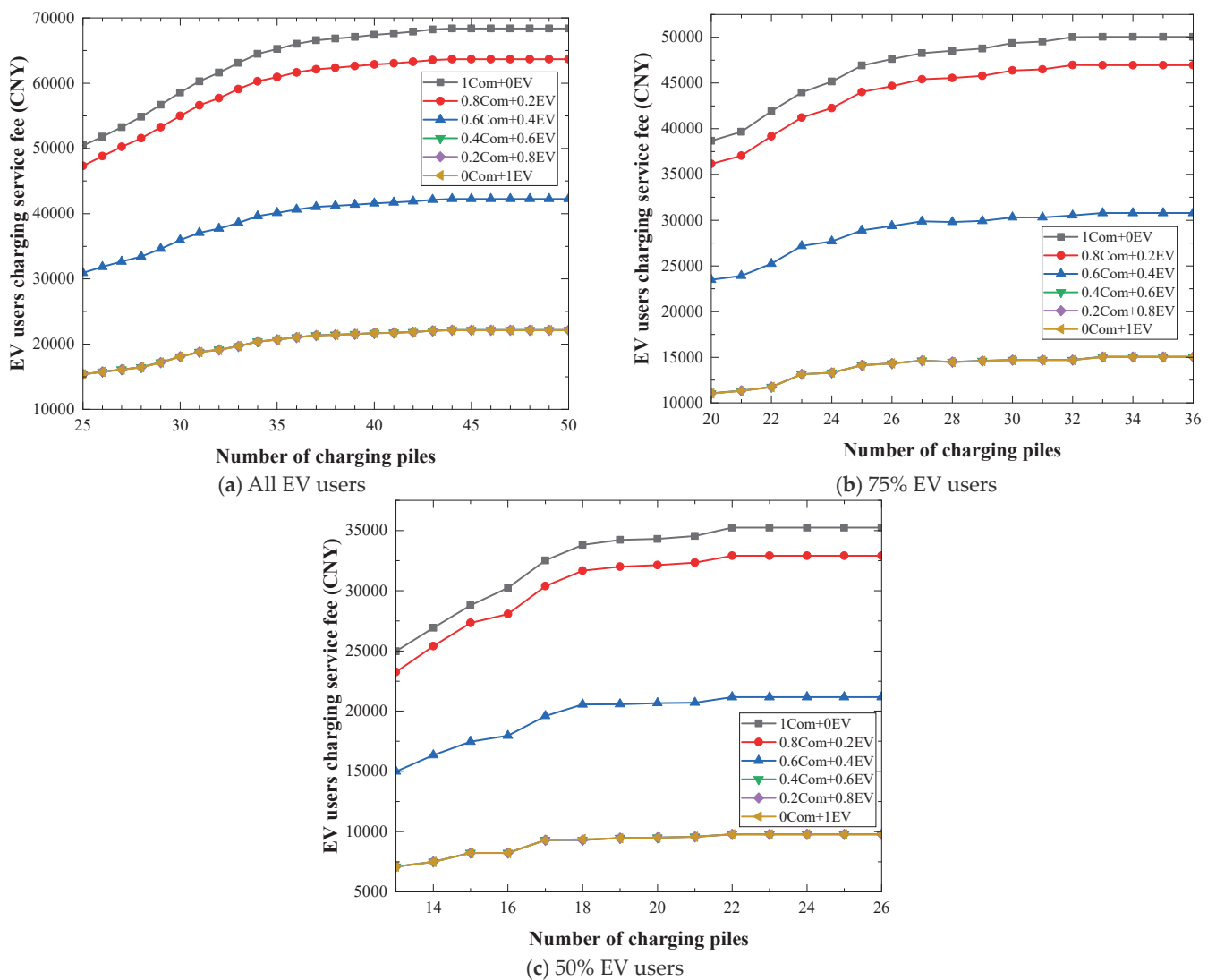


Figure 22. EV users' charging service fee under different weights in the objective function.

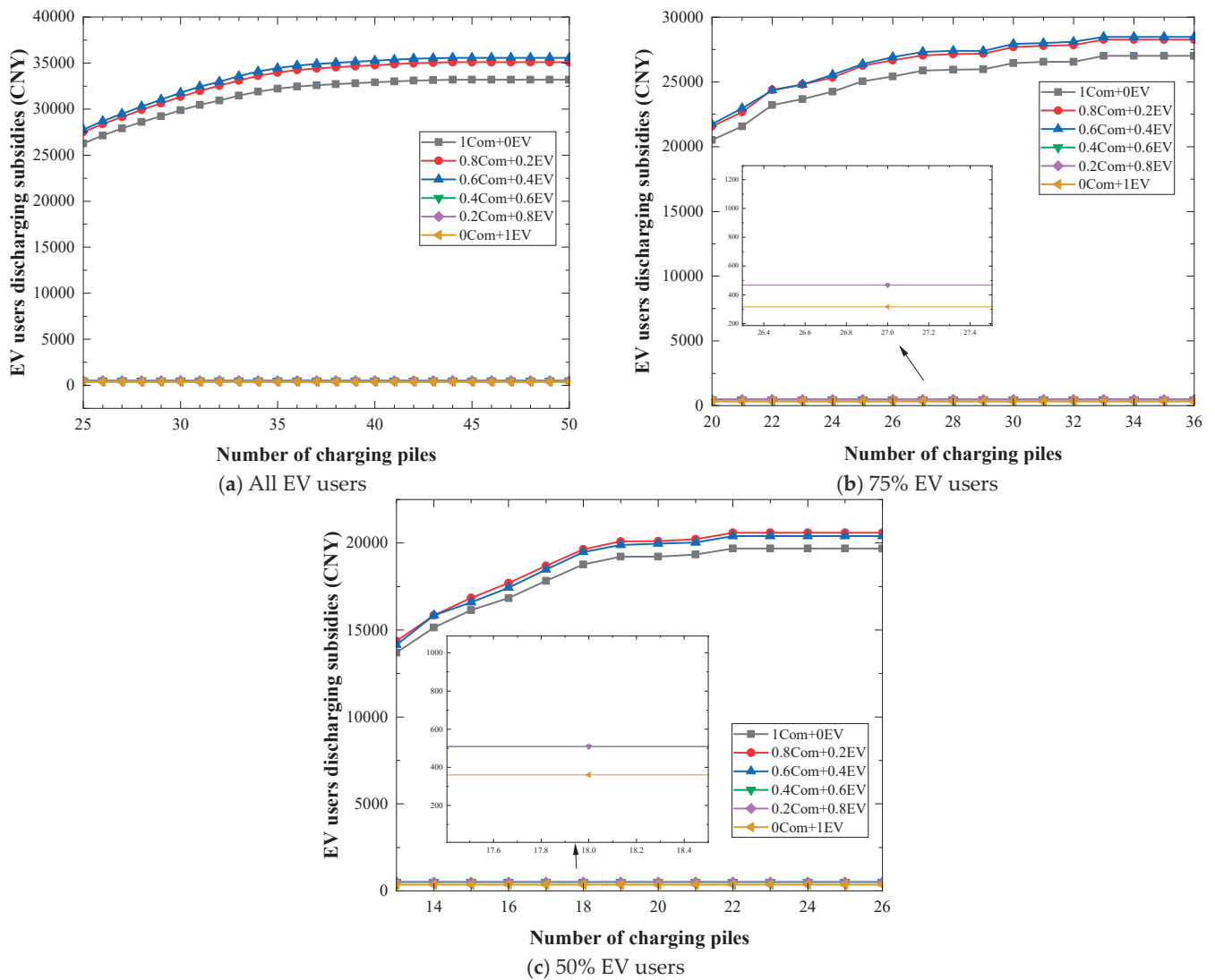


Figure 23. EV users' discharging subsidies under different weights in the objective function.

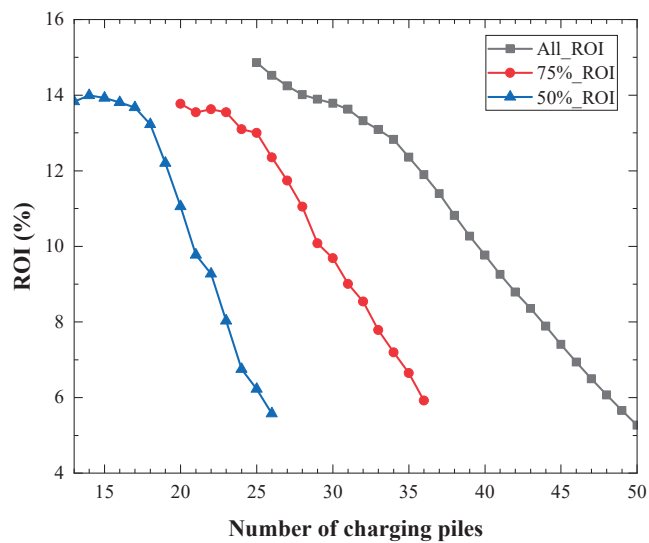


Figure 24. Changes in the return of the company's investment.

6. Conclusions

This paper presents an optimization model for EV charging and discharging strategies that considers both company and employee (EV user) benefits to minimize their combined annual costs. The relationship between the number of charging piles and the company's and EV users' benefits is discussed in depth to explore the optimal charging pile investment size for the company. Considering the different travel modes of employees using EVs, the EV charging and discharging strategies are optimized. Based on the research results, the following conclusions can be drawn:

- (1) With the regular number of EV trips and travel habits, when the goal is to minimize the company's expenses, the company's annual spending will reach a minimum at a certain determined number of charging piles, that is, the optimal charging pile investment size for the company.
- (2) When the expense of EV users dominates the objective function, EV users are more concerned about battery depletion and are significantly less motivated to participate in scheduling.
- (3) The responsiveness of EV users to participate in charge/discharge scheduling at a constant tariff does not change with an increase in EV users. Flexible incentives are needed to motivate EV users to deeply participate in charge/discharge scheduling.

This article studies the charging and discharging strategies for EVs based on considering the user's travel mode and the operational efficiency of charging piles, but it still lacks comprehensive consideration. In future research, the micro factors that affect the charging and discharging of EVs can be further considered. The charging and discharging laws of EVs are influenced by battery materials, including cathode materials, anode materials, and electrolytes. To optimize the performance of EVs, it is necessary to choose appropriate battery materials to achieve a balance between energy density, charge and discharge rate, cycle life, and safety. At the same time, it is also necessary to optimize the battery management system to better control the charging and discharging process of the battery, and improve the efficiency and lifespan of the battery.

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Article

Enhanced Management of Unified Energy Systems Using Hydrogen Fuel Cell Combined Heat and Power with a Carbon Trading Scheme Incentivizing Emissions Reduction

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Abstract: In the quest to achieve “double carbon” goals, the urgency to develop an efficient Integrated Energy System (IES) is paramount. This study introduces a novel approach to IES by refining the conventional Power-to-Gas (P2G) system. The inability of current P2G systems to operate independently has led to the incorporation of hydrogen fuel cells and the detailed investigation of P2G’s dual-phase operation, enhancing the integration of renewable energy sources. Additionally, this paper introduces a carbon trading mechanism with a refined penalty–reward scale and a detailed pricing tier for carbon emissions, compelling energy suppliers to reduce their carbon footprint, thereby accelerating the reduction in system-wide emissions. Furthermore, this research proposes a flexible adjustment mechanism for the heat-to-power ratio in cogeneration, significantly enhancing energy utilization efficiency and further promoting conservation and emission reductions. The proposed optimization model in this study focuses on minimizing the total costs, including those associated with carbon trading and renewable energy integration, within the combined P2G-Hydrogen Fuel Cell (HFC) cogeneration system. Employing a bacterial foraging optimization algorithm tailored to this model’s characteristics, the study establishes six operational modes for comparative analysis and validation. The results demonstrate a 19.1% reduction in total operating costs and a 22.2% decrease in carbon emissions, confirming the system’s efficacy, low carbon footprint, and economic viability.

Keywords: integrated energy systems; hydrogen fuel cells; optimized operation; carbon trading; adjustable heat-to-power ratio

1. Introduction

Across the globe, nations have recognized the importance of diminishing carbon emissions as an essential metric. At its 75th session, the United Nations General Assembly heard China’s commitment to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 [1,2]. In the realm of carbon emissions, the electricity sector, predominantly powered by fossil fuels, contributes approximately 40% [3,4]. With the intrinsic potential for emission reductions, the electricity sector leads in China’s national unified carbon emission trading market, hastening the transition of Chinese electrical companies towards low-carbon operations. This transition facilitates the progression towards a sustainable energy supply that is both cleaner and lower in carbon emissions [5,6]. The advent of the Integrated Electricity–Heat Energy System (IEHS) has heralded a new era in energy optimization. This system efficiently harnesses both electric and thermal energy, thereby enhancing the overall energy efficiency and fostering a low-carbon economy through the synergistic interaction of these energy forms [7,8].

Wind and solar power exhibit considerable fluctuations and unpredictability. These energy sources, without sufficient grid management strategies, might lead to underutilization. Power-to-gas (P2G) technology emerges as an innovative approach to enhance the

utilization of these renewable energies. Research in [9] established a low-carbon economic dispatch model incorporating P2G storage, showing its effectiveness in augmenting the grid's capacity to integrate energy from wind and solar sources. Further studies in [10,11] explore how P2G can convert excess wind energy into hydrogen through electrolysis using an electrolyzer (EL), and subsequently produce synthetic natural gas by combining this hydrogen with CO₂, which markedly improves wind energy absorption and serves as a model for low-carbon operations. According to [12], the conversion efficiency from hydrogen to synthetic natural gas stands at 55%, with an electrolysis efficiency of 80%, and the combustion process emits zero carbon while offering superior efficiency compared to natural gas. However, [13] indicates that current research on the energy conversion cycle between EL, hydrogen fuel cells, and methane reactors (MRs) does not account for the potential heat recovery from fuel cells. This suggests significant opportunities to further explore the emission reduction potential of dual-stage P2G processes, making it crucial to delve deeper into this area.

In addition, to unleash the emission reduction potential of industrial park areas, the literature [14] indicates that applying a carbon trading mechanism to IEHS can effectively promote carbon emission reductions. Recent studies have introduced a carbon trading framework into IEHS, examining the influence of carbon trading prices [15]. Subsequent research developed a low-carbon economic model for IEHS that incorporates these mechanisms [16]. Further enhancements have been made to carbon emission estimation techniques, introducing a stepwise carbon trading approach that significantly cuts emissions [17,18]. An optimized version of this model refines the carbon trading calculation methodologies, improving both the low-carbon efficiency and economic performance of the system [19]. Another approach introduces a penalty-tiered carbon trading system derived from a stepwise model but it lacks detailed carbon emission-price ranges, leaving the impact on carbon reduction ambiguous [20]. An analysis of these studies reveals a gap in the detailed consideration of dual-stage P2G operations and the effect of carbon emission-price ranges on carbon trading mechanisms, which results in vague outcomes regarding carbon reductions. Addressing these issues, this paper utilizes the penalty-tiered carbon trading system to coordinate the dual-stage operations of P2G, refines the emission-price ranges, and evaluates the effectiveness of various reward factors.

In addition, the predominant approach in IEHS research has focused on Combined Heat and Power (CHP) units with fixed thermal–electric ratios [21–23]. Recent proposals advocate for a “heat dictates power” strategy, which leads to significant electricity losses, increased wind curtailment, and diminished system regulation capabilities, thereby reducing economic efficiency [24,25]. Although there is research exploring the adjustability of thermal–electric ratios within CHP units to enhance system operations, it overlooks the potential heat utilization from High-Temperature Fuel Cells (HFCs) and the flexibility of thermal–electric ratios, thus not fully capitalizing on possible energy savings and emission reductions [26]. Therefore, it is imperative to consider the utilization of heat from HFCs and conduct in-depth research on the roles of adjustable thermal–electric ratios of both HFCs and CHP in IEHS to further enhance energy-saving and emission reduction efforts.

To achieve the dual-carbon goals, this study introduces an advanced energy system optimization approach using a dynamic reward–penalty carbon trading framework for P2G systems integrated with HFCs, aimed at optimizing both the carbon footprint and economic performance. Initially, the model incorporates a sophisticated two-phase P2G process within an IEHS framework, utilizing a tiered carbon trading mechanism. This model also takes into account the flexible thermal–electric ratio of HFCs and CHP configurations to minimize the total operational costs, expenses associated with carbon trading, and utilization costs of renewable energies. Subsequently, the optimization challenges are tackled using the versatile Bacterial Foraging Optimization Algorithm, ensuring a thorough global search capability. Comparative evaluations of various operational strategies validate the efficiency of the tailored IEHS, underlining its effectiveness.

2. The Award and Punishment Step-by-Step Carbon Trading Mechanism and the IEHS Model

In this study, we explore the refined operation of P2G technologies within an IEHS, focusing on a two-stage process. This is examined under a dynamic reward–punishment carbon trading mechanism. The paper delves into the optimization of an adjustable energy system incorporating combined CHP. A comprehensive analysis is provided on the structure of the IEHS model, which is tailored to operate under the dynamic reward–punishment carbon trading mechanism. Additionally, the operational strategy for HFC in this framework is elaborated.

2.1. The Structure of IEHS

Figure 1 illustrates the conceptual architecture of the IEHS. Within the established framework of energy and power systems, sources such as wind turbines, solar photovoltaic arrays, and Combined CHP units deliver electrical energy primarily to various electrical loads and P2G systems. Subsequently, the electricity is transformed into hydrogen via EL units, which are then utilized directly by HFC to generate both electricity and heat. Excess hydrogen is transformed into natural gas by MR equipment to supply gas loads, further achieving cascaded consumption of energy for efficient utilization. In the thermal network, HFCs, CHP, and gas boilers (GBs) provide heat to thermal loads. In the gas network, the demand for gas loads mainly involves purchasing higher-level gases and a joint supply of methane-synthesized natural gases. In IEHS, apart from the complementary coordinated use of electrical and thermal energies, it also includes storage devices for gases, thermal energies, and hydrogen energies to achieve energy storage and time shifting. These storage devices can transfer energy between high-demand peak periods and low-demand off-peak periods to balance and optimize energy supply. Meanwhile, CO₂ generated or absorbed within the system is ultimately traded through carbon trading markets to achieve dual benefits in terms of the economy and the environment.

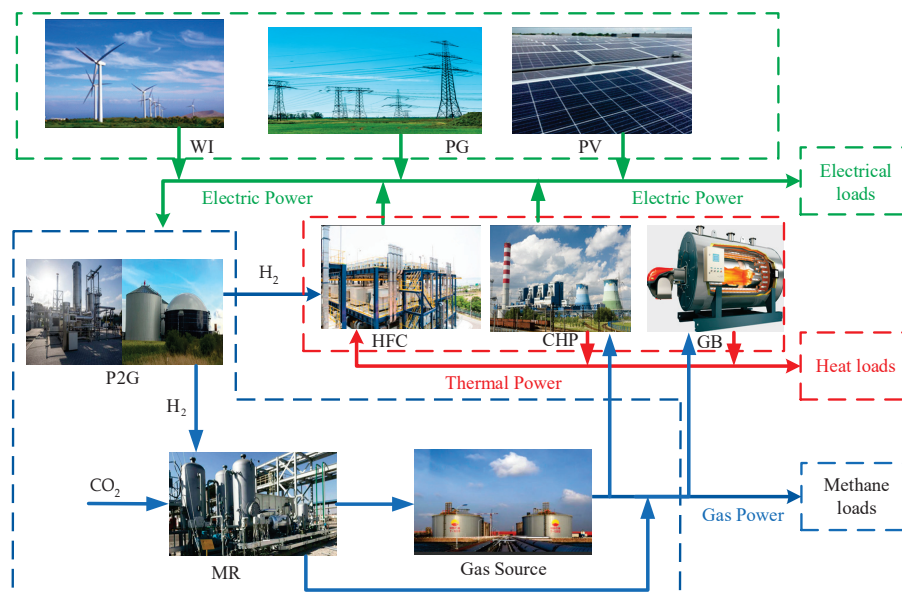


Figure 1. IEHS operation diagram.

2.2. The Principle and Model of Adjustable Thermal–Electric Ratio

(1) The principle of the adjustable thermal–electric ratio.

The CHP system utilizes the waste heat generated by fuel combustion in gas turbines to improve energy efficiency. The system can achieve real-time adjustment of electricity generation by controlling the intake of the gas turbine. At the same time, by controlling the absorption of waste heat by the heat recovery boiler, the system can change the amount

of heat supplied. Through this method, the system can achieve a real-time adjustable thermal–electric ratio while adjusting the thermal–electric capacity. Specifically, when the load demand is high, the system can increase the intake of the gas turbine and burn more fuel to increase electricity generation. Meanwhile, the heat recovery boiler can fully absorb the heat in the waste gas to meet the higher heat demand. Thus, the system can achieve a higher thermal–electric ratio under high load. Based on this, this paper proposes an adjustable thermal–electric ratio model.

(2) The adjustable thermal–electric ratio model.

Reference [27] provides the range of the adjustable thermal–electric ratio. The working model is as follows:

$$\begin{cases} P_e^{\text{CHP}}(t) = (1 - k_h)\eta_e^{\text{CHP}} L_{\text{NG}} P_g^{\text{CHP}}(t) \\ P_h^{\text{CHP}}(t) = k_h(1 - k_{\text{loss}})\eta_h^{\text{CHP}} L_{\text{NG}} P_g^{\text{CHP}}(t) \\ P_{g,\min}^{\text{CHP}} \leq P_g^{\text{CHP}}(t) \leq P_{g,\max}^{\text{CHP}} \\ \Delta P_{g,\min}^{\text{CHP}} \leq P_g^{\text{CHP}}(t+1) - P_g^{\text{CHP}}(t) \leq \Delta P_{g,\max}^{\text{CHP}} \\ \kappa^{\text{CHP}} = P_h^{\text{CHP}}(t)/P_e^{\text{CHP}}(t) = k_h(1 - k_{\text{loss}})\eta_h^{\text{CHP}}/(1 - k_h)\eta_e^{\text{CHP}} \\ \kappa_{\min}^{\text{CHP}} \leq P_h^{\text{CHP}}(t)/P_e^{\text{CHP}}(t) \leq \kappa_{\max}^{\text{CHP}} \end{cases} \quad (1)$$

where $P_g^{\text{CHP}}(t)$ represents the input power of natural gas for a CHP unit during a specific time period t ; concurrently, $P_e^{\text{CHP}}(t)$ denotes the electrical power output; $P_h^{\text{CHP}}(t)$ symbolizes the thermal power output of the CHP unit during the same interval; L_{NG} is defined as the low calorific value of natural gas and is consistently set at 9.7 kW/m^3 ; the conversion efficiencies for electricity and thermal energy within the CHP system are represented by η_e^{CHP} and η_h^{CHP} , respectively; k_h and k_{loss} quantify the rates of heat loss and the ratio of heat utilized for heating by the CHP unit; constraints on the natural gas power input are defined by $P_{g,\max}^{\text{CHP}}$ and $P_{g,\min}^{\text{CHP}}$, which delineate the maximum and minimum allowable values; $\Delta P_{g,\max}^{\text{CHP}}$ and $\Delta P_{g,\min}^{\text{CHP}}$ describe the maximum and minimum permissible rates of change in gas power input; the thermoelectric ratio of the CHP, along with its maximum and minimum allowable values, are designated as κ^{CHP} , $\kappa_{\max}^{\text{CHP}}$, and $\kappa_{\min}^{\text{CHP}}$.

2.3. P2G Two-Stage Operational Process

P2G technology facilitates the transformation of electrical power into a gas form, predominantly hydrogen or methane. In order to describe the operation of P2G systems more accurately, this paper introduces EL, MR, and HFC models to refine the P2G process into two steps: electric hydrogen production and methanation. The refined P2G two-phase operation is shown in Figure 2.

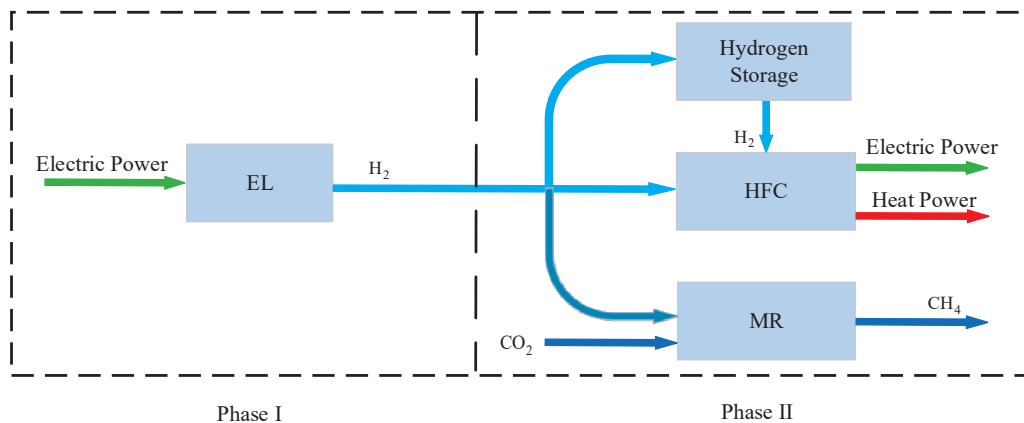


Figure 2. Refinement of the P2G two-phase operating map.

In the EL model, electrical energy is initially converted into hydrogen. Subsequently, this hydrogen serves a dual purpose: it is either directly utilized in the HFC model to generate both electricity and heat or it is transferred to the MR where it reacts with carbon dioxide to produce synthetic natural gas, thereby fulfilling the demands of the gas load, GBs, and CHP systems. Direct utilization of hydrogen in HFCs offers several advantages compared to its conversion to natural gas for subsequent combustion in GBs or CHP. Primarily, it streamlines the energy transformation process by reducing the steps involved, thus curtailing the cascading loss of energy. Moreover, hydrogen demonstrates superior energy efficiency relative to natural gas and emits no CO₂ during consumption. Therefore, a direct supply of HFCs can achieve higher energy efficiency and environmental friendliness.

The above model of energy conversion can be described as follows [28].

2.3.1. EL Equipment

P2G can convert electrical energy into chemical energy in the gas to realize the conversion of energy in time and space, and its core component is the EL equipment. The EL is divided into three types: the proton exchange membrane EL, alkaline EL, and high-temperature solid oxide EL, of which the more widely used is the proton exchange membrane EL. The high-temperature solid oxide EL's efficiency can reach approximately 85%, which is higher than the remaining two types, but its operating temperature is high, which is not ideal, and it is not currently promoted on a large scale. This paper does not elaborate on the specific types and working principles of the EL, as a more detailed description can be found in reference [29]. This paper selects the more widely used alkaline EL, the structure and principle of which are shown in Figure 3.

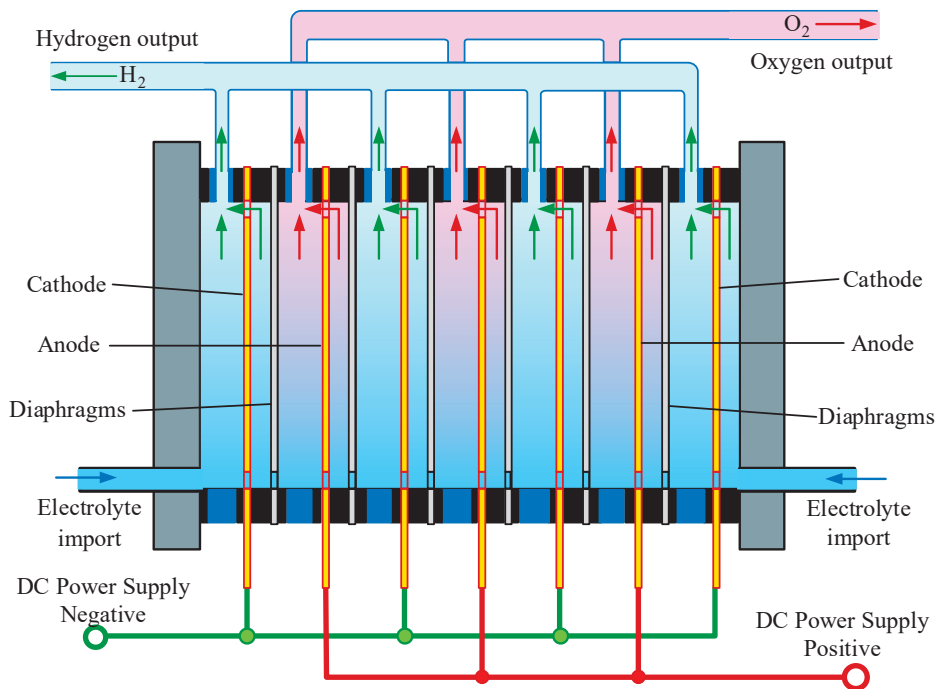


Figure 3. Refinement of the P2G two-phase operating map.

The EL model constructed in this paper is as follows:

$$\begin{cases} P_{EL,H_2}(t) = \eta_{EL} P_{e,EL}(t) \\ p_{e,EL}^{min} \leq P_{e,EL}(t) \leq p_{e,EL}^{max} \\ \Delta p_{e,EL}^{min} \leq P_{e,EL}(t+1) - P_{e,EL}(t) \leq \Delta p_{e,EL}^{max} \end{cases} \quad (2)$$

where at time period t , the EL generates hydrogen energy output, designated as $P_{EL,H_2}(t)$, while the electrical energy input to the EL is indicated by $P_{e,EL}$; the efficiency of converting hydrogen energy in the EL is captured by the metric η_{EL} ; the operational parameters for the EL include a defined range for power input, with $P_{e,EL}^{\min}$ representing the minimum threshold and $P_{e,EL}^{\max}$ serving as the maximum permissible value; the rate of increase in the EL's operation is bounded by $\Delta P_{e,EL}^{\max}$ as the upper limit and $\Delta P_{e,EL}^{\min}$ as the lower limit.

2.3.2. Methanation of MR Equipment

The methanation reaction is the reduction in carbon dioxide by hydrogen to synthesize methane and water under specific temperature conditions and catalysts, and this reaction is a volume reduction reaction usually accompanied by the release of energy, i.e., the thermal effect. The methanation reaction is the core reaction of coke oven gas to natural gas, especially in the adiabatic multi-stage cycle. In order to obtain industrialization research, this paper does not elaborate further on the working principle, as a more detailed description can be found in reference [30]. The structure and principle of MR is shown in Figure 4.

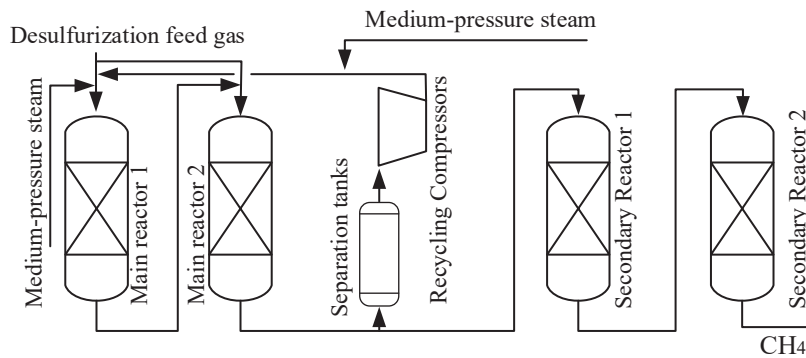


Figure 4. MR structure and schematic diagram.

The model delineated in this study represents the operational dynamics of an MR.

$$\begin{cases} P_{MR,g}(t) = \eta_{MR} P_{H_2,MR}(t) \\ P_{H_2,MR}^{\min} \leq P_{H_2,MR}(t) \leq P_{H_2,MR}^{\max} \\ \Delta P_{H_2,MR}^{\min} \leq P_{H_2,MR}(t+1) - P_{H_2,MR}(t) \leq \Delta P_{H_2,MR}^{\max} \end{cases} \quad (3)$$

where at any given time t , the natural gas output, denoted as $P_{MR,g}(t)$, is generated from the MR, influenced by the hydrogen input, labeled $P_{H_2,MR}(t)$; the conversion efficiency of this process, represented by η_{MR} , indicates the effectiveness of converting hydrogen into methane; operational constraints are defined by $P_{H_2,MR}^{\max}$ and $P_{H_2,MR}^{\min}$, which are the maximum and minimum thresholds for hydrogen energy inputs to the MR; the operational flexibility of MR, concerning its capability to adjust output levels, is bounded by $\Delta P_{H_2,MR}^{\max}$ and $\Delta P_{H_2,MR}^{\min}$, representing the upper and lower limits of the MR's operational ramping.

2.3.3. Hydrogen Fuel Cell (HFC) Equipment

In HFCs, only hydrogen reacts with oxygen to form water, and the whole process is pollution-free, does not emit carbon, and does not follow the Carnot cycle. HFCs have a high energy conversion efficiency and have become an important direction for future battery research. The specific reaction principle is not elaborated on further in this paper, and for a detailed understanding, readers are directed to reference [31]. The structure and principle of HFCs are shown in Figure 5.

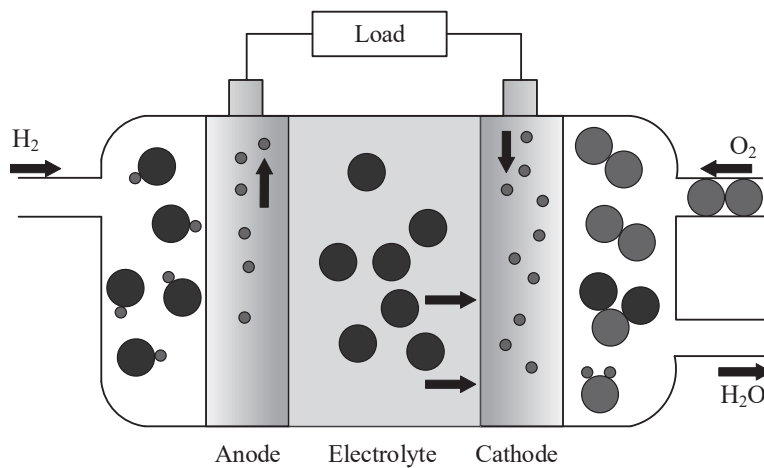


Figure 5. HFC structure and schematic diagram.

In this study, the model for HFC energy dynamics is delineated as:

$$\begin{cases} P_{\text{HFC},e}(t) = \eta_{\text{HFC}}^e P_{\text{H}_2,\text{HFC}}(t) \\ P_{\text{HFC},h}(t) = \eta_{\text{HFC}}^h P_{\text{H}_2,\text{HFC}}(t) \\ P_{\text{H}_2,\text{HFC}}^{\min} \leq P_{\text{H}_2,\text{HFC}}(t) \leq P_{\text{H}_2,\text{HFC}}^{\max} \\ \Delta P_{\text{H}_2,\text{HFC}}^{\min} \leq P_{\text{H}_2,\text{HFC}}(t+1) - P_{\text{H}_2,\text{HFC}}(t) \leq \Delta P_{\text{H}_2,\text{HFC}}^{\max} \\ \kappa_{\text{HFC}}^{\min} \leq P_{\text{HFC},h}(t) / P_{\text{HFC},e}(t) \leq \kappa_{\text{HFC}}^{\max} \end{cases} \quad (4)$$

where $P_{\text{H}_2,\text{HFC}}(t)$ represents the hydrogen energy required by the HFC at any given time t ; η_{HFC}^e and η_{HFC}^h quantify the conversion efficiencies of the HFC for electricity and heat; the outputs in terms of electrical and thermal energies are denoted as $P_{\text{HFC},e}(t)$ and $P_{\text{HFC},h}(t)$ for time t , respectively; the model defines $P_{\text{H}_2,\text{HFC}}^{\max}$ and $P_{\text{H}_2,\text{HFC}}^{\min}$ as the upper and lower limits for the hydrogen energy input into the HFC, respectively; $\Delta P_{\text{H}_2,\text{HFC}}^{\min}$ and $\Delta P_{\text{H}_2,\text{HFC}}^{\max}$ serve as the creepage bounds, while $\kappa_{\text{HFC}}^{\max}$ and $\kappa_{\text{HFC}}^{\min}$ establish the constraints for the thermoelectric ratio of the HFC.

2.4. Reward and Penalty Laddering Carbon Trading Mechanism Modeling

The Incentive Laddering Mechanism for Carbon Trading, a market-oriented model predicated on carbon emissions, seeks to foster a reduction in these emissions through structured incentives. This mechanism employs a hierarchical system of carbon emission thresholds coupled with rewards for compliance and penalties for breaches. It introduces an incentive coefficient β concept to further refine the categorization and handling of various carbon emission levels. Should the carbon emissions from an energy provider fall below the government-allocated free emission quota, a defined subsidy is granted to encourage continued adherence to low-carbon practices. The framework for this mechanism encompasses a model for actual carbon emissions, a tiered system for carbon trading rewards and penalties, and a model for managing carbon emission rights.

(1) Carbon Emission Allowance Model

In the IEHS, the primary contributors to carbon emissions include GBs, CHP systems, and power acquired from higher authorities. The prevalent allocation method in China currently utilizes a non-cost allocation system. This analysis posits that all power acquisitions from higher-level sources are attributable to coal-fired thermal power plants.

$$\begin{cases} E_{ct} = E_{CHP} + E_{GB} + E_{e,buy} + E_{g,load} - E_{MR} \\ E_{CHP} = \lambda_h \sum_{t=1}^T (\lambda_{e,h} P_{CHP,e}(t) + P_{CHP,h}(t)) \\ E_{GB} = \lambda_h \sum_{t=1}^T P_{GB,h}(t) \\ E_{e,buy} = \lambda_e \sum_{t=1}^T P_{e,buy}(t) \\ E_{g,load} = \lambda_g \sum_{t=1}^T P_{g,load}(t) \end{cases} \quad (5)$$

where E_{ct} , E_{CHP} , E_{GB} , $E_{e,buy}$, $E_{g,load}$, and E_{MR} are the carbon credits required for IEHS, CHP, GB, upstream power purchase, gas load, and methanization, respectively. Carbon allowances for gas and coal-fired units are designated as λ_h , λ_e , and λ_g for thermal power production, electric power generation, and gas load management, respectively; upstream power purchases during time slot t are denoted as $P_{e,buy}(t)$, while $P_{GB,h}(t)$ represents the thermal energy produced by the GB within the same interval; $P_{g,load}(t)$ indicates the gas load at any given time during the scheduling period t ; $\lambda_{e,h}$ refers to the conversion factor from electric to heat power in CHP unit.

(2) Real carbon emissions modeling

Within the MR protocol, it is essential to account for the absorption of a segment of CO_2 during the transformation of hydrogen into natural gas. The true carbon emissions are consequently formulated in the following manner:

$$\begin{cases} E_{\text{CO}_2} = E_{e,buy,a} + E_{\text{total},a} - E_{\text{MR},a} \\ E_{e,buy,a} = \sum_{t=1}^T (a_1 + b_1 P_{e,buy}(t) + c_1 P_{e,buy}^2(t)) \\ E_{\text{total},a} = \sum_{t=1}^T (a_2 + b_2 P_{\text{total}}(t) + c_2 P_{\text{total}}^2(t)) \\ P_{\text{total}}(t) = P_{CHP,e}(t) + P_{CHP,h}(t) + P_{GB,h}(t) \\ E_{\text{MR},a} = \sum_{t=1}^T \omega P_{\text{MR},g}(t) \end{cases} \quad (6)$$

where for the IEHS, the actual carbon emissions, denoted as E_{CO_2} , are recorded; when the IEHS sources electricity from a superior level, the emissions are represented by $E_{e,buy,a}$; the MR process captures CO_2 , quantified as $E_{\text{MR},a}$; the cumulative carbon emissions from the CHP unit, the MR facility, and the GB are calculated as $E_{\text{total},a}$, whereas $P_{\text{total}}(t)$ indicates the equivalent power output of these units at any given time t . The parameter ω represents the CO_2 absorption efficiency in the conversion of hydrogen to natural gas at the MR plant; parameters a_1 , b_1 , c_1 , and a_2 , b_2 , and c_2 are employed to estimate emissions from coal-fired and gas-fired power systems, respectively.

(3) Reward and penalty ladder carbon emissions trading model

Calculation of both the carbon emission allowances and the real emissions from IEHS enables the precise quantification of carbon emission rights that are exchanged within the carbon trading market.

$$E_{\text{CO}_2,t} = E_{\text{CO}_2} - E_{ct} \quad (7)$$

where $E_{\text{CO}_2,t}$ is the carbon credit trading amount of the IEHS.

This research proposes an enhanced carbon pricing model in carbon trading to further incentivize power companies towards emission reductions and boost the efficacy of the carbon trading scheme. The model introduces a tiered carbon trading structure that applies variable rewards and penalties based on how well companies meet their carbon quotas. Rewards are granted for emissions that fall below the allocated quota, encouraging the adoption of low-carbon technologies and further reducing carbon dioxide emission coefficients per kilowatt-hour to maximize revenue. Conversely, companies that exceed their carbon quotas by specific thresholds face escalating penalty costs. This tier-based approach

to carbon pricing through linear segmentation aims to actively engage power enterprises in modifying their production strategies or adopting low-carbon technologies. Such adjustments are intended to control carbon emissions effectively, ensuring the precision and rationality of carbon trading and generating substantial economic benefits. The dynamics between the tiered pricing in this trading model and the segmented function reflecting the variance between actual emissions and the quota are depicted in Figure 6.

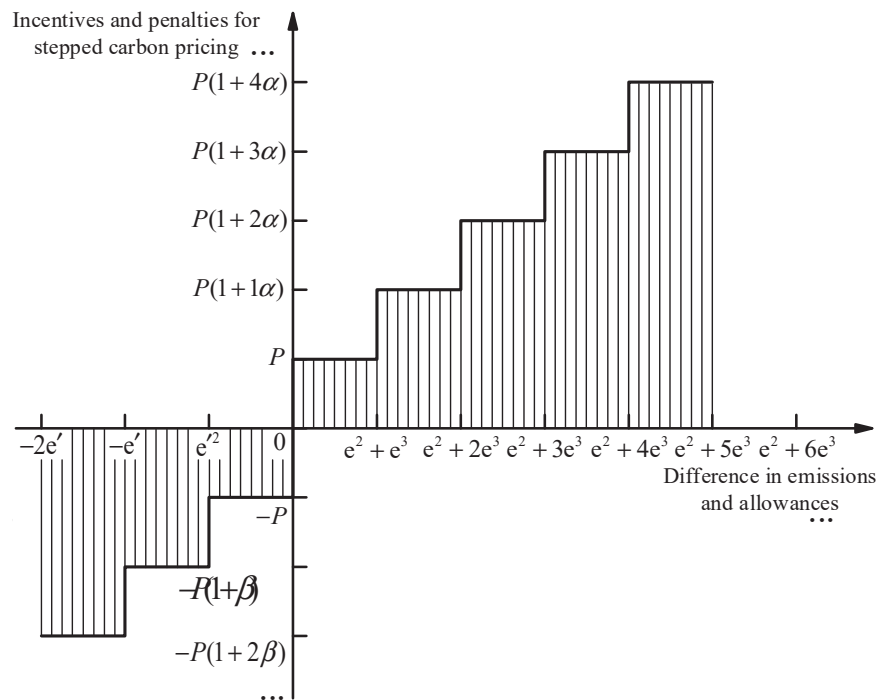


Figure 6. Relationship between carbon trading prices and carbon trading volumes.

In Figure 6, the stepped structure in the carbon trading price function reflects the cost situation faced by energy supply companies when carbon emissions exceeded the quota, and this structure is represented by the coordinates and shaded area in the first quadrant, symbolizing the role of the multi-energy complementary system. In scenarios where carbon emissions surpass allocated quotas, the financial burden of carbon credits on energy suppliers escalates. Conversely, when emissions remain below the allotted limits, delineated by coordinates in the third quadrant, these companies may accrue revenue through carbon trading. This potential revenue increases incrementally with further emission reductions, thereby encouraging power providers to adopt more stringent emission control strategies. This financial mechanism effectively motivates a reduction in emissions. A tiered pricing system for carbon emission credits, which differs from traditional methods, implements a graded approach. As companies acquire more carbon allowances, the cost associated with these increasing tiers escalates accordingly. Therefore, the cost of reward and punishment tiered carbon trading can be calculated in the following way:

$$C_{CO_2} = \begin{cases} P_{ct}(E_{CO_2} - E_{ct}) + P_{ct}\beta(2E_{ct} - 2E_{CO_2} - e) & E_{CO_2} < E_{cl} - e' \\ P_{ct}(E_{CO_2} - E_{ct}) + P_{ct}\beta(E_{ct} - E_{CO_2}) & E_{ct} - e' \leq E_{CO_2} < E_{ct} \\ P_{ct}(E_{CO_2} - E_{ct}) & E_{ct} \leq E_{CO_2} \leq E_{ct} + E \\ P_{ct}(E_{CO_2} - E_{ct}) + P_{ct}\alpha(E_{CO_2} - E_{ct} - e) & E_{ct} + E < E_{CO_2} \leq E_{ct} + E + e \\ P_{ct}(E_{CO_2} - E_{ct}) + P_{ct}\alpha(2E_{CO_2} - 2E_{ct} - 3e) & E_{ct} + E + e < E_{CO_2} \leq E_{ct} + E + 2e \\ P_{ct}(E_{CO_2} - E_{ct}) + P_{ct}\alpha(3E_{CO_2} - 3E_{ct} - 6e) & E_{ct} + E + 2e < E_{CO_2} \leq E_{ct} + E + 3e \\ \dots\dots\dots & \dots\dots\dots \\ P_{ct}(E_{CO_2} - E_{ct}) + P_{ct}\alpha\left(nE_{CO_2} - nE_{ct} - \frac{n(n+1)}{2}e\right) & E_{ct} + E + ne < E_{CO_2} \leq E_{ct} + E + (n+1)e \end{cases} \quad (8)$$

where, in the carbon trading market, the Cost of System Operation (C_{CO_2}) functions as a dynamic adjustment mechanism, modifying charges according to the incentive–penalty step model; this model is further defined by the baseline carbon trading price (P_{ct}), which anchors the market’s initial valuation of carbon credits; the actual carbon emissions of system operation (E_{CO_2}), when juxtaposed with the Initial quota allocated by the government (E_{ct}), underscore the operational reality of emissions versus regulatory benchmarks.

The carbon price parity interval without incentives and penalties (E) delineates the range within which carbon prices stabilize without regulatory interference. The incentive–penalty step carbon trading model distinguishes itself through two primary intervals: the length of the step incentive interval (e) and the length of the step penalty interval (e'), with each dictating the extent of fiscal adjustments for compliance or deviation; the degree of balance at the time of carbon allowance settlement (n) is assessed across multiple gradients, ensuring a nuanced evaluation of emissions management; within this framework, the carbon price penalty factor per unit of emission reduction in each class interval (α) is activated when emissions exceed government-issued quotas, imposing financial disincentives; the carbon price incentive factor per unit of emission reduction in each class interval (β) rewards operations that maintain emissions below the stipulated benchmarks, promoting environmentally beneficial practices.

3. Optimized Operation Model of IEHS Considering Reward–Penalty Stepped Carbon Trading Mechanism with Adjustable Heat-to-Power Ratio

3.1. Objective Function Establishment

This chapter develops an operational model for HFCs and CHP based on thermoelectric ratios, employing an optimized P2G-HFC-IEHS framework. The model is engineered to ensure low-carbon, economical, and stable performance while adhering to operational constraints, leveraging a reward and punishment mechanism within carbon trading. Comprising various cost considerations—including stepped carbon trading expenses, penalties for unused renewable energy, operational costs, and energy purchase expenditures—the model is detailed through an optimally minimized objective function. Equation (9) presents the scheduling objective function.

$$C = \min(C_{WP} + C_M + C_{buy} + C_{CO_2}) \quad (9)$$

where C represents the total operational costs, encompassing C_{WP} , which details the fines for abandoning new energy sources. C_{buy} covers the expenses for energy acquisition, while C_M accounts for the costs associated with system maintenance and operations.

(1) Cost of energy purchases

$$C_{buy} = \sum_{t=1}^T (\alpha_t P_{e, buy}(t) + \beta_t P_{g, buy}(t)) \quad (10)$$

where α_t specifies the electricity rates at a given time period t , β_t denotes the gas prices at the same time interval, and $P_{e, buy}(t)$ indicates the volume of gas procured during period t .

(2) Rewards and penalties for stepped carbon transaction costs (See (9))

(3) Penalty costs for abandoning new energy sources C_{WP}

$$C_{WP} = \begin{cases} C_{DG, cut} = \sum_{t=1}^T \varepsilon_{DG} (P_{DG, pre}(t) - P_{DG}(t)) \\ C_{PV, cut} = \sum_{t=1}^T \varepsilon_{PV} (P_{PV, pre}(t) - P_{PV}(t)) \\ 0 \leq P_{DG}(t) \leq P_{DG}^{max} \\ 0 \leq P_{PV}(t) \leq P_{PV}^{max} \end{cases} \quad (11)$$

where the costs associated with the cessation of wind operations ($C_{DG,cut}$) are influenced by ε_{DG} , a coefficient that penalizes the abandonment of wind turbines; predictions of wind turbine output at a specific time, t , are denoted as $P_{DG,pre}(t)$; the costs tied to abandoning solar energy operations are represented by $C_{PV,cut}$, while ε_{PV} indicates the penalty coefficient for photovoltaic turbine abandonment; the forecasted power output of photovoltaic units during a time period t is symbolized as $P_{PV,pre}(t)$; $P_{DG}(t)$ and $P_{PV}(t)$ are the actual power outputs of wind and photovoltaic systems, respectively, at time t ; the maximum outputs for wind and photovoltaic systems are indicated by P_{DG}^{max} and P_{PV}^{max} .

(4) System operation and maintenance costs C_M

$$C_M = \sum_{i=1}^N C_i P_{i,t} \Delta t \quad (12)$$

where maintenance and operational costs for equipment i within the IEHS are referred to as C_i ; the output of a specific i at time t within the IEHS is expressed as $P_{i,t}$, and Δt represents the operational duration of the device.

3.2. Constraint Establishment

3.2.1. Power Balance Constraints

(1) Electrical power constraints

In this paper, the model assumes that electricity consumption is precisely balanced by the generation, without incorporating any transactions where IIES sells electricity back to the main grid.

$$P_{DG}(t) + P_{PV}(t) + P_{CHP,e}(t) + P_{HFC,e}(t) + P_{e,buy}(t) = P_{e_Load}(t) + P_{e,EL}(t) + P_{in}^e(t) \quad (13)$$

where at time t , $P_{e_Load}(t)$ represents the electrical demand; $P_{in}^e(t)$ denotes the power entering the electrical storage system; $P_{DG}(t)$ and $P_{PV}(t)$ are the wind and light power generation at time t , respectively.

(2) Thermal power balance constraints

$$\begin{cases} \delta_{1,min} P_{hl}(t) \leq P_{CHP,h}(t) + P_{GB,h}(t) + P_{HFC,h}(t) - P_{h_Load}(t) - P_{in}^h(t) \leq \delta_{1,max} P_{hl}(t) \\ P_{HFC,h}(t) + P_{CHP,h}(t) + P_{GB,h}(t) = P_{h_Load}(t) + P_{in}^h(t) \end{cases} \quad (14)$$

where $\delta_{1,max} P_{hl}(t)$ and $\delta_{1,min} P_{hl}(t)$ are the upper and lower limit ratios of thermal load adjustment; $P_{h_Load}(t)$ is the thermal load in time period t ; for the same time period t , $P_{in}^h(t)$ indicates the energy input into the thermal storage, while $P_{GB,h}(t)$ reflects the thermal energy produced by the GB system.

(3) In the context of gas power systems

MR synthetic methane fulfills part of the gas demand, complemented by a natural gas feed. It is important to note that this analysis excludes the commercial transactions of IES gas with the superior gas network.

$$P_{g,buy}(t) + P_{MR,g}(t) = P_{g_Load}(t) + P_{in}^g(t) + P_{g,CHP}(t) + P_{g,GB}(t) \quad (15)$$

where at any given time t , $P_{g_Load}(t)$ denotes the gas demand, while $P_{in}^g(t)$ represents the energy channeled into natural gas reserves.

(4) In the context of hydrogen power systems

$$P_{EL,H_2}(t) = P_{H_2,MR}(t) + P_{H_2,HFC}(t) + P_{in}^{H_2}(t) \quad (16)$$

where the energy directed towards hydrogen storage at time t is symbolized by $P_{in}^{H_2}(t)$.

3.2.2. Balancing Constraints across Segments

(1) For CHP, EL, MR, HFC, and wind PV operating constraints, see Equations (1)–(4) and (9)

(2) GB Operational Constraints

$$\begin{cases} P_{GB,h}(t) = \eta_{GB} P_{g,GB}(t) \\ P_{g,GB}^{\min} \leq P_{g,GB}(t) \leq P_{g,GB}^{\max} \\ \Delta P_{g,mB}^{\min} \leq P_{g,GB}(t+1) - P_{g,GB}(t) \leq \Delta P_{g,GB}^{\max} \end{cases} \quad (17)$$

where η_{GB} represents the efficiency of energy transformation in the GB; at time t , $P_{g,GB}(t)$ quantifies the energy supplied to the GB; the parameters $P_{g,GB}^{\max}$ and $P_{g,GB}^{\min}$ delineate the maximum and minimum permissible power inputs for the GB; $\Delta P_{g,GB}^{\max}$ and $\Delta P_{g,mB}^{\min}$ establish the maximum and minimum rates at which this power input can increase.

3.2.3. Energy Storage Operational Constraints

The study also incorporates a unified model that encapsulates electric, thermal, gas, and hydrogen energy storage systems.

$$\begin{cases} S_m(t) = (1 - \varepsilon)S_m(t-1) + \eta_{m,in}P_{m,in}(t) - \frac{P_{m,out}(t)}{\eta_{m,out}} \\ S_m(t) = S_m(t-1) + \frac{P_{out,m}(t)}{P_m^{cap}} \\ S_m^{\min} \leq S_m(t) \leq S_m^{\max} \\ 0 \leq P_{m,in}(t) \leq B_m^{\text{in}}(t)P_{m,in}^{\max} \\ 0 \leq P_{m,out}(t) \leq B_m^{\text{out}}(t)P_{m,out}^{\max} \\ S_m(0) = S_m(T) \\ S_m(1) = S_m(T) \\ 0 \leq B_m^{\text{in}}(t) + B_m^{\text{out}}(t) \leq 1 \end{cases} \quad (18)$$

where for the m-type energy storage device during a specific time period t , $P_{m,in}(t)$ and $P_{m,out}(t)$ denote the power inputs during charging and outputs during discharging, respectively. The binary variables $B_m^{\text{in}}(t)$ and $B_m^{\text{out}}(t)$ indicate the device's state of operation: charging ($B_m^{\text{in}}(t) = 1$, $B_m^{\text{out}}(t) = 0$) or discharging ($B_m^{\text{in}}(t) = 0$, $B_m^{\text{out}}(t) = 1$). The peak capacities for charging and discharging are captured by $P_{m,in}^{\max}$ and $P_{m,out}^{\max}$. The output power from the m-type device for the given period is recorded as $P_{out,m}(t)$, whereas $S_m(t)$ reflects its storage capacity. The rated maximum capacity of the device is termed P_m^{cap} . The efficiencies with which the device charges and discharges are represented by $\eta_{m,in}$ and $\eta_{m,out}$, respectively. Additionally, $S_m^{\max}$ and $S_m^{\min}$ define the maximum and minimum storage capacities permissible for the device.

3.3. Model Solution

This paper develops an IEHS low-carbon economic dispatch model that incorporates a refined P2G two-stage operation with adjustable CHP and HFC thermoelectric ratios. While it operates as a single-objective optimization challenge under fully cooperative conditions, it transitions into a multi-objective optimization quandary when considering partially cooperative and non-cooperative scenarios. The model incorporates intricate constraints and employs the Bacterial Foraging Optimization Algorithm (BFOA) for resolution. This algorithm outshines traditional methods due to its bio-heuristic nature, its tendency for stochastic global searches, and its sensitivity to parameter adjustments. Traditional algorithms often struggle to maintain a balance between global and local search capabilities, which can diminish algorithmic diversity and convergence efficacy in later iterations. Therefore, BFOA is chosen for its superior performance in managing these challenges, as discussed in the literature [28]. The process of solving the model is shown in Figure 7.

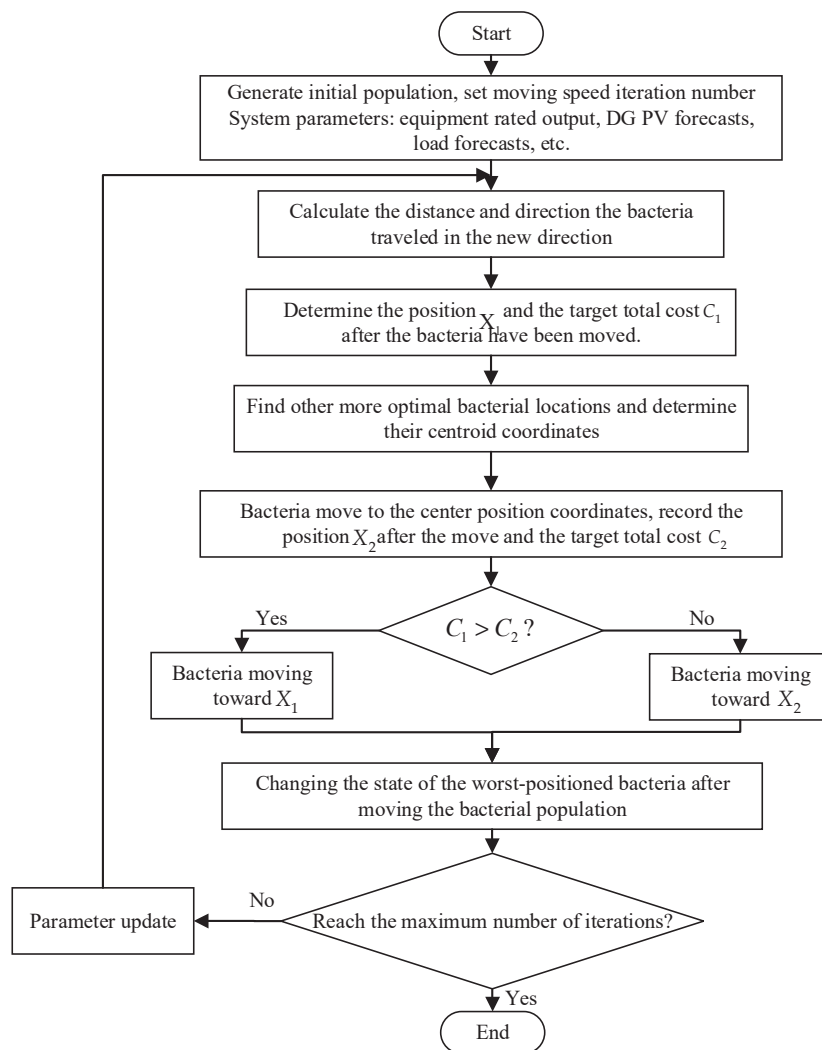


Figure 7. Flowchart of BFOA algorithm.

4. Calculus Analysis

4.1. Algorithm Parameterization

To assess the efficacy of the proposed model, optimization of cycle operations is conducted, ensuring compliance with diverse 24-h load requirements, with operations broken down into hourly intervals. The model utilizes forecasts for wind, solar, electric, thermal, and gas demands, along with operational parameters for each segment as cited in [11]. Figure 8 displays the projected curves for these loads. A daily carbon trading volume limit is set at 4000 kg. Should this threshold be exceeded, the carbon trading price growth rate will see a 25% increment, with the baseline price of carbon trading rising by ¥0.25 per kg. Additionally, reward coefficients are set at $\lambda = 0.2$ and the carbon trading price growth rate at $\alpha = 0.25$. Penalties for discarding wind-generated power are calculated at ¥0.2 per kWh; similarly, penalties for unused solar power also stand at ¥0.2 per kWh.

This study meticulously considers the impact of variable time-of-use tariffs on the system's performance. By analyzing the fluctuations in tariffs across different periods, the model aims to minimize system costs, enhance the efficiency of load dispatch, and devise an energy storage system that mitigates discrepancies between load demands and tariff rates. Additionally, it facilitates the development of a versatile operational strategy for the system. The time-of-day tariff segments and prices are shown in Table 1.

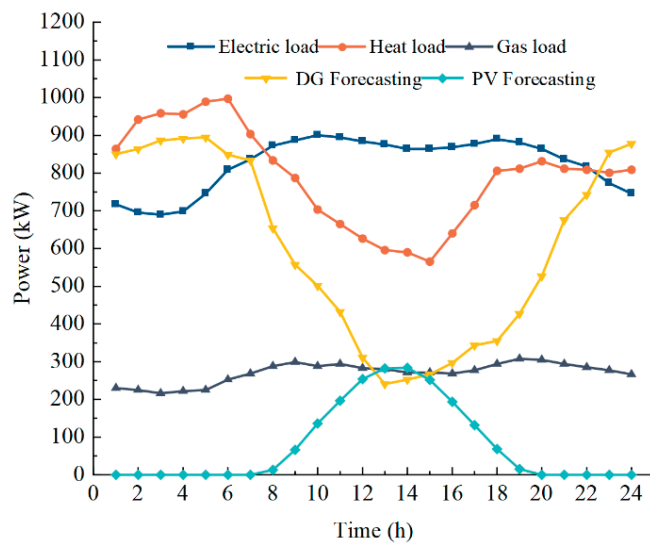


Figure 8. Wind and light and each load forecast curve.

Table 1. Time-sharing tariffs and natural gas prices.

Program	Timeframe	Numerical
Electricity price /[¥/(kWh)] [11]	22:00–next day 7:00	0.38
	7:00–11:00, 14:00–18:00	0.54
	11:00–14:00, 18:00–22:00	1.10
Gas price/(¥/m ³)	00:00–24:00	3.50

In this paper, we model P2G-HFC-IEHS and optimize the operating parameters of various devices. By optimizing the device parameters, the model promotes more sustainable energy practices, supports grid stability, and facilitates the transition to a greener, more resilient energy infrastructure. Device specifications are detailed in Tables 2–4.

Table 2. Energy storage parameters.

Equipment	Capacity/kW	Capacity Upper/Lower Limit Constraints/%	Climb Constraints/%
Electricity Storage	450	90/10	20
Heat storage	500	90/10	20
Gas storage	300	90/10	20
Hydrogen storage	200	90/10	20

Table 3. Equipment parameters.

Equipment	Capacity/kW	Energy Conversion Efficiency [11]/%	Climb Constraints/%
CHP	800	35(Q-P)	20
		45(Q-H)	20
HFC	600	50(Q-P)	20
		42(Thermal efficiency)	20
GB	500	95	20
EL	500	87	20
MR	250	60	20

Table 4. Actual carbon emission model parameters.

a_1	b_1	c_1	a_2	b_2	c_2
36	−0.38	0.0034	3	−0.04	0.001

4.2. Scene Setting

To assess the effectiveness of the proposed IEHS model, six different operational models have been established for a comparative evaluation. Each model is described as follows:

Model 1: Fixed thermoelectric ratios for CHP and HFCs are utilized within the IEHS, without the capability of adjustment. This model excludes the application of both the traditional and two-stage P2G processes as well as any form of carbon trading mechanisms, including the traditional and ladder-based reward and punishment systems.

Model 2: Excluding CHP from the IEHS, this configuration allows for adjustable thermoelectric ratios in HFCs and includes the traditional P2G process but omits the two-stage P2G and the ladder-based reward and punishment carbon trading mechanisms.

Model 3: This variant excludes CHP and incorporates an adjustable heat-to-electricity ratio for HFCs, the two-stage P2G process, and the ladder-based reward and punishment carbon trading mechanism.

Model 4: Without CHP integration, this model allows for an adjustable thermoelectric ratio in HFCs and includes both the two-stage P2G process and the traditional carbon trading mechanism but does not consider the ladder-based system.

Model 5: This setup also excludes CHP and features adjustable thermoelectric ratios for HFCs, integrating the two-stage P2G process alongside the ladder-based reward and punishment carbon trading mechanism.

Model 6: Including CHP, this model in IEHS permits adjustable thermoelectric ratios for HFCs and incorporates both the two-stage P2G process and the ladder-based incentive and punishment carbon trading mechanism.

4.3. Comparative Analysis of Optimization Results of Different Models of the Proposed IEHS Model

4.3.1. Refinement of P2G Two-Phase Operational Benefit Analysis

This work advances the traditional P2G by introducing a two-stage operational approach, capitalizing on the enhanced efficiency of this method. Details regarding this operational mode have been thoroughly discussed earlier; thus, further elaboration here is unnecessary. Consequently, the analysis establishes three distinct comparison scenarios: Mode 1, Mode 2, and Mode 3. Each mode undergoes a detailed comparative analysis based on various economic and environmental metrics such as the costs associated with electricity and gas procurement, wind and solar energy curtailment, carbon emissions, carbon trading expenses, and the overall cost implications. The comparison of the three modes of operation is shown in Table 5.

Table 5. Enhanced analysis contrasts the advantages derived from the initial and subsequent stages of the P2G process.

Parameter	Parameter Value [11]		
	Models 1	Models 2	Models 3
Purchased power cost/¥	1963.2	1758	1056.2
Purchased gas cost/¥	12,426.7	11,862.9	12,038.6
Abandoned WI cost/¥	490.6	132.4	0
Abandoned PV cost/¥	387.3	136.2	0
Carbon emission/kg	24,712	23,835	23,298
System O&M cost/¥	2136.5	2365.6	2453.8
Total cost/¥	17,404.3	16,255.1	15,548.6

From the data in the table, it is evident that Mode 3 offers the lowest total operating costs, achieving reductions of ¥1855.7 and ¥706.5 compared to modes 1 and 2, respectively. Furthermore, it significantly lowers carbon emissions by 1414 kg and 537 kg compared to the aforementioned modes. In Mode 1, the non-synchronous output peaks of wind energy at night lead to considerable wind waste. Similarly, the variability in solar power generation often surpasses system regulation capabilities, resulting in excess generation being discarded. Consequently, this mode relies heavily on purchasing power and gas from higher levels, incurring the highest operational costs. Mode 2 introduces P2G technology, using electrolysis-derived hydrogen to synthesize natural gas through the MR, which is then used to meet gas demands or stored during surplus periods of wind and solar generation. This approach utilizes surplus electricity more effectively, thereby decreasing the need for higher-level gas purchases and cutting down on electricity procurement costs. Mode 3, building on the framework established by Mode 2, implements an enhanced two-stage P2G process. Although MR facilitates the conversion of hydrogen to natural gas, which initially absorbs some CO₂, the subsequent utilization of this gas in CHP and GB systems releases CO₂ again, posing challenges to achieving carbon neutrality goals. To address this, Mode 3 prioritizes the use of hydrogen in high-efficiency HFC for cogeneration, minimizing energy losses and operating without carbon emissions during peak performance. This adjustment not only contributes to carbon emission reductions but also enhances operational efficiency by storing any surplus hydrogen.

Figure 9 presents varied forecasts for wind power PV consumption across different modes. Mode 1 exhibits the highest level of wind abandonment and the least efficient wind power utilization. This inefficiency stems from the wind turbines' high nocturnal output coupled with minimal load demand, leading to a pronounced issue of both wind and light abandonment. Conversely, Mode 2 demonstrates an enhancement in the abandonment rates of wind and light by incorporating standard P2G processes. During the dispatch cycle in this mode, the cumulative wind abandonment totals 1021.2 kW, while light abandonment reaches 151.9 kW. This reduction is attributed to P2G systems utilizing excess electricity for hydrogen production via electrolysis, subsequently used in HFCs.

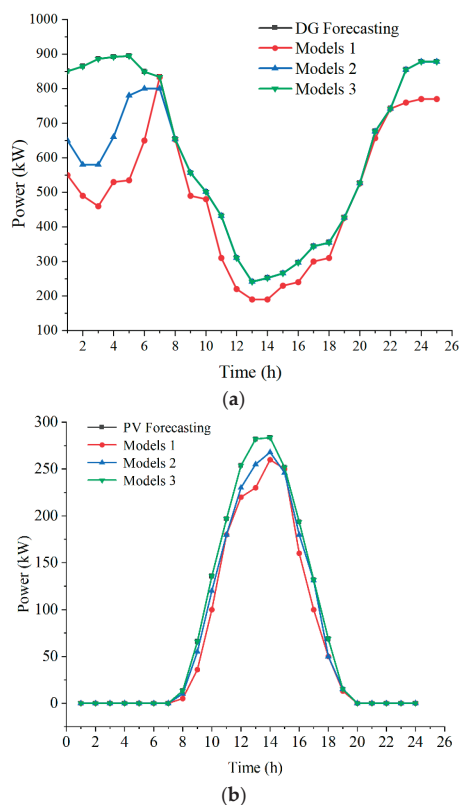


Figure 9. Wind (a) and light (b) and each load forecast curve.

4.3.2. Analysis of Carbon Trading Mechanisms for Incentives and Disincentives

This study examines the efficacy of a proposed reward–penalty carbon trading system through empirical analysis employing three distinct scenarios: Scenario 3, Scenario 4, and Scenario 5. These scenarios facilitate an examination of carbon emissions and operational costs arising from different carbon trading models. The analysis encompasses the expenses associated with sufficient electricity supply, natural gas purchases, and the costs incurred from the curtailment of wind and solar power. Additionally, the total cost of each program is compared in Table 6.

Table 6. Comparison of the benefits of carbon trading mechanisms considering a ladder of rewards and penalties.

Parameter	Parameter Value [11]		
	Models 3	Models 4	Models 5
Purchased power cost/¥	1056.2	837.2	535.8
Purchased gas cost/¥	12,038.6	13,963.1	14,316.6
Abandoned WI cost/¥	0	0	0
Abandoned PV cost/¥	0	0	0
Carbon emission/kg	23,298	20,786	18,983
Carbon transaction costs/¥	0	−1983.6	−2957.2
System O&M cost/¥	2453.8	2556.9	2637.2
Total cost/¥	15,548.6	15,373.3	15,917

Models 3, 4, and 5 were analyzed to assess their effects on carbon emissions, the costs of carbon trading, and overall expenses. Model 3, which lacks a carbon trading scheme, focuses solely on minimizing energy-related costs. Consequently, it favors cheaper natural gas despite its higher carbon footprint, leading to increased emissions. Conversely, Model 4 integrates a graduated carbon trading system, where carbon prices escalate with higher emissions. This setup encourages the optimization of unit outputs for reduced carbon emissions, and the sale of unused carbon allowances offsets the costs associated with higher carbon prices. As a result, both Models 4 and 5 exhibit significant reductions in emissions and a rise in both natural gas expenditures and overall operational costs. Specifically, Model 3's emissions exceed those of Model 4 by 2512 kg, marking a 10.9% reduction. Model 5 introduces a reward–penalty carbon trading scheme that further lowers emissions by 1803 kg compared to Model 4, though it increases total operational costs by ¥543.7. When compared to Model 3, Model 5 reduces emissions by 4315 kg (18.5%) but raises total costs by ¥368.4. The reward–penalty system not only effectively controls emissions but also minimizes economic expenditures.

Figure 10 illustrates that positive carbon transaction costs are unaffected by variations in the reward coefficient; however, if these costs are negative, an increase in the reward coefficient accelerates their reduction, thereby decreasing overall system carbon emissions more rapidly. As the reward coefficient λ increases, the decline in carbon transaction costs becomes more pronounced. When these costs fall below zero, energy supply companies receive governmental incentives, enhancing the system's profitability. A carbon trading price exceeding ¥0.4/kg makes the reward coefficient significantly influential. If the system's carbon emissions are lower than the government's free carbon emission quotas, an increasing λ markedly reduces carbon transaction costs, thus diminishing the system's carbon emissions and enabling more substantial governmental subsidies.

Data from Figure 11 reveal that carbon trading prices ranging from ¥0.3 to ¥0.4/kg exert a minimal impact on gas purchase costs. Nevertheless, within the ¥0.4 to ¥0.44/kg bracket, as carbon emission restrictions intensify, the influence on gas purchase costs becomes considerable, escalating the system's total cost. Beyond ¥0.44/kg, reaching the operational peak of the CHP unit means further increases in carbon emissions do not affect gas purchase costs. At this stage, both the system's operating costs and carbon trading costs stabilize. Thus, considering the impact of carbon trading prices is crucial in formulating

energy policies and carbon emission regulations to ensure a balance between economic efficiency and environmental sustainability.

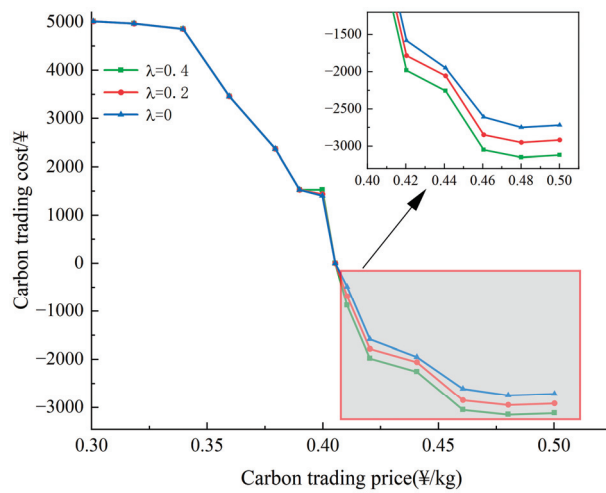


Figure 10. Interrelations of costs and prices in carbon markets influenced by various motivational factors.

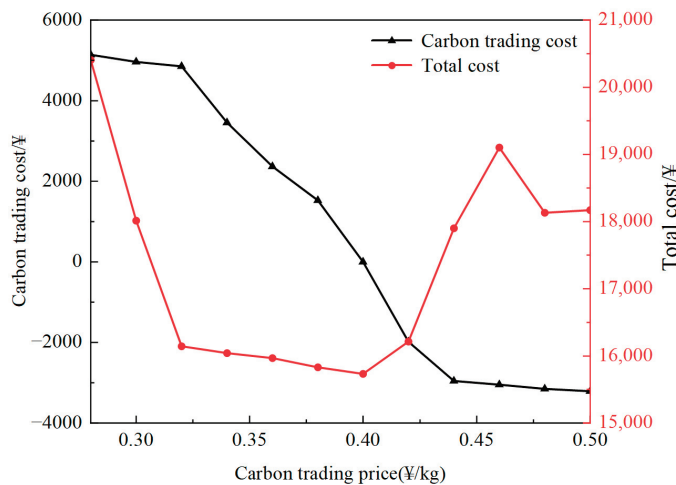


Figure 11. An analysis of aggregate costs, specific expenditures for carbon trading, and the corresponding price dynamics.

4.3.3. CHP and HFC Adjustable Thermoelectric Ratio Operation Analysis

To assess the benefits of the proposed adjustable thermoelectric ratio in CHP and HFC systems, this study delineates two distinct operational modes, namely Mode 5 and Mode 6. Analysis of carbon emissions, along with costs associated with power and gas purchases, serves to substantiate the superiority of the adjustable ratio. The operational specifics of these modes are outlined in Table 7.

Table 7. Comparison of the benefits of different heat-to-power ratios under different models.

Parameter	Parameter Value [11]	
	Models 5	Models 6
Purchased power cost/¥	535.8	0
Purchased gas cost/¥	14,316.6	14,821.6
Abandoned WI cost/¥	0	0
Abandoned PV cost/¥	0	0
Carbon emission/kg	18,983	18,230
Carbon transaction costs/¥	−1572.6	−2189.3
	2556.9	2396.7
System O&M cost/¥	15,917	15,029

Table 7 reveals that the implementation of adjustable thermoelectric ratios in CHP and HFC systems leads to significant economic and environmental benefits. Unlike Modes 6 and 5, Mode 7 eliminates the need to purchase electricity from the main grid, saving 535.8 yuan. Although gas expenses increase by ¥505, the overall energy expenditure decreases by ¥32.8. Additionally, carbon emissions dropped by 753 kg, reflecting a 3.8% reduction. The total cost also diminishes by ¥881, mirroring the same percentage decrease. This improvement stems from the adaptable thermoelectric ratios, which prevent the excess production of heat during increased electrical output, unlike in traditional fixed-ratio systems. Typically, excess heat would result in energy waste due to heat abandonment when supply surpasses demand. Furthermore, in Mode 7, when the CHP load ratio surpasses its natural level, energy costs rise minimally due to the system's flexibility in adjusting the power-to-heat ratios, enhancing efficiency, particularly during off-peak hours from 21:00 to 8:00. This period witnesses substantial wind electricity input and a high demand for heat, allowing for optimized operation of CHP and HFC units at higher heat-to-power ratios, thus better aligning the system's thermal and electrical outputs.

During the hours of 8:00–11:00 and 17:00–21:00, which are characterized by high electricity demand and low heat demand, heat production is mainly facilitated by GBs and a limited number of CHP units. Conversely, from 11:00 to 17:00, the demand for electricity peaks, resulting in the lowest heat-to-electricity production ratio.

Analysis of Figure 12 reveals that the minimum heat-to-electricity ratio occurs between 10:00 and 17:00. During this interval, the demand for thermal load by the Power-to-Gas Hydrogen Fuel Cell-Integrated Energy System (P2G-HFC-IES) diminishes, leading to a reduction in heat output from the HFC, GB, and CHP units. This adjustment in output is attributed to the ability of the HFC and CHP units, which operate under an adjustable heat-to-electricity ratio mode, to modulate their heat and power output in response to the system's load requirements. Such flexibility facilitates the optimal allocation of resources across the system, thereby minimizing total operational costs.

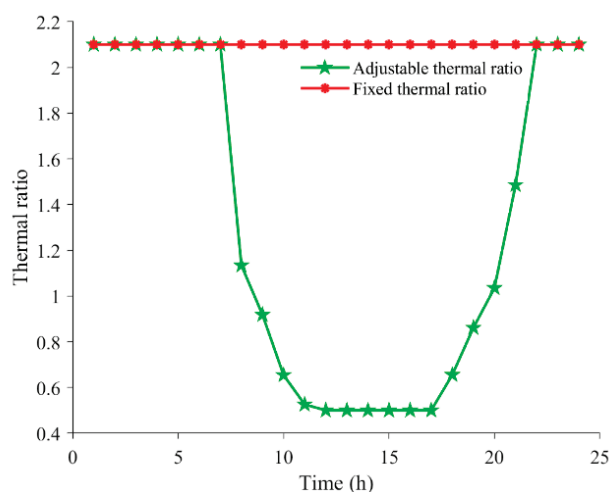


Figure 12. Comparison of thermoelectric ratio of different modes.

4.4. Analysis of the Overall Optimization Results of the Proposed IEHS Model

4.4.1. Analysis of Gas and Hydrogen Optimization Results

Figures 13 and 14 illustrate that under the incentive-based carbon trading framework, IEHS optimizes the dual-stage operation of the P2G system. Initially, surplus electricity from wind and PV sources drives the EL process to generate hydrogen. This hydrogen is first utilized by the HFC for cogeneration. Once the HFC has reached its maximum generation capacity, any surplus hydrogen is directed towards the MR and for hydrogen storage, adhering to the energy limits set by IEHS. During the hours of 0:00–10:00 and 22:00–24:00, when wind turbines are most productive and hydrogen production exceeds demand, the system leverages the flexibility of the ML to adjust electrical output according

to the high wind power output, ensuring no waste of wind energy. Prior to peak wind output, the wind-generated electricity is fully utilized to minimize waste. In the later stage, any excess hydrogen produced is channeled towards meeting gas demands after the electricity needs are met. During these times, the CHP unit operates at a lower capacity due to a smaller electricity load, resulting in minimal gas storage and promoting the efficient use of the energy gradient to enhance renewable energy consumption.

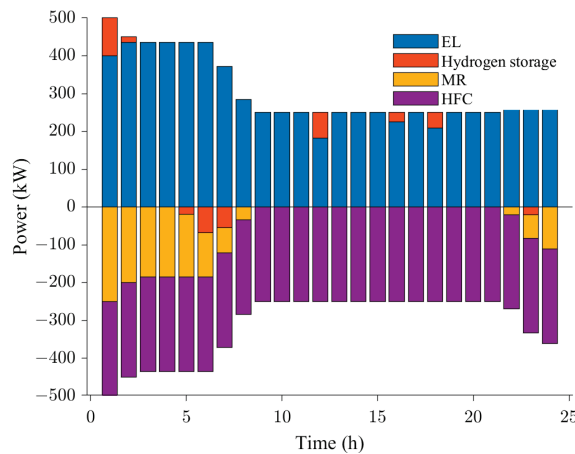


Figure 13. Optimal hydrogen load result analysis chart.

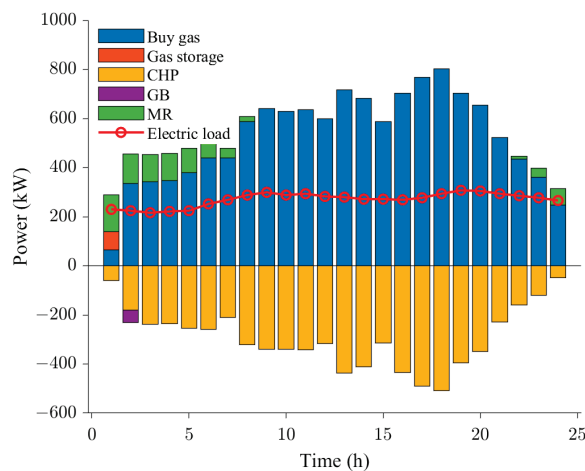


Figure 14. Optimal gas load result analysis chart.

4.4.2. Analysis of Electrical and Thermal Optimization Results

Figures 15 and 16 illustrate the refinement of the two-stage P2G operation within the reward and punishment carbon trading framework. This study emphasizes the interplay between energy generation systems under flexible CHP and HFC modes, which optimize equipment performance. During the early hours (0:00–10:00) and late evening (19:00–24:00), wind turbines reach their production peaks while the demand for electricity remains comparatively low. This discrepancy often results in surplus energy. To address this, surplus electricity primarily fuels the P2G system for hydrogen production via two-stage electrolysis, supporting both HFC and MR operations. Conversely, between 11:00 and 16:00, when solar energy production peaks and the system's thermal demand is at its minimum, solar power substitutes for CHP generation. Constraints within the system ensure that HFC operates at full capacity consistently, thus minimizing energy gradient losses and significantly reducing carbon emissions. Under the demand of thermal load, due to the influence of the adjustable CHP–HFC thermoelectric ratio, the thermal energy of the fuel cell is always absorbed at full load. Coupled with the storage of excess thermal energy,

the GB works for a very short period of time, which greatly improves the efficiency of energy utilization.

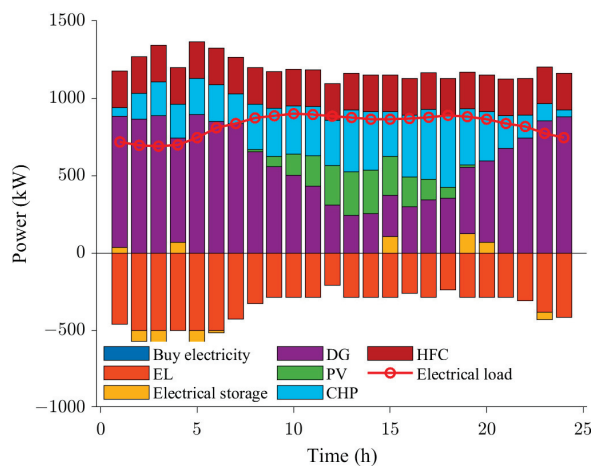


Figure 15. Optimal electric load result analysis chart.

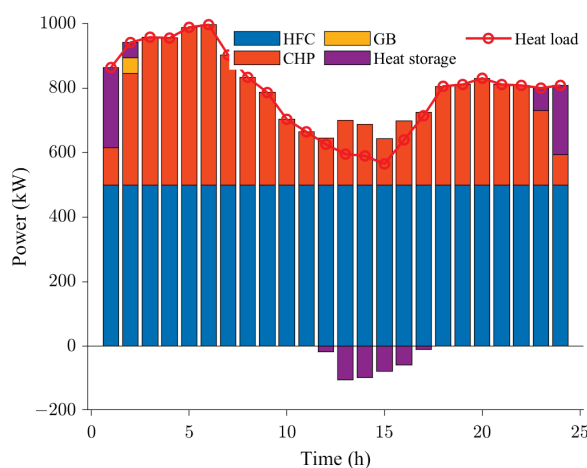


Figure 16. Optimal heat load result analysis chart.

5. Conclusions

To expedite the achievement of the dual-carbon objective and enhance the transition towards a low-carbon framework, this study finetunes the two-phase operational mode of P2G within the IEHS framework. It incorporates a carbon trading scheme that employs incentives and penalties, examines flexible heat and power ratios in CHP and HFC systems, and establishes a minimal objective function governed by IEHS constraints to optimize economic efficiency across the entire network. Employing BFOA to solve the model, insights are derived from examining six different operational modes alongside arithmetic exemplifications.

(1) Modifying the conventional P2G process by incorporating a dual-phase HFC strategy can significantly mitigate the issue of abandoning wind and solar energies. This adaptation enhances the efficiency of harnessing wind and solar power, achieving a utilization rate exceeding 90%. Furthermore, it facilitates a 5.71% reduction in carbon emissions and minimizes losses in energy gradients, thus enhancing overall energy efficiency.

(2) Incorporating a dynamic rewards and penalties carbon trading scheme into the IEHS could potentially reduce the operating costs of this system. The BFOA was employed to address the model designed for this purpose. Comparative analysis of various carbon trading frameworks revealed that setting suitable coefficients for rewards and punishments can align the carbon prices across different systems with the cost variations observed in

the economic dispatch system. Within a specified range, as the carbon price fluctuates, a decrease in the system operating costs is observed, aligning with the goals of the integrated energy system's participation in the carbon market.

(3) In the adjustable thermoelectric ratio mode, a thermoelectric ratio below 2.1% reduces the CHP system's contribution to energy supply, consequently diminishing carbon emissions. Conversely, maintaining a thermoelectric ratio above 0.5% and inversely tuning the thermoelectric load alongside the CHP ratio enhances unit efficiency and satisfies integrated load demands more effectively. This approach supports an increase in CHP output while minimizing energy costs. The current study does not encompass refined modeling of renewable energy tailored to fluctuating demand scenarios, nor does it address carbon management for diverse operational demands. Moreover, the implications of integrating a carbon capture system within the IEHS remain unexplored, earmarking it as a primary focus for subsequent research.

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Abbreviations

Acronyms nomenclature

IES	Integrated Energy System
P2G	Power to Gas
HFC	Hydrogen Fuel Cell
IEHS	Integrated Electricity-Heat Energy System
EL	Electrolier
MR	Methane Reactors
CHP	Combined Heat and Power
HFCs	High-Temperature Fuel Cells
GB	Gas Boilers

Parameters nomenclature

$P_g^{\text{CHP}}(t)$	input power of natural gas for a CHP unit
$P_e^{\text{CHP}}(t)$	electrical power output
$P_h^{\text{CHP}}(t)$	thermal power output of the CHP unit
$P_{e,\text{EL}}(t)$	the electrical energy input to the EL
$P_{\text{EL},\text{H}_2}(t)$	the EL generates hydrogen energy output
$P_{\text{MR},\text{g}}(t)$	the natural gas output
$P_{\text{H}_2,\text{MR}}(t)$	influenced by the hydrogen input
$P_{\text{H}_2,\text{HFC}}(t)$	the hydrogen energy required by the HFC
$P_{\text{HFC},\text{e}}(t)$	the outputs in terms of electrical energies by the HFC
$P_{\text{HFC},\text{h}}(t)$	the outputs in terms of thermal energies by the HFC
$P_{e,\text{buy}}(t)$	upstream power purchases
$P_{\text{GB},\text{h}}(t)$	the thermal energy produced by the GB
$P_{\text{g},\text{load}}(t)$	the gas load at any given
$P_{\text{total}}(t)$	the equivalent power output of these units
$P_{\text{DG},\text{pre}}(t)$	Predictions of wind turbine output
$P_{\text{PV},\text{pre}}(t)$	the forecasted power output of photovoltaic units
$P_{m,\text{in}}(t)$	the power inputs during charging
$P_{m,\text{out}}(t)$	the power outputs during discharging

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Article

A Quantitative Method of Carbon Emission Reduction for Electrochemical Energy Storage Based on the Clean Development Mechanism

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Abstract: Electrochemical energy storage (EES) plays a crucial role in reducing the curtailed power from wind and solar PV power (WSP) generation and enhancing the decarbonization effects of power systems. However, research on quantifying the carbon emission reduction effects of EES methods in the engineering field is still insufficient, which constrains decision-makers from making intuitive assessments of the decarbonization effects of energy storage. Therefore, drawing on the principles of the clean development mechanism (CDM), this paper proposes a method for quantifying the carbon emission reductions of a standalone EES station. Firstly, based on the design principles of building marginal emission factor in the CDM, a method for calculating the BM weight of WSP is proposed. Secondly, three quantification methods for the carbon emission reductions of EES are presented based on the complexity of the calculations. Lastly, to analyze the impacts of different operational conditions and calculation methods on the carbon emission reduction of energy storage systems, a dispatch model is constructed for various operational scenarios. The results of the case study indicate that different calculation methods yield varying results in terms of the carbon emission reductions of energy storage systems, with the sharply value method yielding the smallest reduction and the output curve method yielding the largest reduction. Additionally, when considering the losses in the state of charge (SOC) of an energy storage system and reducing the overall output fluctuations of WSP-EES, the carbon emission reduction potential of the energy storage will decrease. This study establishes a theoretical basis for quantifying the carbon emission reductions of standalone electrochemical energy storage systems, aiding decision-makers in gaining a deeper understanding of the role of electrochemical energy storage in carbon reduction and operational value.

Keywords: renewable power system; clean development mechanism; carbon reduction; electrochemical energy storage

1. Introduction

To meet the goals of peaking carbon emissions and achieving carbon neutrality, China has proposed the construction of a new type of power system centered around renewable energy sources [1–3]. However, the variability and uncertainty of renewable energy have led to challenges in integrating green electricity into the power grid [4,5]. Without addressing the issue of integrating renewable energy sources, the formation of a new power system dominated by renewable energy remains difficult. Electrochemical energy storage technology, being relatively mature and flexible in its operation, stands out among various energy storage methods. It can effectively mitigate fluctuations in renewable energy and facilitate its integration [6–8]. In March 2021, the State Grid Corporation of China released the “Peak Carbon Emissions and Carbon Neutrality” action plan [9], focusing on research into carbon reduction methods related to electricity substitution, electrochemical energy

storage, and comprehensive energy services to offer carbon reduction services along the industrial chain. Therefore, studying the carbon reduction benefits of electrochemical energy storage are crucial research directions.

However, the current research on electrochemical energy storage mainly focuses on its operational profits, involving strategies like low storage and high discharge arbitrage, backup power, frequency regulation, and delaying grid upgrades [10–14]. Concerning the evaluation of carbon emission reduction benefits, the literature [15] calculates the carbon emissions of energy storage over its entire life cycle; the literature [16] combines life cycle assessments, Monte Carlo simulations, and size optimization to determine the life cycle costs and carbon emissions of different battery technologies in practical applications. One study [17], through production simulation methods, analyzes the fuel consumption variations in a pumped hydro storage system under different operating conditions to calculate the energy savings and emission reduction benefits of pumped hydro storage. Another study [18] discusses the potential of energy storage relative to equivalent diesel and natural gas power generation in mitigating climate change. Despite the establishment of carbon emission reduction models for energy storage and the analysis of carbon emission reduction benefits from various perspectives in the above studies, relevant research in the clean development mechanism (CDM) field is relatively scarce, making it challenging to provide effective references for carbon accounting and participation in carbon trading for energy storage systems.

The CDM, as the most representative cooperative emission reduction mechanism, is a crucial avenue for companies to develop clean production and participate in carbon trading markets. It allows developed countries with emission reduction obligations to invest in emission reduction projects in developing countries, earning certified emission reductions (CERs) to fulfill their emission reduction tasks, while developing countries can sell CERs to gain carbon trading income [19,20]. The CDM achieves a win-win situation for both cooperating parties. Therefore, many scholars apply CDM methodologies to quantitatively assess carbon emission reductions across various research subjects. For instance, one study [21] views CDM as a quasi-natural experimental research subject and constructs a multi-period difference-in-differences model to evaluate the effectiveness of CDM projects. Another study [22] studies methods to evaluate the impact of CDM projects on sustainable development, along with a set of non-carbon benefit indicators assessing the environmental, developmental, and equitable impacts of CDM projects. Using small-scale hydropower CDM projects as an example, they analyze the impact of CDM projects on sustainable development in China. One study [23] develops a mixed-integer two-level hierarchical planning model to investigate the potential impact of CDM application on the optimization of energy–water–carbon relationships in China’s power system regions.

From the above literature, it can be observed that there is already a research foundation regarding optimizing scheduling in power systems with energy storage and the application of CDM methodologies. However, in the research on low-carbon energy storage, often based on scheduling models, the overall carbon emission reductions before and after optimization scheduling are analyzed, or energy storage power stations are analyzed based on life cycle assessment (LCA). These methods are complex or have low precision and cannot adapt well to the engineering needs required for carbon trading that makes use of energy storage power stations during operation. With the rapid growth of wind and solar photovoltaic capacities, the issue of integrating wind and solar power is becoming increasingly prominent. Energy storage can facilitate the consumption of wind and solar power, reducing the waste of green electricity. In practical engineering applications, energy storage power stations are connected to the grid via separate connection lines. The proportion of wind and solar power in the grid-connected electricity from energy storage power stations cannot be determined. This uncertainty makes it difficult to determine the carbon emission reductions from energy storage. Additionally, previous studies have often only considered optimizing the scheduling of energy storage, and the extent to which different operational objectives affect the carbon emission reductions from energy storage

is still uncertain. Therefore, this study designs a methodology for quantifying the carbon emission reductions of energy storage power stations based on the CDM and analyzes the impact of different calculation methods and operational objectives on the quantification of emission reductions.

The main contributions of this paper are as follows:

- (1) To the best of our knowledge, this is the first study on optimizing the BM weight of wind power and PV power in CDM;
- (2) Based on the CDM methodology, three methods for calculating the carbon emission reductions of energy storage were established, considering the difficulty of data acquisition and computation;
- (3) Building upon the foundational scheduling model, we analyzed the impacts of different operational objectives on carbon emission reduction through energy storage.

2. Problem Description

The methodology of this study, as shown in Figure 1, is divided into four parts: (1) BM weight optimization; (2) constructing a calculation method for carbon emission reduction of energy storage stations; (3) the construction of scheduling models; (4) results and discussion. In the first part, the emission reduction calculation methods for wind power and photovoltaic power in the CDM were introduced, and the weights of the BM were optimized based on the reasons for setting these factors. In the second part, three methods for calculating carbon emission reductions in energy storage stations were proposed based on the optimization of weight, considering the ease of data acquisition and calculation. To compare the differences between various carbon emission reduction calculation methods and different operational objectives, this study established multiple scheduling model scenarios in Section 3. Finally, Section 5 provides a comprehensive discussion and analysis of the content.

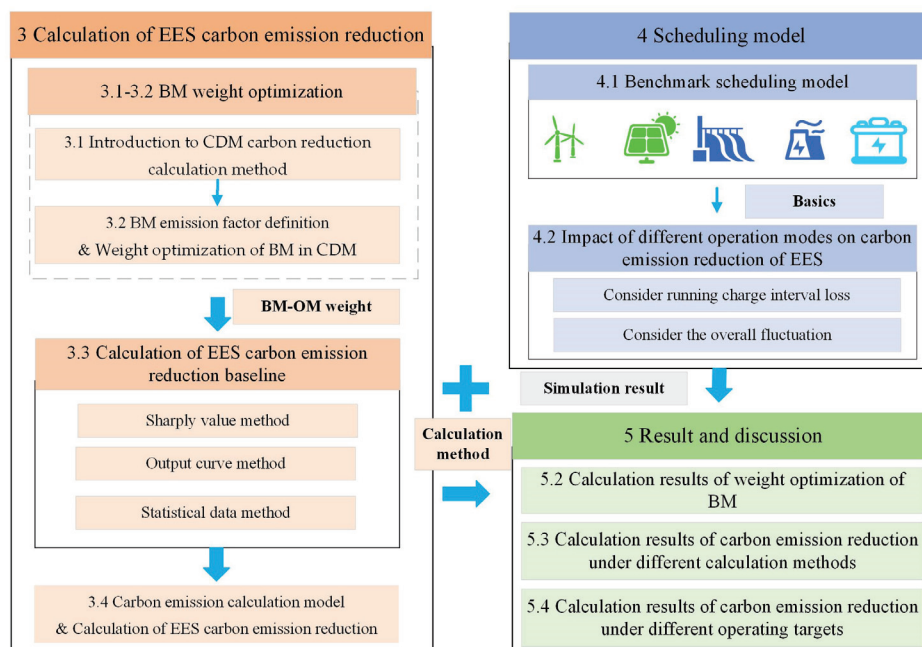


Figure 1. Article overall technical route.

3. Calculation of EES Carbon Emission Reduction

The carbon reduction principle proposed in this paper for standalone EES stations aims to absorb excess WSP generation through charging, relieving the grid pressure, reducing green energy waste, and, consequently, lowering carbon emissions. In this chapter, we first introduce the calculation methods for carbon emission reductions related to wind and solar clean energy in the CDM. Subsequently, based on the setting criteria of the BM emission

factor, we optimize the weight of the BM and propose three methods to determine the carbon reduction benchmarks for standalone power stations.

3.1. Introduction to CDM Carbon Reduction Calculation Method

In the clean development mechanism (CDM), the calculation method for clean energy carbon emission reduction is as follows: the carbon emissions from fossil fuel electricity generation replaced by the clean energy source serve as the baseline for carbon emission reduction. The carbon emission reduction is then calculated by subtracting the actual emissions of the project from this baseline. The calculation method is as follows:

$$ER_y = BE_y - PE_y \quad (1)$$

$$BE_y = EG_{PJ,y} * EF_{grid,CM,y} \quad (2)$$

where ER_y is the emission reduction in year y (tCO_2/yr), BE_y is the baseline emission in year y (tCO_2/yr), PE_y is the project emission in year y (in wind and photovoltaic clean energy generation projects, the CDM methodology sets carbon emissions to 0), $EG_{PJ,y}$ is the on-grid electricity generated by new energy stations in year y (MWh/yr), and $EF_{grid,CM,y}$ is the combined marginal CO_2 emission factor (tCO_2/MWh) of the grid-connected power generation in year y .

The combined marginal emission factor is usually calculated according to the statistical data published by the relevant national statistical departments as follows:

$$EF_{grid,CM,y} = EF_{grid,OM,y} * W_{OM} + EF_{grid,BM,y} * W_{BM} \quad (3)$$

where $EF_{grid,OM,y}$ is the y th year, the operating marginal emission factor (tCO_2/MWh), $EF_{grid,BM,y}$ is the y th year, the build marginal emission factor (tCO_2/MWh), W_{OM} is the operating marginal weight (%), and W_{BM} is the build marginal weight (%).

3.2. Weight Optimization of BM in CDM About WSP Projects

The calculation method for combined marginal emission factors in the CDM methodology is shown in Equation (3), where $W_{om} = 0.75$, $W_{bm} = 0.25$. However, the methodology does not provide a specific calculation method for these weights. This paper focuses on defining the BM emission factor and proposes a method for calculating the weight of the BM, providing a theoretical basis for setting these weights. The calculation principle is as follows (Figure 2).

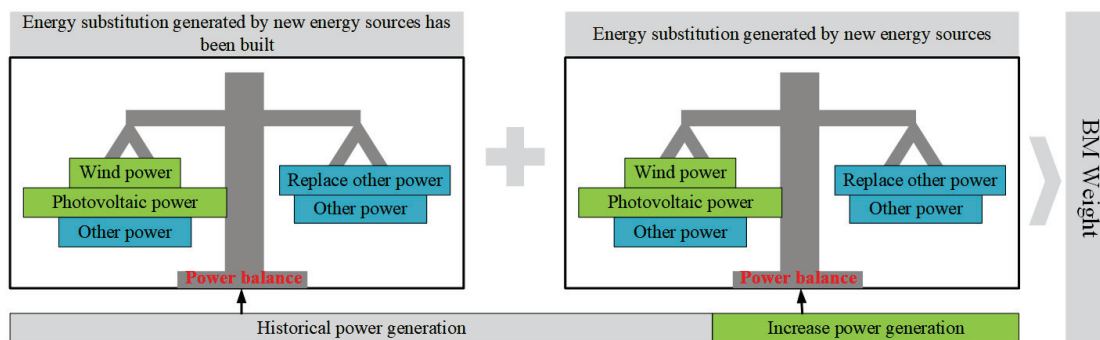


Figure 2. Calculation principle of W_{BM} .

The sum of the weights of the BM and OM is 1, so it is sufficient to calculate one of the weights. In the methodology, the BM emission factor considers the delayed impacts of clean energy projects on the construction of new power plants [24]. Therefore, it can be assumed that, in the absence of clean energy projects, an increase in electricity demand would lead to the construction of more conventional power plants, while clean energy

projects would delay the increase in the number of conventional power plants. Influenced by energy policies, grid operations, and electricity demand, the delayed impact of clean energy projects on conventional power plants may vary at different time points. This paper divides the weight calculation into two parts by setting time points, calculating the substitution coefficient of WSP for other power sources separately for each part (i.e., the W_{bm} weight for different time periods). W_{bm} can be obtained by summing the products of the electricity share at different time periods and the substitution coefficient. The specific calculation method is as follows:

$$R_{his} = \frac{E_{ws}}{E} \quad (4)$$

$$C_{his,sum} = \frac{C_{his} - C_{his,ws}}{1 - R_{his}} \quad (5)$$

$$FAC_{his} = \frac{C_{his,sum} - C_{his}}{C_{his}} \quad (6)$$

$$R_{ris} = \frac{E_{wsad}}{E_{ad}} \quad (7)$$

$$C_{ris,sum} = \frac{C_{ad} - C_{ad,ws}}{1 - R_{ris}} \quad (8)$$

$$FAC_{ris} = \frac{C_{ris,sum} - C_{ad}}{C_{ad}} \quad (9)$$

$$W_{bm} = \frac{E}{E + E_{ad}} FAC_{his} + \frac{E_{ad}}{E + E_{ad}} FAC_{ris} \quad (10)$$

$$W_{om} = 1 - W_{bm} \quad (11)$$

where R_{his} is the ratio of WSP generation to the overall power generation at the time node, E_{ws} is the WSP generation at the time node, E is the overall power generation at the time node, C_{his} is the overall installed capacity at the time node, $C_{his,ws}$ is the installed capacity of WSP at the time node, and $C_{his,sum}$ is the remaining power supply installed capacity required to maintain the power balance after removing the WSP installed capacity at the time node. FAC_{his} is the delay coefficient of WSP to other power sources at the time node; R_{ris} is the ratio of the newly added power generation of renewable energy sources to the overall newly added power generation after the time node; E_{wsad} is the newly added power generation of WSP; E_{ad} is the overall newly added installed capacity of the region; $C_{ad,ws}$ is the newly installed capacity of WSP; $C_{ris,sum}$ is the newly installed capacity of other power sources if the installed capacity of WSP is not increased by the newly added power generation. FAC_{ris} is the delay coefficient of the newly added wind power and the photovoltaic power installed capacity in relation to the construction of other power sources.

3.3. Calculation of EES Carbon Emission Reduction Baseline

The electricity structure of the EES is illustrated as follow (Figure 3): these stations store electricity sourced from the grid, which includes a portion of green energy. However, uncertainties in determining the amount of green electricity output by these stations in practical applications obscure their carbon emission reduction baselines. To address this issue, this study introduces three methods for computing the carbon emission reduction baselines of energy storage facilities. The first method involves assessing the renewable energy grid integration under various scenarios using scheduling models and applying cooperative game theory to determine the station's carbon reduction baseline. The second method calculates the proportion of green electricity within the EES by analyzing the output time series of renewable energy sources and other units, factoring in the overall efficiency of the EES facility. The third method derives the carbon emission reduction

baseline by considering the proportion of new energy grid-connected electricity in regional power grid statistics. The carbon emission reduction achieved by the EES is obtained by subtracting its baseline from its actual carbon emissions.

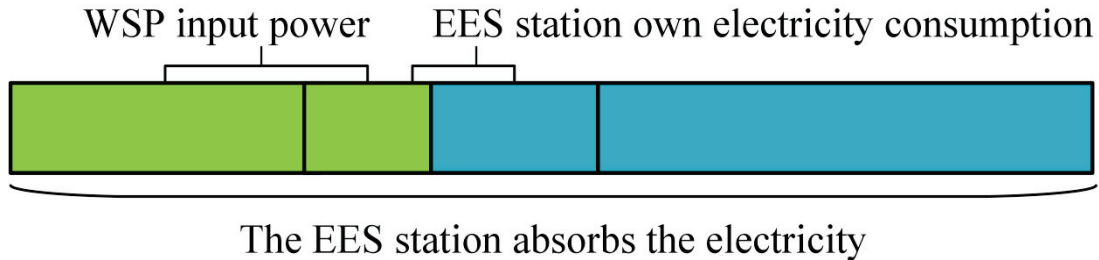


Figure 3. Power structure of energy storage power station.

- (1) Calculate the baseline of carbon emission reduction for EES based on cooperative game theory (sharply value method).

The cooperative game model used in this paper is sharply valued [25]. The calculation method for the carbon reduction baseline based on the sharply value method is as follows. The marginal contribution between different power sources was calculated using the sharply value model. We calculate the contribution degree of the energy storage based on the marginal contribution, obtaining the baseline of the energy storage carbon emission reduction. The specific calculation model is shown as follows:

$$X_i(V) = \sum_{S \in M_i} W(|S|) \cdot [V(S) - V(S \setminus \{i\})] \quad (12)$$

$$W(|S|) = \frac{(m - |S|)! (|S| - 1)!}{m!} \quad (13)$$

$$R_i = X_i / \sum_{i=1}^m X_i \quad (14)$$

$$BE_{erss} = R_{erss} \times BE_{all} \times EF_{grid,CM,y} \quad (15)$$

where $X_i(V)$ is the sharply value of the income distribution of element i in cooperation; V is the characteristic function of the cooperation income, that is, the income obtained by the cooperation of various elements (in this paper, it is expressed as the newly added carbon emission reduction after the introduction of power supply i); m is the number of elements in the total set; $|S|$ is the number of elements in subset S ; $W(|S|)$ is the corresponding weighting factor; R_i is i -th power supply contribution; BE_{erss} is the baseline of the energy storage carbon emission reduction resulting from energy storage; R_{erss} is the contribution of the carbon emission reduction resulting from energy storage; BE_{all} is the on-grid power of the WSP when the WSP and EES are operating together in the power system.

- (2) Based on the output curve of WSP and other units (output curve method).

The calculation method of the carbon emission reduction reference line based on the WSP output curve and the residual power supply output curve is as follows: by calculating the proportion of the WSP output at the time of EES charging, the WSP stored in the EES station is obtained, combined with the storage efficiency of the power station, and so the baseline of the carbon emission reduction of the EES is determined. The calculation method is as follows:

$$E_{erss,td,wsp} = \sum (P_{td,t} \times \frac{E_{wsp,t}}{E_{tot,t}}) \quad (16)$$

$$BE_{erss} = E_{erss,td,wsp} \times \frac{E_{erss,ts}}{E_{erss,td}} \times EF_{grid,CM,y} \quad (17)$$

where $E_{\text{erss,td,wsp}}$ is the total charging amount of the WSP of the EES station, $P_{\text{td,t}}$ indicates the power input to the EES station at time t , $E_{\text{wsp,t}}$ is the on-grid electricity of the WSP station at t , $E_{\text{tot,t}}$ is the total regional power generation at t , BE_{erss} is the carbon emission reduction of the EES station, $E_{\text{erss,td}}$ is the total electricity input to the power station by the grid per unit time of the energy storage power station, and $E_{\text{erss,ts}}$ is the total on-grid electricity of the EES station at statistical time.

- (3) Based on the output ratio of each power supply in the regional power grid (statistical data method).

Since the above two methods have large data requirements and complicated calculations, simple statistical methods can be considered to calculate the carbon emission reduction of energy storage power stations. Based on regional power grid or national statistical data, the calculation method of the carbon emission reduction of energy storage power stations is as follows:

$$BE_{\text{erss}} = \alpha \times E_{\text{erss,on}} \times EF_{\text{grid,CM,y}} \quad (18)$$

where α is the proportion of electricity in the statistical time of the WSP, and $E_{\text{erss,on}}$ is the total output electricity in the statistical time of the EES station.

3.4. EES Carbon Emission Calculation Model

The energy stored in the EES station will also be ‘returned’ to the grid in the future, so we cannot directly calculate all the electricity absorbed by the EES station from the grid as EES carbon emissions. As an EES station will have certain losses during storage and the operation of the power station, this paper regards the energy loss of the EES station as the carbon emission of the EES station, and the specific calculation method is as follows:

$$PE_{\text{erss}} = (E_{\text{off}} - E_{\text{on}}) \times EF_{\text{grid}} \quad (19)$$

where PE_{erss} is the carbon emissions of the EES station, E_{off} is the electricity absorbed by the EES station from the grid, and E_{on} is the on-grid electricity of the EES station.

After calculating the carbon emission baseline of the energy storage and the carbon emission of the energy storage power station, the carbon emission reduction of the energy storage power station is calculated as the carbon emission baseline of the carbon emission reduction minus the carbon emission of the energy storage system. The calculation method is as follows:

$$ER_{\text{erss}} = BE_{\text{erss}} - PE_{\text{erss}} \quad (20)$$

where ER_{erss} is the carbon emission reduction of the energy storage power station.

4. Scheduling Model

To analyze the differences between different calculation methods of carbon emission reduction and the influence of different operation modes on carbon emission reduction, this paper builds relevant scheduling models. Firstly, the benchmark scheduling model is built, and then different operation modes are designed based on the benchmark scheduling model.

4.1. Baseline Scheduling Model

The power supply of the benchmark dispatching model established in this paper includes wind power, photovoltaic power, hydro power, thermal power, and electrochemical energy storage [26–31]. By considering the operation cost and characteristics of each power supply, different power supply operation costs and constraints are set to make the simulation results of the system as close as possible to the actual operation conditions, and at the same time, it lays a foundation for calculating the carbon emission reduction of energy storage systems under different operation targets.

4.1.1. Objective Function

The objective function established by the benchmark model is as follows: the WSP operation cost is the power generation cost, the thermal power operation cost is the power generation cost and unit start-up and shutdown cost, the hydro power operation cost is the unit start-up and shutdown cost, and the EES operation cost is the operation start-up depreciation cost.

$$f = \sum_{t=1}^{24} (f_{G,t} + f_{DG,t} + f_{hydro,t} + f_{erss,t}) \quad (21)$$

$$f_{G,t} = \sum_{i=1}^{N_G} (a_i P_{i,t}^{DG^2} + b_i P_{i,t}^{DG} + c_i) + S_i (1 - u_{i,t-1}^G) u_{i,t}^G \quad (22)$$

$$f_{DG,t} = \sum_{i=1}^{N_{DG}} C(P_{i,t}^{DG}) \quad (23)$$

$$f_{hydro,t} = \sum_{i=1}^{N_{hydro}} [B_{i,t}^{hydro} (1 - B_{i,t-1}^{hydro}) D_i^{hydro}] \quad (24)$$

$$f_{erss,t} = \sum_{i=1}^{N_{erss}} \pi(u_{td,t} + u_{ts,t}) \quad (25)$$

where $f_{G,t}$, $f_{DG,t}$, $f_{erss,t}$ and $f_{hydro,t}$, respectively, represent the costs of thermal power generation, WSP generation, EES generation, and hydro power generation. $P_{i,t}^G$ and $P_{i,t}^{DG}$ represent the output of thermal power unit i and WSP station i at time t . $u_{i,t}^G$ and $B_{i,t}^{hydro}$ are both variable 0–1, representing the operating state of thermal power unit i and hydro power unit i at time t . a_i , b_i , and c_i represent the cost factor of thermal power unit i . S_i represents the start-up and shutdown cost of thermal power unit i . C represents the cost of WSP generation. D_i^{hydro} represents the start-up and shutdown cost of hydro power unit i . N_G , N_{DG} , N_{hydro} , and N_{erss} , respectively, correspond to different power supply quantities. π is the depreciation coefficient of the EES, and $u_{td,t}$ and $u_{ts,t}$ are the charge and discharge state of the EES, respectively. When the EES system works, the value is 1.

4.1.2. Constraints

Based on the overall operation and different characteristics of the power sources, this study establishes corresponding models for each. The overall operational constraints are as follows, where Equation (26) represents the electricity balance constraint and Equations (27) and (28) represent the spinning reserve constraints.

$$P_{load,t} = \sum_{i=1}^{N_G} P_{i,t}^G + \sum_{i=1}^{N_{DG}} P_{i,t}^{DG} + \sum_{i=1}^{N_{hydro}} P_{i,t}^{hydro} + \sum_{i=1}^{N_{erss}} P_{i,t}^{erss} \quad (26)$$

$$\sum_{i=1}^{N_G} (P_i^{G,max} - P_{i,t}^G) * u_{i,t}^G + \sum_{i=1}^{N_{hydro}} (P_i^{hydro,max} - P_{i,t}^{hydro}) * B_{i,t}^{hydro} + \sum_{i=1}^{N_{erss}} (P_i^{erss,max} - P_{i,t}^{erss}) \geq \alpha P_{load,t} \quad (27)$$

$$\sum_{i=1}^{N_G} (P_{i,t}^G - P_i^{G,min}) * u_{i,t}^G + \sum_{i=1}^{N_{hydro}} (P_{i,t}^{hydro} - P_i^{hydro,min}) * B_{i,t}^{hydro} + \sum_{i=1}^{N_{erss}} (P_{i,t}^{erss} - P_i^{erss,min}) \geq \alpha P_{load,t} \quad (28)$$

where $P_{load,t}$ is the power load demand at time t . $P_{i,t}^G$, $P_{i,t}^{DG}$, $P_{i,t}^{erss}$, and $P_{i,t}^{hydro}$, respectively, represent the power generation of the thermal power unit i at time t , the power generation of WSP station i at time t , the power generation of EES station i at time t , and the power generation of hydro power unit i at time t . $P_i^{G,max}$ and $P_i^{G,min}$ are the maximum and minimum output parameters of thermal power unit i . $P_i^{hydro,max}$ and $P_i^{hydro,min}$ are the maximum and minimum generating power parameters of hydro power unit i . $P_i^{erss,max}$ and

$P_i^{perss,min}$ are the maximum and minimum power of EES unit i , and α represents the load confidence interval.

The constraints related to thermal power units are as follows, where Equations (29) and (30) represent the climbing rate for thermal power units, Equations (31) and (32) represent the minimum start-up and shut-down time constraints for the units, and Equation (13) represents the upper and lower limits of the output power.

$$(P_{i,t}^G - P_{i,t-1}^G)u_{i,t}^G \leq R_i \quad (29)$$

$$(P_{i,t-1}^G - P_{i,t}^G)u_{i,t-1}^G \leq R_i \quad (30)$$

$$\sum_t^{t+TS_i^G-1} (1 - u_{i,t}^G) \geq TS_i^G (u_{i,t}^G - u_{i,t-1}^G) \quad (31)$$

$$\sum_t^{t+TO_i^G-1} u_{i,t}^G \geq TO_i^G (u_{i,t-1}^G - u_{i,t}^G) \quad (32)$$

$$u_{i,t}^G * P_i^{G,min} \leq P_{i,t}^G \leq u_{i,t}^G * P_i^{G,max} \quad (33)$$

where R_i is the maximum upward/downward climbing rate of thermal power unit i . TS_i^G and TO_i^G are the minimum downtime and minimum start-up time of thermal power unit i .

In the day-ahead scheduling simulation, the WSP output cannot be greater than the day-ahead forecast output.

$$0 \leq P_{i,t}^{DG} \leq P_{i,t}^{DG,pre} \quad (34)$$

where $P_{i,t}^{DG,pre}$ is the predicted output power of renewable energy power station i at time t .

In hydro power generation, there is a close relationship between the power generation and water consumption of hydro power units. In this study, the functional relationship between the water consumption and power generation is linearized by setting segments. The relationship between the water consumption and power generation is shown in Equations (35) and (36). The generation constraints for hydroelectric units are as follows, where Equations (37) and (38) represent the segment sequence constraints for the same unit, Equations (39) and (40) represent the minimum start-up and shut-down time constraints for the units, Equations (41) and (42) represent the hydroelectric reservoir capacity constraints, and Equation (43) represents the flow rate's upper and lower limit constraints.

$$H_{i,t}^{hydro} = B_{i,t}^{hydro} (H_{i0}^{hydro} + \sum_{n=1}^{N_i^{hydro}} H_{i,n,t}^{hydro}) \quad (35)$$

$$P_{i,t}^{hydro} = (P_{i0}^{hydro} + \sum_{n=1}^{N_i^{hydro}} H_{i,n,t}^{hydro} r_{i,n}^{hydro}) B_{i,t}^{hydro} \quad (36)$$

$$0 \leq v_{i,n+1,t}^{hydro} \leq v_{i,n,t}^{hydro} \leq B_{i,t}^{hydro} \quad (37)$$

$$H_{i,n,\Delta}^{hydro} v_{i,n+1,t}^{hydro} \leq H_{i,n,t}^{hydro} \leq H_{i,n,\Delta}^{hydro} v_{i,n,t}^{hydro} \quad (38)$$

$$\sum_{t=t}^{t+TS_i^{hydro}-1} (1 - B_{i,t}^{hydro}) \geq TS_i^{hydro} (B_{i,t}^{hydro} - B_{i,t-1}^{hydro}) \quad (39)$$

$$\sum_{t=t}^{t+TO_i^{hydro}-1} B_{i,t}^{hydro} \geq TO_i^{hydro} (B_{i,t-1}^{hydro} - B_{i,t}^{hydro}) \quad (40)$$

$$V_{i,t}^{\text{lak}} = H_{i,t}^R - H_t^v - \sum_{i=1}^{N_{\text{hydro}}} H_{i,t}^{\text{hydro}} \quad (41)$$

$$V_{i,\min}^{\text{lak}} \leq V_{i,0}^{\text{lak}} + \sum_{t=1} V_{i,t}^{\text{lak}} \leq V_{i,\max}^{\text{lak}} \quad (42)$$

$$H_{i,\min} \leq \sum_{i=1}^{N_{\text{hydro}}} H_{i,t}^{\text{hydro}} + H_t^v \leq H_{i,\max} \quad (43)$$

where $H_{i,0}^{\text{hydro}}$ is the minimum water consumption of generator set i . $P_{i,0}^{\text{hydro}}$ is the initial generation power of the start-up of unit i , $r_{i,n}^{\text{hydro}}$ is the power generation per unit of water consumption in the n section of hydro power unit i , $H_{i,t}^{\text{hydro}}$ represents the water consumption of hydro power unit i at time t , and $H_{i,n,t}^{\text{hydro}}$ represents the water consumption of hydro power unit i at time t in the n section. $v_{i,n,t}^{\text{hydro}}$ is the auxiliary variable of unit operation. $H_{i,n,\Delta}^{\text{hydro}}$ represents the segmented linearized segment of the water consumption characteristics of the hydro power units. TS_i^{hydro} and TO_i^{hydro} are the minimum down time and minimum operating time of hydro power unit i . $V_{i,t}^{\text{lak}}$ and H_t^v , respectively, represent the changing water quantity and discarded water quantity in the reservoir, and $H_{i,t}^R$ is the incoming water flow of the hydro power station. $V_{i,\min}^{\text{lak}}$ and $V_{i,\max}^{\text{lak}}$ represent the minimum and maximum water volumes of the reservoir. $H_{i,\min}$ and $H_{i,\max}$ are the upper and lower limits of the hydro power station's changed to station.

The constraints for the EES are as follows, where Equations (44) and (45) represent the charging and discharging power constraints, Equation (46) represents the charging and discharging state constraints, Equations (47) and (48) represent the state-of-charge constraints for energy storage, and Equation (49) enforces consistency between the state of charge at the beginning and at the end.

$$0 \leq P_{i,t}^{\text{erss,td}} \leq P_i^{\text{erss,td,max}} \quad (44)$$

$$P_i^{\text{erss,ts,max}} \leq P_{i,t}^{\text{erss,ts}} \leq 0 \quad (45)$$

$$u_{td,t} + u_{ts,t} \leq 1 \quad (46)$$

$$\text{SOC}_{i,t} \times \text{CAP}_{\text{erss},i} = \text{SOC}_{i,t-1} \times C_{\text{erss},i} + P_{i,t}^{\text{erss,td}} \eta_{td,i} + \frac{P_{i,t}^{\text{erss,ts}}}{\eta_{ts,i}} \quad (47)$$

$$\text{SOC}_{i,\min} \leq \text{SOC}_{i,t} \leq \text{SOC}_{i,\max} \quad (48)$$

$$\text{SOC}_{i,\text{init}} \leq \text{SOC}_{i,\text{end}} \quad (49)$$

where $P_{i,t}^{\text{erss,td}}$ and $P_{i,t}^{\text{erss,ts}}$ are, respectively, the charge and discharge powers of the energy storage battery i at time t , $P_i^{\text{erss,td,max}}$ and $P_i^{\text{erss,ts,max}}$ are the maximum charge and discharge powers of the energy storage battery i . In this paper, the charge of the energy storage battery is set as negative, and the discharge is set as positive. $\text{SOC}_{i,t}$ is the charge state of energy storage i at time t , $C_{\text{erss},i}$ is the capacity of energy storage i , $\eta_{td,i}$ and $\eta_{ts,i}$ are the charge and discharge efficiencies of energy storage i , $\text{SOC}_{i,\max}$ and $\text{SOC}_{i,\min}$ are the upper and lower limits of the charge state of energy storage i . $\text{SOC}_{i,\text{init}}$ and $\text{SOC}_{i,\text{end}}$ are the start and end of the charged energy of energy storage i .

4.2. Impact of Different Operation Modes on Carbon Emission Reduction of EES

Different operation modes and objectives of the EES will lead to changes in the charge and discharge of the EES. To explore the impacts of different operation modes on the carbon emission reduction of the EES, in this paper, the following two modes are set up to calculate their impact on the carbon emission reduction of energy storage systems.

4.2.1. Consider the Loss Caused by the Charging Range of the EES

In the benchmark scheduling model, to simulate the scheduling results, the depreciation cost generated by the energy storage operation only considers the charging and discharging states of the energy storage system. Existing studies show that the SOC range of the energy storage battery will also affect the life of the energy storage system [32]. This paper considers the influence of the SOC on the operating cost of the energy storage system. Specifically, this paper adopts the calculation method of partial cycling (PC) provided in the literature for energy storage [32] and divides the SOC of the battery into four levels: A (100–80%), B (79–60%), C (59–40%), and D (39–0%). The probability that the output of each interval is in the X range is shown by Equation (51); Equation (52) highlights the influence of different SOC levels on the operating cost of the energy storage system, and assigns the corresponding weight ρ_X to each probability. The energy storage charge depreciation factor, multiplied by PC, is added to the energy storage objective function, and Equation (25) in the benchmark model is changed to Equation (50), as the objective function. The specific modeling method is shown as follows:

$$f_{\text{erss},t} = \sum_{i=1}^{N_{\text{erss}}} \pi(u_{\text{td},t} + u_{\text{ts},t}) + \text{PC} \times \varepsilon \quad (50)$$

$$\text{PC}_X = \frac{\int_0^T \text{SOC}_{X,t} dt}{\int_0^T \text{SOC}_t dt} \quad (51)$$

$$\text{PC} = \text{PC}_A \times \rho_A + \text{PC}_B \times \rho_B + \text{PC}_C \times \rho_C + \text{PC}_D \times \rho_D \quad (52)$$

where ε is the depreciation coefficient of the energy storage discharge state, PC is the score calculated by the partial cycle—the smaller the score, the smaller the loss cost of the charged state to the energy storage— PC_X is the probability of being in the SOC interval, and $\text{SOC}_{X,t}$ is the charged state in the interval X at time t. If $\text{SOC}_{X,t}$ is in the interval X, $\text{SOC}_{X,t} = \text{SOC}_t$, or else $\text{SOC}_{X,t} = 0$. ρ_X is the weight assigned by PC_X , and the weight size is sorted as $\rho_A < \rho_B < \rho_C < \rho_D$.

4.2.2. Consider the Output Fluctuation in WSP and EES

Both wind power and photovoltaic power's outputs are volatile, and the large-scale fluctuations in the WSP in a short period of time have generated operational pressure on the regional power grid, resulting in the inability to fully absorb the electricity generated by WSP. Therefore, in this paper, the single-objective optimization of the scheduling model was changed to multi-objective optimization, which not only considered the overall operation economy but also considered reducing the output difference of adjacent moments within the day of the WSP-EES system and changed the overall objective function as follows:

$$f_{\text{multi}} = \omega_1 \frac{f_1}{f_0} + \omega_2 \frac{\text{flu}_1}{\text{flu}_0} \quad (53)$$

$$\text{flu} = \sum_{t=1}^T (X_t - X_{t-1})^2 \quad (54)$$

$$X_t = P_t^{\text{DG}} + P_t^{\text{erss}} \quad (55)$$

where f_{multi} is the EES overall objective function, and f is the operating cost of the scheduling model. The calculation method is shown in Equation (21), where flu represents the fluctuation in the overall output of the WSP-EES system at adjacent moments. f and Equation (21) are expressed in the same way; when the lower corners of f and flu are marked as 0, the result obtained by the benchmark model are represented, and when the lower angle is 1, the solution targets of this model are achieved. ω_1 and ω_2 are the weight values set for the two objectives. X_t is the overall output of the WSP-EES system at time t .

5. Results and Discussion

5.1. Basic Data

In this paper, the parameters of the thermal power units [33] are shown in Table 1; the parameters of the hydro power units and flow are shown in the literature [34]; the parameters of the EES station are shown in Table 2; and the time-series data of the wind-solar forecast output and load are shown in the following Figure 4.

Table 1. Thermal power unit parameters.

Number	Output Limit/MW	Lower Output Limit/MW	Climbing Speed/(MW/h)	Cost Coefficient
1	460	138	80	0.021/21/1313.5
2	300	90	80	0.07/24/471
3	240	72	60	0.08/21.6/480.3
4	120	36	45	0.05/23.2/639.4
5	130	39	45	0.06/16.5/502.7

Table 2. Parameters of energy storage.

Installed Capacity/MWh	Rated Power/MW	Upper and Lower Limits of the SOC	Charge and Discharge Efficiency	Initial Charge/MWh
300	100	0.1/0.9	0.96	100

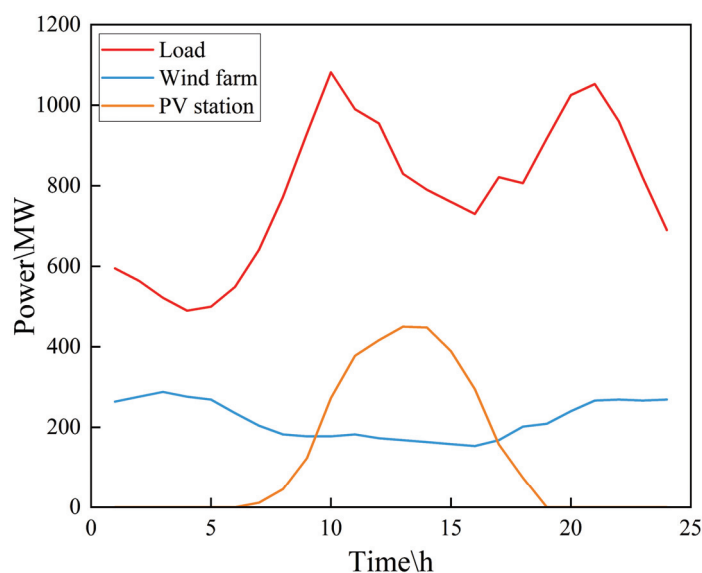


Figure 4. Wind power, photovoltaic power, and load forecasting curves.

5.2. Calculation Results of Weight Optimization of BM

In this paper, the statistical data [35] of power generation in a province in North China from 2021–2022 are selected to calculate the weight of the baseline emission reduction line, and the required data for 2021 are calculated according to the incremental data given in this paper. The specific values are shown in Table 3.

According to the above data, 2021 is selected as the time node. In 2021, the replacement effect of the wind power and PV power on other power sources in the region is 20.6%, and the replacement effect of the newly added WSP on other power sources is 8.5% from 2021 to 2022 (WSP generation increase in 2022 is calculated as Equation (56)). The weight calculation result is $W_{bm} = 19.6\%$. Combined marginal emission factors were selected from the statistical data of North China in 2022, for which $EF_{grid,OM,2022} = 0.9704$ (tCO₂/MWh), $EF_{grid,BM,2022} = 0.3629$ (tCO₂/MWh) [36]. According to the emission reduction method proposed in this paper, the overall emission reduction of the wind power and photovoltaic power clean energy projects in 2022 was 579.4×10^5 t, and the CDM calculation result is 561.1×10^5 t.

Table 3. Data used in weight calculation.

Year	Overall Installed Capacity (1×10^4 kw)	Wind Power Installed Capacity (1×10^4 kw)	Photovoltaic Installed Capacity (1×10^4 kw)	Total Annual Power Generation (1×10^8 kwh)
2021	11,337.9	2123.3	1457.7	3842.6
2022	12,079.5	2317.8	1695.7	4184.4
	Wind Power Generation (1×10^8 kwh)	Photovoltaic Power Generation (1×10^8 kwh)	Thermal Power Generation (1×10^8 kwh)	
2021	469.2	189.5		
2022	466.4	219.1	3229.2	

Assuming no WSP, by 2022, the province will have a 685.5×10^8 kwh power shortfall. In the power system, thermal power is the main emission source, according to the structure of energy and power generation in 2022 [35]. According to Equation (57), thermal power generation accounts for 92.3% of the remaining power generation. Since the average emission intensity of thermal power in the region has not been published, according to the national power grid emission factor data in 2022 [37], which lists that $EF_{grid} = 0.5703$, the proportion of non-fossil energy power generation in China $\lambda = 36.2\%$ [38]. Based on $EF_{grid} / (1 - \lambda)$, the average carbon emission intensity of fossil energy power generation in China is 0.8939 (tCO₂/MWh), and this value is assumed to be the carbon emission intensity of thermal power generation in the province; therefore, the calculated result is 565.6×10^5 t. The BM weight optimization method mentioned in this article yields slightly higher results than the theoretical emission reduction amount, while the CDM method produces slightly lower results than the expected emission reduction amount. Despite the differences between these two methods, the BM weight calculation method introduced in this article provides theoretical support for future research.

$$E_{WSPad} = E_{2022,w} \times \frac{C_{2022ad,w}}{C_{2022,w}} + E_{2022,s} \times \frac{C_{2022ad,s}}{C_{2022,s}} \quad (56)$$

$$\frac{\text{Thermal power generation}}{\text{Total power generation after removing WSP}} \quad (57)$$

where E_{WSPad} is the generated electricity added by WSP in 2022, $E_{2022,w}$ is the wind power generation by 2022, $C_{2022ad,w}$ is the newly installed capacity of wind power in 2022, $C_{2022,w}$ is the total installed wind power capacity in 2022, $E_{2022,s}$ is the solar power generation by 2022, $C_{2022ad,s}$ is the newly installed capacity of solar power in 2022, and $C_{2022,s}$ is the total installed solar power capacity in 2022.

5.3. Calculation Result Carbon Emission Reduction Under Different Calculation Methods

According to the above emission factor data and the weight calculation results proposed in this paper, the emission reduction of the energy storage power station is calculated, and the specific calculation results are shown as follows.

5.3.1. Sharply Method Carbon Emission Reduction Baseline Calculation

When calculating the carbon emission reduction baseline of the EES based on the sharply method, it is necessary to conduct a scheduling simulation of different power supply combination scenarios to calculate the carbon emission reductions under different scenarios. Then, we calculate the carbon emission reduction contribution of each wind power, photovoltaic power, energy storage system using the sharply model. The carbon emission reduction baseline of the EES is calculated according to the carbon emission reduction contribution degree. The scheduling simulation results for different power supply combination scenarios are as follows.

It can be seen from Figure 5 that the energy storage is discharged during peak periods and charged during low periods, which verifies the rationality of the model established in this paper. As can be seen from Figures 5 and 6, it is difficult for the regional power grid to fully absorb the WSP generation due to the high proportion of WSP connected to the grid. The addition of energy storage can significantly increase the on-grid electricity supply of renewable energy, contributing greatly to regional carbon emission reduction. Based on the calculation of the sharply method, the carbon emission reduction contributions of wind, solar, and storage were 62.2%, 35.8%, and 2.0%, respectively. The baseline of the typical daily EES carbon emission reduction was 140 t.

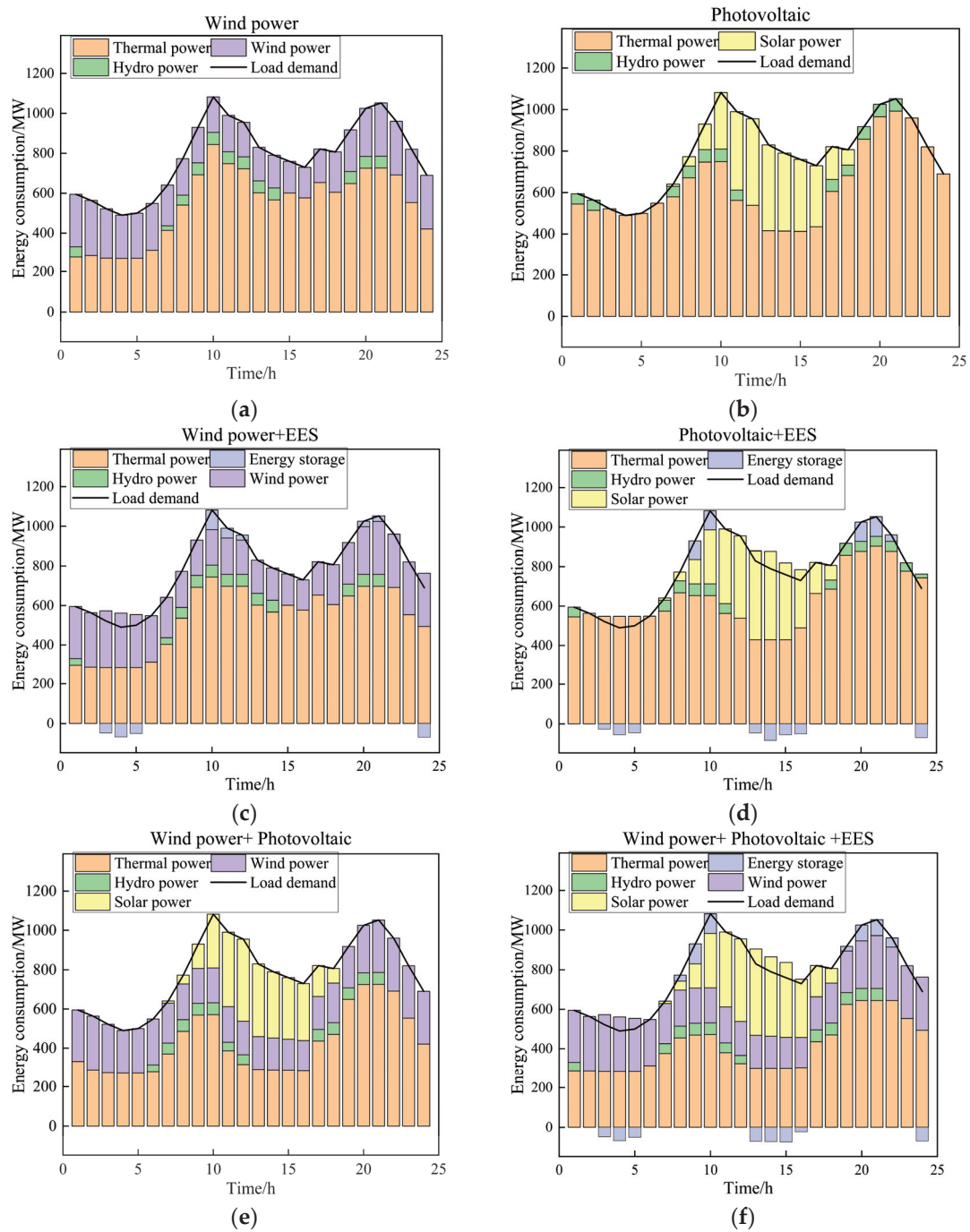


Figure 5. Scheduling simulation results of different scenarios. (a) Wind power; (b) Photovoltaic; (c) Wind power + EES; (d) Photovoltaic + EES; (e) Wind power + Photovoltaic; (f) Wind power + Photovoltaic + EES.

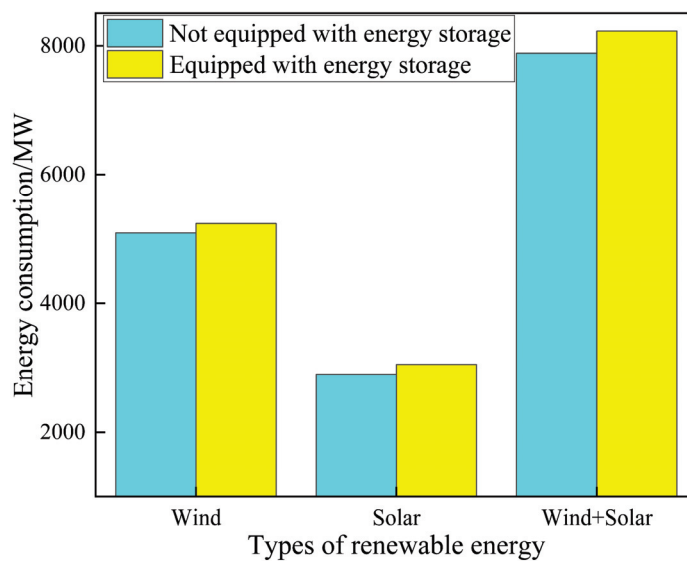


Figure 6. New energy online power in different scenarios.

5.3.2. Output Curve Method Carbon Emission Reduction Baseline Calculation

The output proportion of the WSP at different times and the charging and discharging power of the EES are shown in Figure 7. It can be seen from the figure that the EES has a large charging power when the WSP generation is large or the load demand is small, which is conducive to the absorption of WSP and the overall operation of the power grid. Based on the method proposed in Section 3.3, the overall input of WSP to the EES is 305.4 MWh, and based on this method, the baseline of the carbon emission reduction of EES is 239.6 t.

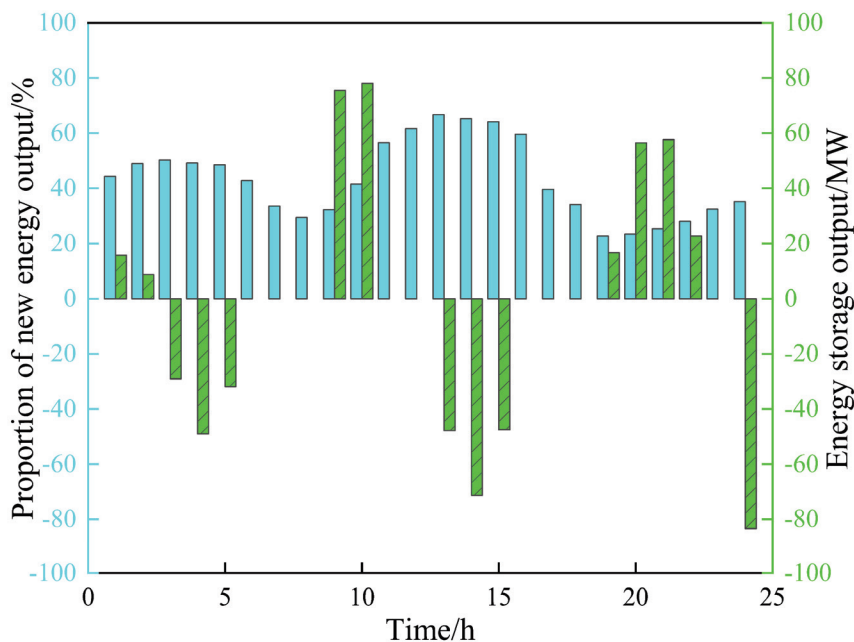


Figure 7. The proportion of WSP on-grid electricity and EES operation.

5.3.3. Statistical Data Method Carbon Emission Reduction Baseline Calculation

According to the scheduling simulation results, the output ratios of different power sources in a typical day are shown in the Figure 8, in which thermal power occupies a large share of power generation, followed by wind power and photovoltaic power, and the overall on-grid electricity of WSP accounts for 43.7%. Based on statistical data, the baseline of the carbon emission reduction of EES is 171.3 t.

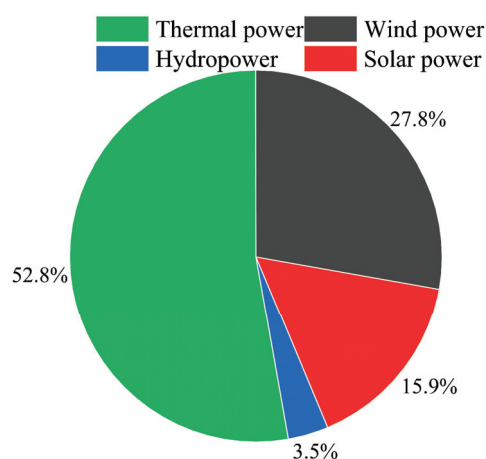


Figure 8. Ratio of on-grid power of different power sources.

5.3.4. EES Carbon Emission Reduction Under Different Calculation Methods

Based on the output results of the scheduling model, the EES charge is 359.9 MWh, and the discharge is 331.7 MWh. According to the calculation methods for EES carbon emission proposed in this paper, combined with the average carbon emission data of the power grid in North China [39], the EES carbon emission is 27.9 t during typical daily operation. The calculation results of the carbon emission reduction by different methods are shown in Table 4.

Table 4. EES carbon reduction under different calculation methods.

Computing Method	Sharply Method	Output Curve Method	Statistical Data Method
Carbon reduction (t)	112.1	211.7	143.4

It can be seen from the above calculation results that the calculation of the EES carbon emission reduction based on the output curve method has the highest result, while the calculation of the EES carbon emission reduction based on the sharply method has the lowest result. The main reasons for this are: the output curve method considers the timing characteristics of the system output; the EES is charged when the WSP generation is large, or the load demand is small; the proportion of WSP generation in the system is relatively large; and the calculation result of the carbon emission reduction is larger. The calculation results based on the sharply value method take into account the marginal contribution of the wind power, photovoltaic power, EES power supplies to the WSP on-grid electricity. That is, when equipped with EES to increase renewable energy on-grid electricity, the increased carbon emission reduction of energy storage is not fully calculated into the EES, as the WSP supplies will also produce emission reduction contributions, which makes the final calculation result slightly less than the other two methods; however, the operation of the statistical data method is relatively simple, ignoring the proportion of the WSP input into the EES on different time scales, so that the final calculation result is small, but the operation is simple and easy to apply to engineering applications. In the calculation of the EES carbon reduction below, the output curve method is chosen to calculate the EES carbon reduction, which is not as complicated as the sharply method and considers the time sequence information output by the scheduling model.

5.4. Calculation Result of Carbon Emission Reduction Under Different Operating Targets

5.4.1. The Loss Simulation Results Are Generated by Considering the SOC Range of EES

Based on the method shown in Section 4.2.1, this section carries out scheduling simulation for the overall operation and compares and analyzes the baseline scheduling model. The simulation results are shown in Figure 9. From the figure, we can see that, compared with the baseline scheduling model, when considering the loss of the EES SOC

range, the SOC of the EES is slightly improved during periods 2–4 and 11–14. However, in the period 22–23, the SOC was still in the lowest state, mainly because, before this period, the load was in the evening peak and the power demand was large, resulting in large-scale discharge of the EES to reduce the power supply pressure. Based on the force curve method proposed in this paper, the carbon emission of the EES was 27.8 t and the carbon emission reduction was 209.4 t. Considering the SOC, the EES operation cost is increased, so the EES discharge power is slightly limited, and the carbon emission reduction is slightly lower than that of the baseline scheduling model.

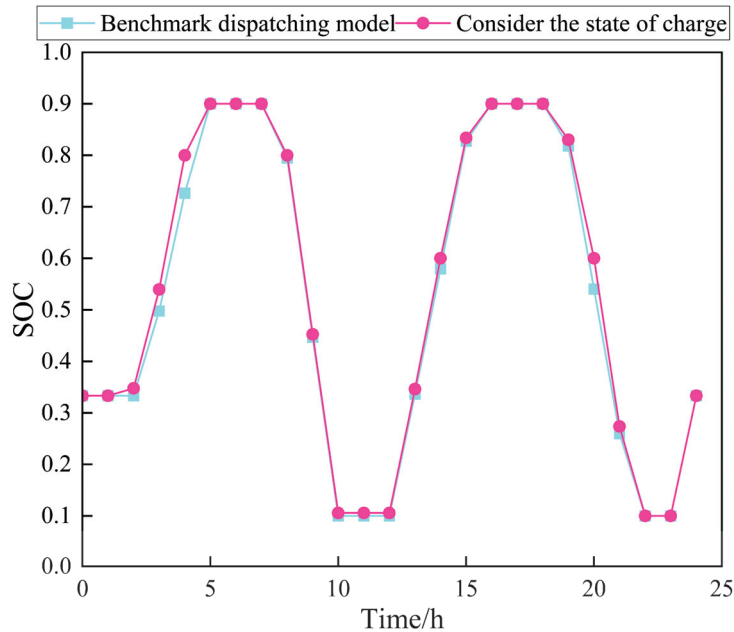


Figure 9. SOC of EES in different scenarios.

5.4.2. Considering the Simulation Results of the Overall Output Fluctuation in WSP-EES

The simulation results considering the overall output fluctuation in the WSP-EES are shown in Figure 10, as the method shown in Section 4.2.2 takes into account the reduction of the volatility of the WSP-EES output at adjacent times. Compared with the benchmark scheduling model, the overall fluctuation in the WSP-EES decreases, and the on-grid power of the WSP is lost while the operating pressure of the power grid is reduced. The overall fluctuation in the WSP-EES output decreases significantly between 6:00 and 16:00 and between 19:00 and 23:00. In this scenario, the EES carbon emission is 27.7 t, and the carbon reduction is 176.9 t. When the overall output fluctuation in the WSP-EES is considered, the carbon emission is like that of the baseline scheduling model, but the carbon emission reduction is reduced by 34.8 t. This is mainly because the proposed scenario reduces the on-grid electricity of the WSP, which leads to power abandonment when the theoretical power generation of the WSP is large, such as at 10–16 h, resulting in a decrease in the proportion of WSP electricity during these periods.

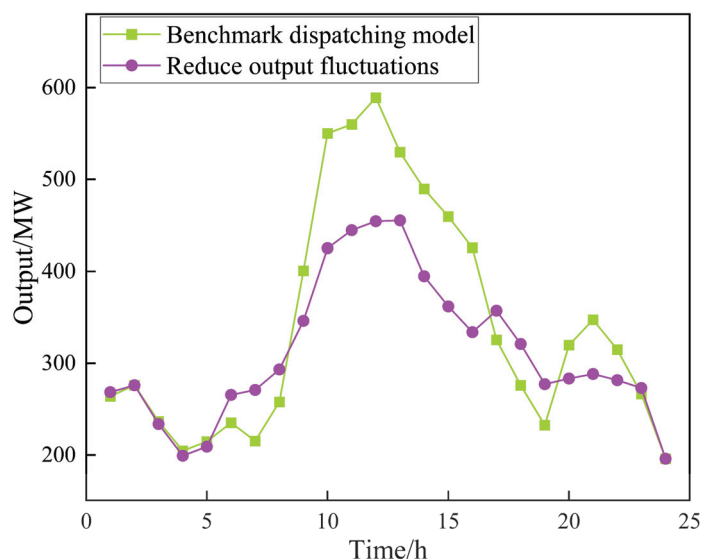


Figure 10. The WSP-EES overall output of different scenes.

6. Conclusions

In the context of a dual carbon environment, the installed capacity of WSP is rapidly increasing. Due to the stochastic and fluctuating nature of WSP, it becomes more challenging for power systems to absorb clean energy. Electrochemical energy storage (EES) can effectively alleviate the absorption issues of the grid with respect to WSP, thereby enhancing the overall carbon reduction of the system. Therefore, quantifying the carbon emission reduction potential of EES can help decision-makers gain a clear understanding of the role of EES in carbon reduction and enhance the operational value of EES. Based on the CDM, this paper optimizes the BM weight for WSP projects, proposes quantification methods for the carbon emission reduction of EES stations, and analyzes the impact of different operational objectives on the carbon reduction potential of EES. The specific tasks are outlined as follows:

1. Based on the design concept of BM emission factors in the CDM method for clean energy projects, we have proposed an optimization method for the BM weights in the WSP project. This offers a fresh perspective and opens new possibilities for future research and practical applications;
2. According to the feasibility of data acquisition and operation, three quantification methods of EES station carbon emission reduction were presented: the sharply method, output curve method, and statistical data method. The results show that the EES station carbon emission reduction calculated based on the output curve method has the highest result of 211.7 t, while the EES station carbon emission reduction calculated based on the sharply value method is the lowest at 112.1 t;
3. The influence of different operation objectives on the carbon emission reduction of EES stations was analyzed. In the case of considering the loss cost of the EES SOC and reducing the overall fluctuation of the WSP-EES in the system, the carbon emission reduction of the EES station was reduced by 2.3 t and 34.8 t respectively.

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