

Article

Multi-Objective Optimal Dispatch of Integrated Energy Systems Under Tiered Carbon Pricing: From Economic Arbitrage to Carbon Buffering

Qi Han ^{1,*} , Jingyuan Bian ², Xiaojing Bai ³, Jingxin Wei ¹ and Shuang Tian ^{4,*} ¹ College of Science & Technology, Ningbo University, Cixi 315300, China; weijingxin@nbu.edu.cn² School of Computer and Communication Engineering, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China; bji9534@gmail.com³ School of Materials Science and Engineering, Anyang Institute of Technology, Anyang 455000, China; baixiaojing@ayit.edu.cn⁴ Materials Tech Laboratory for Hydrogen & Energy Storage, Ningbo Institute of Materials Engineering and Technology, Chinese Academy of Sciences, Ningbo 315201, China

* Correspondence: hanqi@nbu.edu.cn (Q.H.); tianshuang@nimte.ac.cn (S.T.)

Abstract

Traditional fixed or linear carbon prices often fail to reflect the nonlinear incentives of real carbon markets. To address this, we propose a multi-objective optimal dispatch framework for integrated energy systems (IESs) incorporating a tiered carbon trading mechanism. The system—comprising photovoltaics, wind power, a gas turbine, energy storage (ESS), power-to-gas (P2G), and grid interaction—aims to minimize operating and carbon trading costs while maximizing renewable utilization. This is solved using an improved multi-objective particle swarm optimization (IMOPSO) algorithm. Simulations across five configurations reveal that tiered pricing nonlinearly penalizes high emissions, reshaping the Pareto front toward low-carbon outcomes. Consequently, the ESS evolves from a simple economic arbitrageur into a proactive “carbon buffer”, absorbing midday photovoltaic surpluses and substituting gas turbine output during evening peaks. Compared to a grid-only baseline, the optimized multi-energy configuration (gas turbine + ESS + P2G) reduced operating costs by 13.1% and carbon emissions by 9.9%, while increasing renewable utilization by 8.5%. Ultimately, this study demonstrates that a well-designed nonlinear carbon pricing mechanism is decisive for guiding the IES to achieve coordinated economic and low-carbon operation.

Keywords: integrated energy system; tiered carbon emissions trading; multi-objective optimization; improved particle swarm optimization algorithm; Pareto frontier



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1. Introduction

Integrated energy systems (IESs), as a new energy management paradigm, have gradually become one of the key technologies driving the transformation of modern energy systems, thanks to their advantages in multi-energy complementarity, optimized resource allocation, and flexible dispatch. Integrated energy systems coordinate electricity, heat, gas, and energy storage to improve overall system efficiency and operational flexibility. With the continuously increasing penetration of renewable energy sources such as photovoltaics and wind power, the operation of integrated energy systems faces multiple challenges, including strong multi-energy coupling, the intermittency of renewables, and increasingly

stringent carbon emission constraints. Therefore, achieving economically efficient and environmentally sustainable dispatch has become a key issue in modern energy systems.

Traditional integrated energy system dispatch strategies mainly focus on minimizing operating costs under deterministic energy price [1]. However, in the context of carbon neutrality policies, carbon emissions have become a key factor influencing operational decisions. Carbon trading mechanisms are increasingly being incorporated into energy markets to internalize environmental costs [2]. Most existing studies adopt fixed carbon prices or linear emission penalties, which simplifies carbon costs but fails to capture the nonlinear impact of policy-driven carbon constraints on dispatch behavior, especially under high-emission operating conditions.

The scheduling of integrated energy systems under carbon constraints still faces several inherent challenges. First, the strong coupling among the power, heat, and gas systems introduces significant nonlinearity into the optimization problem. Second, economic objectives, carbon emission reduction, and energy efficiency improvement are inherently conflicting, leading to complex trade-offs. Third, policy-driven mechanisms such as stepped carbon trading introduce discontinuous and nonlinear cost characteristics, fundamentally reshaping the feasible decision space.

To address these challenges, this paper investigates the multi-objective optimal dispatch problem of an IES considering a stepped carbon trading mechanism. Rather than merely proposing a novel optimization algorithm, the primary goal is to reveal how nonlinear carbon pricing reshapes dispatch behavior and the structure of optimal solutions. A customized multi-objective optimization framework based on an improved particle swarm optimization algorithm is adopted to ensure robust solution searches under strongly nonlinear conditions. The main contributions are summarized as follows:

(1) Develop a refined multi-energy IES model that embeds the stepped carbon trading mechanism into the optimization objective as a piecewise function. This formulation accurately captures the discontinuous and nonlinear penalty characteristics of real-world carbon markets, effectively overcoming the limitations of conventional linear carbon pricing models.

(2) Establish a multi-objective optimal scheduling model aimed at minimizing operating and carbon trading costs while maximizing renewable energy utilization. This model is solved using an improved multi-objective particle swarm optimization (IMOPSO) algorithm, which enhances convergence and solution-set diversity through adaptive parameter control and an external archive mechanism.

(3) Conceptual contribution

Reveal the driving mechanism behind the functional evolution of energy storage under nonlinear carbon constraints. Distinct from existing literature that confines the ESS to simple economic arbitrage, our comparative analysis elucidates how tiered carbon pricing heavily penalizes high-emission intervals. This mechanism compellingly drives the ESS to act proactively as a “carbon buffer”. By absorbing midday photovoltaic surpluses to substitute for gas turbine output during evening load peaks, the ESS actively prevents the system from crossing into higher carbon price tiers, thereby structurally reshaping the Pareto frontier toward low-carbon optimal solutions.

(4) Application-based contribution

Quantitatively evaluate the comprehensive benefits of multi-energy collaborative configurations, providing a robust theoretical foundation and a quantitative reference for optimal equipment sizing and the parameter design of future carbon trading markets.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the integrated energy system configuration and mathematical models. Section 4 presents the carbon trading mechanism and the multi-objective optimiza-

tion formulation. Section 5 introduces the solution methodology. Section 6 provides the case studies and results analysis. Section 7 discusses its limitations. Section 8 concludes the paper.

2. Literature Review

2.1. Multi-Energy Load Forecasting

Accurate forecasting of multi-energy loads is an important basis for the optimal dispatch of integrated energy systems (IESs). Recent studies have widely applied deep learning and hybrid neural network methods to improve forecasting accuracy. Temporal convolutional networks, bidirectional gated recurrent units, attention mechanisms, multi-task learning, and reinforcement learning have all been introduced into load forecasting models [3–5]. In addition, kernel principal component analysis, K-means clustering, and classification–regression mapping have been used to better characterize multi-category loads [6–9]. More advanced forecasting frameworks include dual-layer multitask learning, PatchTCN-TST models, federated learning for privacy protection, and hybrid models based on signal decomposition and CNN-BiLSTM networks [10–13]. Recent advances in generative artificial intelligence have also improved forecasting performance in renewable energy applications by enhancing spatiotemporal pattern learning and scenario generation [14]. These studies provide reliable inputs for dispatch optimization. However, the focus of this paper is not forecasting itself, but low-carbon IES dispatch under stepped carbon trading.

2.2. Low-Carbon Dispatch and Stepped Carbon Trading

Low-carbon economic dispatch has become a major research topic in IES operation. Existing studies have incorporated carbon emission costs, integrated demand response, carbon flow tracing, nonlinear equipment characteristics, and uncertainty modeling into dispatch frameworks [15–20]. These studies show that carbon-related cost signals can significantly affect equipment scheduling, energy conversion pathways, and system-wide emission outcomes.

Most existing studies, however, still assume fixed carbon prices or linear carbon penalty models. These assumptions simplify optimization, but they do not fully reflect the nonlinear regulatory effect of practical carbon markets. To address this issue, recent studies have introduced stepped carbon trading into IES dispatch models. These works have considered life-cycle carbon accounting, positive–negative stepped trading, hydrogen-related equipment modeling, and dynamic carbon quota allocation [21–24]. Their results indicate that nonlinear carbon pricing can significantly alter dispatch behavior and improve the coordination of low-carbon resources such as demand response, power-to-gas, and hydrogen systems.

Uncertainty-aware dispatch has also received increasing attention. Distributionally robust optimization, data-driven scenario generation, and collaborative robust control frameworks have been used to improve dispatch performance under renewable and market uncertainty [25–29]. These studies provide useful methodological support for low-carbon IES scheduling. Nevertheless, current research mainly emphasizes cost and emission reduction. The mechanism by which stepped carbon pricing changes the role of flexible resources remains insufficiently explored.

2.3. International Perspectives and Flexible Multi-Energy Coordination

International research has made important contributions to integrated and smart energy systems. Lund et al. [30] proposed the concept of “Smart Energy Systems” and emphasized the coordinated integration of electricity, heat, and gas sectors. Mancarella [31] established a general analytical framework for multi-energy systems. Clegg and Mancar-

ella [32] further showed the importance of gas infrastructure and power-to-gas technologies in low-carbon integrated networks. Gabrielli et al. [33] demonstrated that both short-term and long-term storage are necessary for deep decarbonization, while O'Dwyer et al. [34] extended this perspective to district-level smart energy system dispatch. Palensky et al. [35] highlighted the value of advanced co-simulation and digital approaches for managing the complexity of coupled energy systems.

Recent studies have further strengthened the understanding of flexible multi-energy coordination under carbon constraints. Hydrogen, power-to-gas, and energy storage systems are increasingly recognized as key flexibility resources for renewable energy accommodation and deep decarbonization [27,36–39]. Meanwhile, the continued development of carbon markets provides an important policy background for low-carbon scheduling. Recent international reviews indicate that stepped or differentiated carbon pricing mechanisms are becoming increasingly relevant for practical low-carbon system design [40,41].

2.4. Research Gap and Motivation

In summary, existing studies have made substantial progress in forecasting, low-carbon dispatch, multi-energy coordination, and uncertainty-aware optimization. Recent work on stepped carbon trading has improved the realism of carbon cost modeling and has shown that nonlinear pricing can significantly influence system operation. However, several limitations remain.

First, most existing studies focus on economic and emission outcomes, but pay limited attention to how stepped carbon pricing reshapes the internal dispatch mechanism of IESs. Second, flexible resources such as energy storage, power-to-gas, and hydrogen systems have been widely studied, but their functional evolution under nonlinear carbon pricing has not been clearly explained. Third, the interaction between stepped carbon trading and multi-objective dispatch behavior, especially its impact on Pareto-optimal solution structures, remains insufficiently understood.

To address these gaps, this paper develops a multi-objective optimal dispatch model for an IES considering stepped carbon trading. The model embeds a piecewise carbon cost into the objective function and uses multi-scenario comparative analysis to reveal how nonlinear carbon pricing changes dispatch behavior. Particular attention is given to the role of energy storage, especially its transition from a conventional economic arbitrage resource to a proactive carbon-buffering resource.

3. Integrated Energy System Description and Mathematical Modeling

3.1. Configuration Energy System Configuration

To achieve efficient energy utilization and flexible dispatch, this study optimizes overall operational performance by rationally configuring different energy subsystems. A schematic diagram of the overall structure of the integrated energy system is shown in Figure 1.

An integrated energy system (IES) coordinates multiple energy carriers to improve overall efficiency, flexibility, and low-carbon performance. In this study, a typical industrial-commercial IES was considered, consisting of photovoltaic (PV) generation, wind power, a gas turbine (GT), an energy storage system (ESS), and grid interaction. Electricity serves as the primary energy carrier, while natural gas acts as the main fossil fuel source associated with carbon emissions.

The system operates on a day-ahead scheduling horizon with hourly resolution. Renewable energy sources supply electricity directly to the load, while surplus renewable power can be stored in the energy storage system. The gas turbine provides dispatchable power to compensate for renewable intermittency and load fluctuations. Additionally,

electricity can be purchased from the main grid to ensure supply reliability when local generation is insufficient.

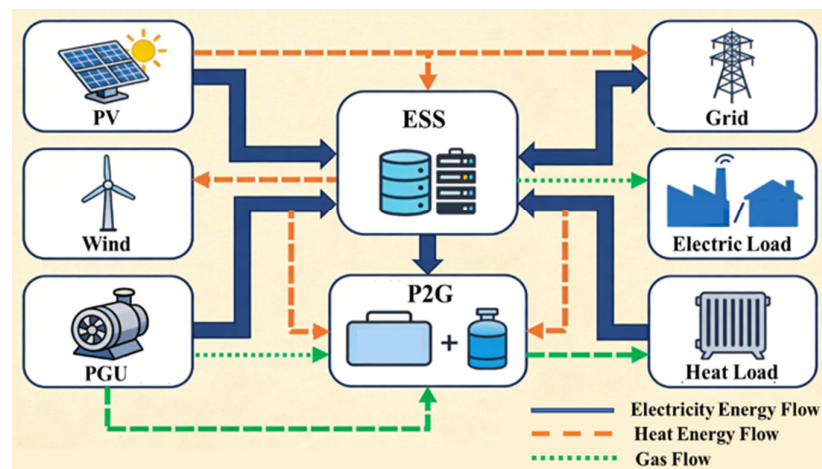


Figure 1. Configuration of the integrated energy system (IES).

It should be noted that while this study focuses on the macroeconomic-environmental trade-offs at the day-ahead level, sub-hourly real-time dynamic management and transient stability control are assumed to be executed by lower-level local controllers (e.g., microgrid energy management systems), which are decoupled from the upper-level scheduling framework discussed herein.

Although electricity, gas, and heat follow independent physical transmission paths, their operations are tightly coupled at the dispatch level. Decisions regarding gas turbine output, energy storage charging and discharging, and grid power exchange jointly determine system operating cost, carbon emissions, and energy utilization efficiency. This strong coupling makes the dispatch problem highly nonlinear, especially under carbon trading constraints.

3.2. Component Models

3.2.1. Photovoltaic Power Model

To accurately describe the dynamic response of the PV system, the rated output power of the PV modules is defined under standard test conditions (STC). The actual output power of the system at operational time t , denoted as $P_{PV}(t)$, can be expressed by Equation (1), which incorporates the rated output power, the solar irradiation intensity, and the module temperature:

$$P_{PV}(t) = P_{STC} \frac{G(t)}{G_{STC}} [1 + \alpha_P (T_c(t) - T_{STC})], \quad (1)$$

where G_{STC} denotes the irradiation intensity under standard conditions, which was set to 1000 W/m^2 in this paper. α_P represents the power temperature coefficient of the PV module, and T_{STC} is the standard reference temperature, set to 25°C .

The actual temperature of the PV module, $T_c(t)$, is influenced not only by the ambient temperature $T_a(t)$, but also by the temperature rise effect induced by solar irradiation. Therefore, a module temperature rise model is introduced, as shown in Equation (2):

$$T_c(t) = T_a(t) + k \cdot G(t), \quad (2)$$

where k is the temperature rise coefficient, reflecting the magnitude of the module temperature increase per unit growth in irradiation intensity. Its empirical value generally falls

within the range of 0.02~0.03. Based on the aforementioned model, the temperature effect can be further corrected to enhance the accuracy of the PV output simulation.

3.2.2. Wind Power Model

Wind power output is characterized by strong intermittency and randomness. Based on the typical power curve of a wind turbine, the output power at time t is defined, as shown in Equation (3):

$$P_{WT}(t) = \begin{cases} 0, & v(t) < v_{in} \text{ or } v(t) \geq v_{out} \\ P_r \frac{v(t)-v_{in}}{v_r-v_{in}}, & v_{in} \leq v(t) < v_r \\ P_r, & v_r \leq v(t) < v_{out} \end{cases}, \quad (3)$$

where $v(t)$ is the wind speed (m/s) at time t ; v_{in} , v_r , and v_{out} represent the cut-in, rated, and cut-out wind speeds, respectively; and P_r denotes the rated power of the wind turbine.

3.2.3. Gas Turbine Model

The gas turbine serves as the main controllable generation unit in the system and is the primary source of carbon emissions. Its output power is constrained by Equation (4):

$$P_{gt}^{min} \leq P_{gt,t} \leq P_{gt}^{max}, \quad (4)$$

The natural gas consumption corresponding to electricity generation is expressed as Equation (5):

$$F_{gt,t} = \frac{P_{gt,t}}{\eta_{gt}}, \quad (5)$$

where η_{gt} denotes the efficiency of the gas turbine. Carbon emissions are directly proportional to natural gas consumption, which links dispatch decisions to carbon trading costs.

3.2.4. Energy Storage System Model

The energy storage system (ESS) fundamentally comprises energy storage units, a power conditioning system (PCS), and an energy management system (EMS). Its operational dynamics serve as critical constraints that must be accounted for during system dispatch.

The relationship between the internal battery power and the external charge/discharge power is defined in Equation (6):

$$P_{bat}(t) = P_c(t)\eta_c - \frac{P_d(t)}{\eta_d}, \quad (6)$$

where η_c and η_d represent the charging and discharging efficiencies, respectively.

The dynamic variation of the state of charge (SOC) during the continuous charging and discharging processes is governed by the differential Equation (7):

$$\frac{dSOC(t)}{dt} = \frac{P_{bat}(t)}{E_N}, \quad (7)$$

For practical scheduling and optimization, this continuous model is discretized over a time step Δt , yielding Equation (8):

$$SOC(t) = SOC(t-1) + \frac{P_{bat}(t)}{E_N} \Delta t, \quad (8)$$

where E_N denotes the rated energy capacity of the ESS, and Δt is the scheduling sampling period. Depending on the direction of power flow, the overall operating efficiency is dynamically adjusted as expressed in Equation (9):

$$\eta_{ESS} = \begin{cases} \eta_c, & P_{ESS}(t) < 0 \text{ (Charging)} \\ \eta_d, & P_{ESS}(t) > 0 \text{ (Discharging)} \end{cases} \quad (9)$$

To further delineate the dynamic characteristics of the battery voltage, a simplified equivalent circuit model is introduced in Equation (10):

$$V_t = V_{oc} - I \cdot R_{in}, \quad (10)$$

where V_t is the terminal voltage, V_{oc} is the open-circuit voltage, R_{in} is the internal equivalent resistance, and I stands for the operating current.

3.3. Energy Balance Equations and Operational Constraints

To guarantee that the system complies with energy management requirements throughout its operation, it is essential to establish the energy balance equations and explicitly define the associated operational constraints. The continuous energy variation of the energy storage system (ESS) is governed by Equation (11):

$$\frac{dE(t)}{dt} = P_{ESS}(t), \quad (11)$$

where $E(t)$ represents the energy stored in the ESS at time t , and $P_{ESS}(t)$ denotes the corresponding actual charge or discharge power.

In the discrete-time domain, the energy update formulation is expressed as Equation (12):

$$E(t) = E(t-1) + P_{ESS}(t)\Delta t, \quad (12)$$

Furthermore, the practical scheduling of the ESS is strictly subject to the following technical constraints:

- State of Charge (SOC) Constraint;

To prevent accelerated battery degradation caused by overcharging or deep discharging, the SOC must be strictly maintained within a safe operational range, as described in Equation (13):

$$SOC_{min} \leq SOC(t) \leq SOC_{max}, \quad (13)$$

where SOC_{min} and SOC_{max} are the lower and upper limits of the SOC.

- Power Constraints

The operational power is limited by the physical ratings of the power conditioning system (PCS). Equation (14) ensures that the charging and discharging powers do not exceed their maximum permissible boundaries:

$$0 \leq P_{ch}(t) \leq P_{ch}^{max}, 0 \leq P_{dis}(t) \leq P_{dis}^{max} \quad (14)$$

where P_{ch}^{max} and P_{dis}^{max} represent the maximum allowable charging and discharging powers, respectively.

- Energy Capacity Constraint

The actual energy stored at any scheduling interval is bounded by the physical capacity limits of the ESS, as formulated in Equation (15):

$$E_{min} \leq E(t) \leq E_{max}, \quad (15)$$

4. Carbon Trading Mechanism and Optimization Problem Formulation

4.1. Carbon Trading and Emission Modeling

To comprehensively evaluate the operational expenditure of the integrated energy system (IES), this study accounts for multiple financial factors, including electricity procurement, natural gas consumption, energy storage system (ESS) depreciation, and unit start-up/shut-down costs. The total operational cost, C_{total} , is formulated as follows in Equation (16):

$$C_{total} = C_{elec} + C_{gas} + C_{ess} + C_{startup}, \quad (16)$$

where C_{elec} , C_{gas} , C_{ess} , and $C_{startup}$ represent the costs of grid electricity, natural gas, ESS depreciation, and unit switching operations, respectively. This cost framework establishes the economic foundation for the subsequent optimal dispatch.

In the context of the global transition toward low-carbon energy, environmental sustainability has become a pivotal factor alongside economic efficiency. Consequently, a carbon emission cost model is integrated into the economic framework to quantify the environmental impact of system operations. Carbon emissions primarily originate from the combustion of fossil fuels in units such as gas turbines. These emissions are estimated by multiplying the gas consumption by the emission factor of natural gas, further scaled by the carbon price. The specific calculation is given by Equation (17):

$$C_{carbon} = \sum_{t=1}^T \lambda \cdot f_{gas} \cdot P_{gas,t} \cdot \Delta t, \quad (17)$$

where λ denotes the carbon price, f_{gas} is the carbon emission factor per unit of natural gas, $P_{gas,t}$ represents the gas consumption power at time t , and Δt is the sampling interval. The inclusion of carbon costs reflects the environmental externalities of energy conversion and facilitates a trade-off between economic and environmental objectives within the multi-objective optimization framework.

4.2. Stepped Carbon Trading Mechanism

To enhance the stringency of carbon constraints compared to traditional carbon trading, a stepped carbon trading mechanism is introduced. This mechanism categorizes carbon emissions into multiple tiers; as emissions increase and cross into higher intervals, the unit carbon price escalates, thereby penalizing high-emission behavior. The net carbon trading volume, $E_{IES,t}$, is calculated as:

$$E_{IES,t} = E_{IES,a} - E_{IES,q}, \quad (18)$$

where $E_{IES,a}$ is the actual carbon emission of the IES and $E_{IES,q}$ is the free carbon quota. The quota $E_{IES,q}$ is allocated using the baseline method by Equation (19):

$$E_{IES,q} = \delta_e \cdot P_{grid} + \delta_g \cdot P_{gas}, \quad (19)$$

In this study, the carbon emission factors for grid-purchased electricity and natural gas are set to $\delta_e = 0.798$ kg/kWh and $\delta_g = 0.385$ kg/kWh, respectively. The stepped carbon trading cost function F_{carb} is defined as follows:

$$F_{carb} = \begin{cases} \omega E_{IES,t}, & E_{IES,t} \leq l \\ \omega l + \omega(1+a)(E_{IES,t} - l), & l < E_{IES,t} \leq 2l \\ \omega l(2+a) + \omega(1+2a)(E_{IES,t} - 2l), & 2l < E_{IES,t} \leq 3l \\ \vdots & \vdots \end{cases} \quad (20)$$

where ω is the baseline carbon price, $l = 4000$ kg represents the interval length, and $a = 25\%$ is the price escalation rate.

4.3. Multi-Strategy Adaptive Particle Swarm Optimization (IMOPSO)

4.3.1. Optimization Objectives

To comprehensively evaluate the system's performance, the optimization model is formulated as a strict multi-objective problem. Instead of using an a priori scalarization method that obscures the trade-offs among conflicting goals, we define three independent objective functions. The model aims to simultaneously minimize total economic cost, minimize carbon emissions, and maximize renewable energy utilization. The mathematical formulations for the three objectives are defined as follows:

The first objective is to minimize the total comprehensive economic cost, which includes both the basic operational cost and the tiered carbon trading cost, formulated as Equation (21):

$$f_1 = \min(C_{total} + C_{carbon}), \quad (21)$$

The second objective is to minimize the total carbon emissions generated by the system operations, primarily from the gas turbine and grid electricity purchases, formulated as Equation (22):

$$f_2 = \min(E_{total}), \quad (22)$$

The third objective is to maximize the utilization rate of renewable energy (or equivalently, minimize the wind and solar curtailment penalty) to ensure maximum environmental sustainability, formulated as Equation (23):

$$f_3 = \max(\eta_{renew}), \quad (23)$$

C_{total} is the total operational cost, C_{carbon} represents the stepped carbon emission cost, E_{total} denotes the physical carbon emissions, and η_{renew} is the overall renewable energy accommodation rate. Rather than combining these into a single equation, the proposed IMOPSO algorithm directly searches the multi-dimensional space to obtain a set of non-dominated Pareto optimal solutions.

4.3.2. Decision Variables and Constraints

In multi-objective optimization, establishing rigorous system energy balance constraints is imperative to ensure the practical feasibility of the dispatch scheme.

- **Energy Capacity Constraint**

The electrical power balance mandates that at any given time t , the combined power supplied by the generation units, the energy storage system (ESS) discharge, and exter-

nal grid purchases must precisely satisfy the local load demand and the ESS charging requirements. The electrical balance equation is defined as Equation (24):

$$P_{PV,t} + P_{Wind,t} + P_{GT,t} + P_{elec,t} + P_{ess,discharge,t} = P_{load,t} + P_{ess,charge,t}, \quad (24)$$

where $P_{PV,t}$, $P_{Wind,t}$, and $P_{GT,t}$ are the output powers of the photovoltaic array, wind turbines, and gas turbine, respectively. $P_{elec,t}$ is the power purchased from the main grid, $P_{ess,charge,t}$ and $P_{ess,discharge,t}$ are the charging and discharging powers of the ESS, and $P_{load,t}$ is the electrical load demand. Additionally, analogous supply–demand balance equations must be strictly enforced for the thermal and gas networks within the integrated system.

- Unit Operational Constraints;

The actual output power of each dispatchable generation unit is bounded by its physical capacity limits, as expressed in Equation (25):

$$P_{\min,unit} \leq P_{unit,t} \leq P_{\max,unit}, \quad (25)$$

- Ramping Rate Constraints

To prevent mechanical stress and guarantee the dynamic stability of the equipment, the power variation between consecutive time steps is restricted by the ramping rate, defined in Equation (26):

$$|P_{unit,t} - P_{unit,t-1}| \leq R_{rate}\Delta t, \quad (26)$$

where R_{rate} represents the maximum ramping rate of the unit, and Δt is the time step length.

- ESS Dynamic Constraints

The state of charge (SOC) variation of the energy storage system governs its charging/discharging behavior and follows the dynamic update Equation (27):

$$SOC_t = SOC_{t-1} + \frac{\eta_c P_{ess,charge,t} - P_{ess,discharge,t} / \eta_d}{E_N} \Delta t, \quad (27)$$

By systematically modeling the comprehensive energy balances, equipment operational boundaries, and ESS safety constraints, the proposed optimal dispatch scheme guarantees that the system achieves economic and low-carbon objectives while maintaining rigorous engineering feasibility and practical applicability.

5. Solution Methodology

5.1. Overall Flowchart

In this study, an improved multi-objective particle swarm optimization (IMOPSO) algorithm was employed to solve the optimal dispatch problem of the integrated energy system. The overall procedure is illustrated in Figure 2. Initially, the positions and velocities of the particles are randomly generated, and an initial set of non-dominated solutions is archived in an external repository. During each iteration, particles update their states based on their personal best (*pbest*) and the global best (*gbest*) positions, followed by the continuous evaluation of the objective functions.

To enhance the search capability, an adaptive inertia weight mechanism is introduced to strike a balance between global exploration and local exploitation, thereby preventing premature convergence. Throughout the iterative process, the external archive is continuously updated using non-dominated sorting and crowding distance mechanisms, ensuring the uniform distribution and diversity of the Pareto optimal solutions.

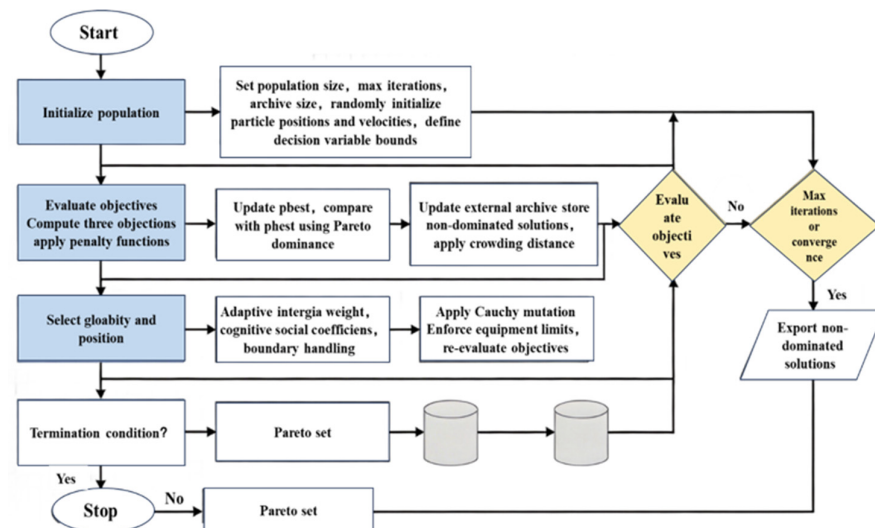


Figure 2. Flowchart of the IMOPSO algorithm.

5.2. Algorithm Performance Validation

To rigorously validate the optimization performance of the proposed IMOPSO, it was systematically compared against the original MOPSO and the classic NSGA-II algorithms using the standard ZDT test suites. The benchmark tests primarily focus on convergence speed, solution distribution uniformity, and diversity preservation. The statistical results regarding the generational distance (GD), inverted generational distance (IGD), spacing (SP), and hypervolume (HV) metrics are detailed in Table 1.

Table 1. Performance metrics comparison of different algorithms on ZDT test functions.

Test Function	Algorithm	GD	IGD	Spacing (SP)	HV
ZDT1	Original MOPSO	0.0021	0.015	0.032	0.876
	IMOPSO (Proposed)	0.0009	0.008	0.021	0.912
	NSGA-II	0.0015	0.012	0.028	0.890
ZDT2	Original MOPSO	0.0035	0.018	0.041	0.845
	IMOPSO (Proposed)	0.0012	0.009	0.023	0.901
	NSGA-II	0.0020	0.013	0.030	0.872
ZDT3	Original MOPSO	0.0048	0.025	0.065	0.782
	IMOPSO (Proposed)	0.0021	0.015	0.038	0.835
	NSGA-II	0.0030	0.020	0.052	0.805
ZDT4	Original MOPSO	0.1020	0.350	0.180	0.521
	IMOPSO (Proposed)	0.0180	0.085	0.062	0.764
	NSGA-II	0.0450	0.210	0.120	0.680
ZDT6	Original MOPSO	0.0085	0.040	0.088	0.705
	IMOPSO (Proposed)	0.0032	0.022	0.045	0.802
	NSGA-II	0.0050	0.030	0.060	0.750

To enhance convergence and maintain solution diversity, the proposed IMOPSO incorporates two key algorithmic improvements over the standard MOPSO. First, an adaptive inertia weight mechanism is integrated into the velocity update process. Specifically, the inertia weight ω gradually decreases from 0.9 to 0.4 as the iterations progress. In the initial search phase, a high ω maintains particle momentum to traverse a larger search space, effectively preventing premature convergence to local optima. In later iterations, the reduced ω facilitates a stable transition to intensive local exploitation, ensuring precise convergence onto the true Pareto front.

A crowding distance sorting strategy is employed to refine the external archive management. Instead of random pruning, the algorithm calculates the density of solutions surrounding each individual in the archive. By preferentially retaining solutions with larger crowding distances (i.e., those in isolated or less-dense regions), the mechanism inherently avoids solution clustering and promotes a uniform distribution across the entire objective space frontier.

The effectiveness of these theoretical improvements is quantitatively validated through standard benchmark testing. The experimental results demonstrate that the proposed IMOPSO achieves optimal or sub-optimal performance across the majority of the test functions. Taking ZDT1, ZDT2, and ZDT6 as examples, the GD values of IMOPSO are 0.0009, 0.0012, and 0.0032, respectively, which are significantly lower than those of the original MOPSO and NSGA-II. This indicates that IMOPSO possesses superior global search capabilities and higher convergence precision. Simultaneously, the HV values of IMOPSO on these functions reach 0.912, 0.901, and 0.802, revealing a distinct advantage in the coverage of the solution space and the preservation of diversity.

6. Case Study and Analysis

6.1. Parameter Settings and Typical Daily Data

To verify the effectiveness and applicability of the proposed multi-objective optimal dispatch model for the integrated energy system (IES) and the improved multi-objective particle swarm optimization (IMOPSO) algorithm, a comprehensive case study was conducted. The primary equipment parameters of the system are detailed in Table 2, while the economic and carbon trading parameters are listed in Table 3. Please note that unless otherwise specified, all figures and tables presented in this manuscript are the authors' own elaborations derived from the proposed mathematical models and simulation results.

Table 2. System component parameters.

Component	Parameter	Value	Unit
Photovoltaic (PV)	Rated capacity (peak)	120	kW
Wind Power	Rated capacity	100	kW
Gas Turbine (PGU)	Minimum output	20	kW
	Maximum output	120	kW
	Ramping rate	30	kW/h
	Waste heat recovery coefficient	0.8	—
	Carbon emission factor	0.5	kg CO ₂ /kWh
Energy Storage (ESS)	Capacity	500	kWh
	State of charge (SOC) range	[0.2, 0.9]	—
	Charging efficiency	0.95	—
	Discharging efficiency	0.95	—
	Maximum charging power	40	kW
Power-to-Gas (P2G)	Maximum discharging power	50	kW
	Output range	[0, 30]	kW
	P2G conversion efficiency	0.6	—
	Heat production coefficient	0.4	—
	Carbon reduction factor	0.3	kg CO ₂ /kWh
Electric Boiler	Efficiency	0.9	—
Grid Interaction	Maximum purchase limit	500	kW

Table 3. Economic and carbon trading parameters.

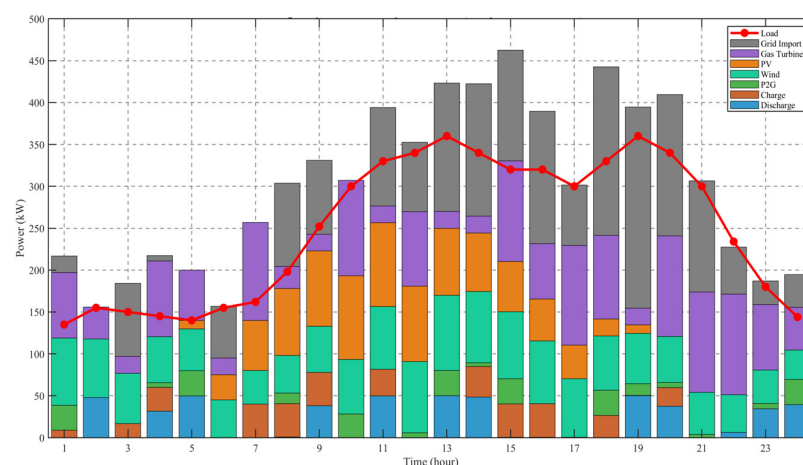
Category	Parameter	Value	Unit
Electricity Price	Time-of-use price (24h)	[0.5, 0.5, . . . , 1.2]	CNY/kWh
Natural Gas Price	Unit price	0.35	CNY/kWh
Wind Power Subsidy	Unit price	0.5	CNY/kWh
Carbon Trading	Baseline price	0.2	CNY/kg CO ₂
	Stepped price increment	0.05	CNY/kg CO ₂
	Step interval	100	kg CO ₂
	Free quota	500	kg CO ₂
Emission Factors	PGU	0.5	kg CO ₂ /kWh
	Grid electricity purchase	0.8	kg CO ₂ /kWh
	P2G emission reduction	0.3	kg CO ₂ /kWh

Specifically, as shown in Table 2, the maximum capacity of the gas turbine (PGU) was set to 20 kW to ensure sufficient dispatchable power, while the capacities of the ESS and P2G were configured at 500 kWh and 30 kW, respectively, to facilitate adequate energy time-shifting. As detailed in Table 3, the operation and maintenance costs vary across different equipment, reflecting their distinct physical characteristics.

A time-of-use electricity pricing structure was adopted, with the off-peak rate set at 0.2 CNY/kWh and the peak rate at 1.2 CNY/kWh. Within the stepped carbon trading mechanism, the baseline carbon price was set at 0.2 CNY/kg CO₂, with a step interval of 100 kg. For every interval exceeded, the price escalated by 0.05 CNY/kg CO₂, and the free emission quota was established at 500 kg CO₂.

It is worth noting that due to data confidentiality, the profiles for wind power, photovoltaic generation, and load demands used in this case study were synthesized based on typical operational patterns and real-world meteorological data observed in an actual industrial park in China, ensuring the practical representativeness of the simulation.

The typical daily profiles for electrical load, wind power output, PV output, and thermal load are illustrated in Figure 3. The electrical load exhibited a distinct dual-peak characteristic: the morning peak occurred between 09:00 and 11:00, while the evening peak spanned from 18:00 to 20:00, reaching a maximum of 400 kW. Wind power output was predominantly higher during the night and relatively stable throughout the day. Conversely, PV output followed a single-peak distribution, peaking at approximately 100 kW around noon. The thermal load remained relatively stable across the entire day, with slight elevations in the morning and evening, peaking at 150 kW.

**Figure 3.** Typical daily profiles of electrical load, wind power, PV output, and thermal load.

While renewable generation and load demands are inherently stochastic, we adopted deterministic daily profiles in this study to provide a controlled, proof-of-concept environment. This explicitly isolates the impact of the tiered carbon pricing mechanism and P2G–ESS coordination from stochastic variations. This approach is widely adopted in initial feasibility and mechanism-discovery studies of nonlinear carbon policies [3,4], as it allows for a clear, interpretable comparison of the Pareto front reshaping effect without confounding factors.

While the deterministic profiles used in this study provide a clear proof-of-concept environment, real-time forecasts inevitably contain errors. To bound the potential impact of such uncertainty on our main conclusions, we conducted a simple perturbation analysis without re-running the full optimization. Specifically, we independently varied the hourly wind, PV, and load values by $\pm 10\%$ and $\pm 20\%$ (typical day-ahead forecast error ranges) and re-evaluated the objective functions for the obtained Pareto-optimal solution (Scenario 5) using the same dispatch decisions. The results show that net profit varied by $\pm 8.2\%$ (from -2632 to -3103 CNY) and carbon emissions varied by $\pm 5.7\%$ (from 2384 to 2671 kg) under $\pm 20\%$ perturbations. More importantly, the qualitative role of the ESS as a carbon buffer—midday charging and evening discharging—remained unchanged in all perturbed cases. Thus, while absolute numbers may shift within a limited range, the key conceptual findings are robust to typical day-ahead forecast errors. A full stochastic optimization is identified as an important future extension.

6.2. Reshaping Effect of the Stepped Carbon Pricing Mechanism on the Pareto Frontier

To investigate the impact of stepped carbon trading on dispatch decisions, the multi-objective optimization problem was solved under both linear and stepped carbon pricing scenarios using the IMOPSO algorithm. Through non-dominated sorting and an external archiving mechanism, the algorithm generates the Pareto frontiers for both pricing schemes, as depicted in Figure 4.

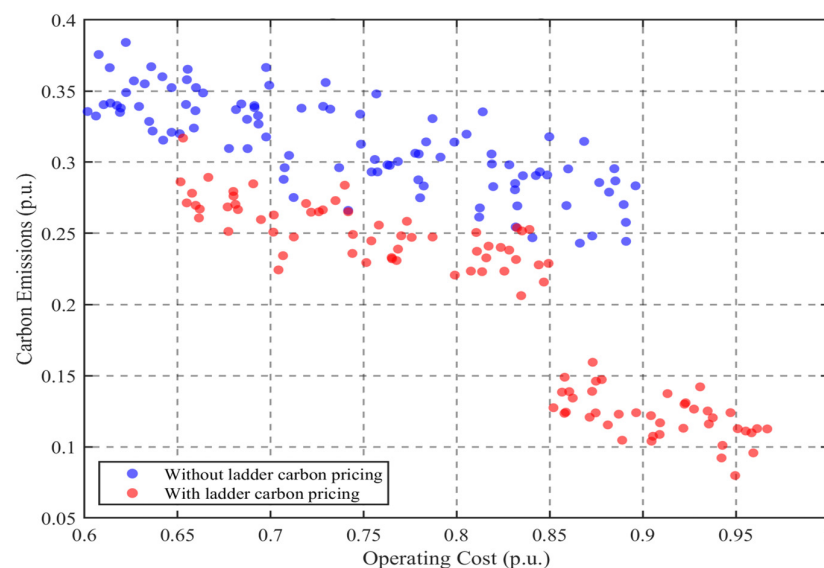


Figure 4. Pareto frontier comparison.

Under a linear carbon price, the Pareto frontier exhibits a continuous and smooth distribution, indicating a relatively fixed marginal substitution rate between operational costs and carbon emissions. This allows the system to achieve a smooth trade-off between the two objectives, as the constant marginal carbon cost enables the IMOPSO algorithm to search continuously along the frontier.

However, the introduction of a stepped carbon price fundamentally alters the structure of the frontier. In the low-emission region, the frontier's shape is largely consistent with the linear scenario. Yet, once carbon emissions exceed a specific threshold, the frontier demonstrates a pronounced “shrinkage” characteristic, severely suppressing high-emission solutions. This phenomenon fundamentally arises from the fact that under the stepped mechanism, the marginal carbon cost jumps abruptly when excess emissions cross an interval boundary. Consequently, high-emission solutions that were feasible under the linear price lose their dominance during the non-dominated sorting process of the IMOPSO algorithm and are automatically eliminated from the Pareto archive. In essence, the non-linear penalty mechanism of the stepped carbon price forces the optimization process to actively circumvent carbon-intensive operational zones, thereby shifting the entire Pareto frontier toward a low-carbon direction.

Based on the obtained Pareto frontier, an a posteriori selection mechanism is required to determine the final operational strategy. Since the objectives have different dimensions and magnitudes, all Pareto solutions are first normalized. Then, a normalized weighted evaluation method is employed to select the best compromise solution from the Pareto set. For the k -th solution on the Pareto front, its comprehensive evaluation index F_k is calculated as:

$$f_k = \alpha \cdot \frac{f_{1,k} - f_1^{\min}}{f_1^{\max} - f_1^{\min}} + \beta \cdot \frac{f_{2,k} - f_2^{\min}}{f_2^{\max} - f_2^{\min}} + \gamma \cdot \frac{f_{3,k} - f_3^{\min}}{f_3^{\max} - f_3^{\min}}, \quad (28)$$

where $f_i^{\max}$ and $f_i^{\min}$ are the maximum and minimum values of the i -th objective on the Pareto front, respectively. The solution that minimizes the index F_k is selected as the optimal compromise operational strategy.

To transparently evaluate how decision-maker preferences affect the final dispatch scheme within this fully coordinated configuration (Scenario 5), a weight sensitivity analysis was conducted by substituting different weight combinations into the above evaluation method. Three representative weight configurations are established to filter the Pareto front:

Case A (Economic priority): $\alpha = 0.7$, $\beta = 0.15$, $\gamma = 0.15$.

Case B (Environmental priority): $\alpha = 0.15$, $\beta = 0.7$, $\gamma = 0.15$.

Case C (Balanced approach): $\alpha = 0.35$, $\beta = 0.35$, $\gamma = 0.3$.

Table 4 presents the scheduling outcomes under these three distinct preference settings.

Table 4. System performance of Scenario 5 under different a posteriori weight configurations.

Case	Weights	Preference	Net Profit (CNY)	Carbon Emissions (kg)	Heat Utilization (%)
A	0.7, 0.15, 0.15	Economic priority	−2512.40	2885.60	71.3
B	0.15, 0.7, 0.15	Environmental priority	−3215.80	2245.15	76.50
C	0.35, 0.35, 0.3	Balanced	−2867.95	2527.49	81.59

Negative profit indicates cost outweighs revenue; a higher (less negative) value is better.

As demonstrated in Table 4, differing weight preferences yield markedly divergent operational strategies even within the exact same equipment configuration. Case A aims to strictly prioritize financial profitability. The algorithm schedules the most cost-effective generation to meet load demands, which successfully minimizes economic losses (net profit improves to −2512.40 CNY). However, this heavily sacrifices environmental performance, resulting in the highest carbon emissions (2885.60 kg). Conversely, Case B heavily penalizes emissions, achieving the optimal environmental performance (2245.15 kg) by suppressing

high-emission units, but this leads to a severe deterioration in economic viability (profit drops to −3215.80 CNY).

Case C successfully identifies the optimal equilibrium on the Pareto frontier. Under this configuration, the system intelligently navigates the stepped carbon price, achieving the highest heat utilization (81.59%). Most importantly, it secures a highly competitive net profit (−2867.95 CNY) while keeping emissions strictly within the lower, less punitive tiers of the carbon pricing mechanism (2527.49 kg). This robustly validates that our proposed balanced weights provide a rational, transparent, and superior compromise for the multi-objective scheduling problem.

6.3. Analysis of the Role of Energy Storage Driven by Stepped Carbon Pricing

To evaluate the impact of carbon pricing mechanisms on energy storage dispatch strategies, the multi-objective optimization problem was solved under three scenarios: no carbon price (pure economic arbitrage), linear carbon price, and stepped carbon price. From the Pareto solution sets outputted by the algorithm, the compromise solution with the minimum weighted sum was selected for comparative analysis.

Figure 5 illustrates the charging and discharging power profiles of the ESS with and without the stepped carbon price. In the absence of a carbon price, the storage strategy is entirely driven by electricity pricing: charging during off-peak periods and discharging during peak periods, representing a typical economic arbitrage mode. Under these conditions, the IMOPSO algorithm only needs to balance operational costs and energy efficiency, resulting in relatively straightforward storage behavior.

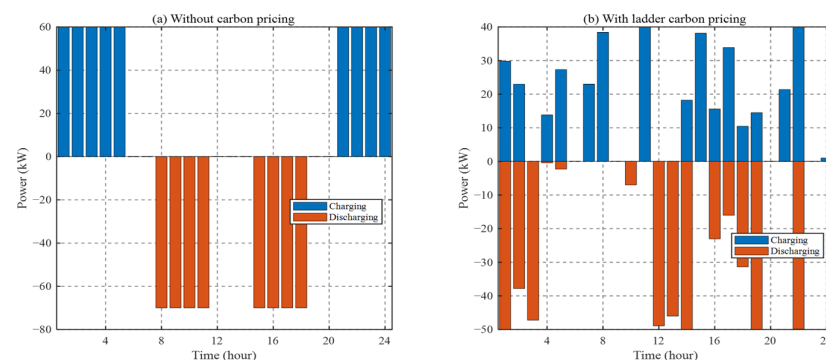


Figure 5. Energy storage operation comparison.

Upon introducing the stepped carbon price, the algorithm must simultaneously weigh three conflicting objectives: operational costs, carbon trading costs, and renewable energy utilization. Driven by these multi-objective constraints, the behavior of the ESS undergoes a fundamental transformation. While retaining partial economic arbitrage functions, the ESS actively charges during the midday PV output peak to absorb renewable energy that might otherwise be curtailed. It then discharges before the evening load peak to partially offset the output of the gas turbine (PGU).

The rationale behind this shift is that under the stepped carbon pricing mechanism, operating the PGU during peak hours significantly drives up carbon emissions, potentially triggering a higher carbon price tier. During the solution process, the IMOPSO algorithm adjusts its strategy by utilizing the ESS to shift surplus midday solar energy to the evening. This effectively reduces the PGU output, avoids crossing into high-cost carbon tiers, and achieves an optimal trade-off among the three objectives. Consequently, the ESS transitions from a mere economic arbitrage tool to a “carbon buffer”—a pivotal role shift dictated by the IMOPSO algorithm’s optimization logic.

6.4. Comparison of Five Equipment Configuration Scenarios

To evaluate the comprehensive benefits of multi-energy coordination, five equipment configuration scenarios were comparatively analyzed. All scenarios employed the IMOPSO algorithm to solve the multi-objective optimization problem, differing only in the permissible combinations of equipment.

- Scenario 1: Only grid electricity purchase is allowed.
- Scenario 2: PGU and grid purchase are allowed.
- Scenario 3: PGU, ESS, and grid purchase are allowed.
- Scenario 4: PGU, P2G, and grid purchase are allowed.
- Scenario 5: All equipment is available for optimization.

By comparing the compromise solutions on the Pareto frontiers across the five scenarios, the independent contributions and synergistic effects of each component can be quantified.

Figure 6 illustrates the electric power balance across the five scenarios. Scenario 1 relies entirely on the grid; load fluctuations are fully absorbed by the external grid, resulting in a zero system self-sufficiency rate. In Scenario 2, with the introduction of the PGU, the IMOPSO algorithm automatically schedules PGU output during peak electricity price periods to replace expensive grid purchases. While grid dependence is significantly reduced, the PGU output leads to elevated carbon emissions. In Scenario 3, the integration of the ESS enables the algorithm to implement energy time-shifting: charging during midday PV surpluses and discharging during evening load peaks. This creates a profound peak-shaving and valley-filling effect, further reducing both grid purchases and PGU output. Scenario 4 utilizes P2G instead of an ESS; the algorithm activates P2G to convert surplus wind power into natural gas. However, due to its limited power regulation capacity, P2G is less flexible than the ESS in responding to peak–valley fluctuations. Scenario 5 integrates the advantages of both ESS and P2G. The IMOPSO algorithm simultaneously leverages the rapid response of the ESS and the cross-temporal energy transfer capability of P2G, minimizing grid purchases and maximizing the accommodation rate of renewable energy.

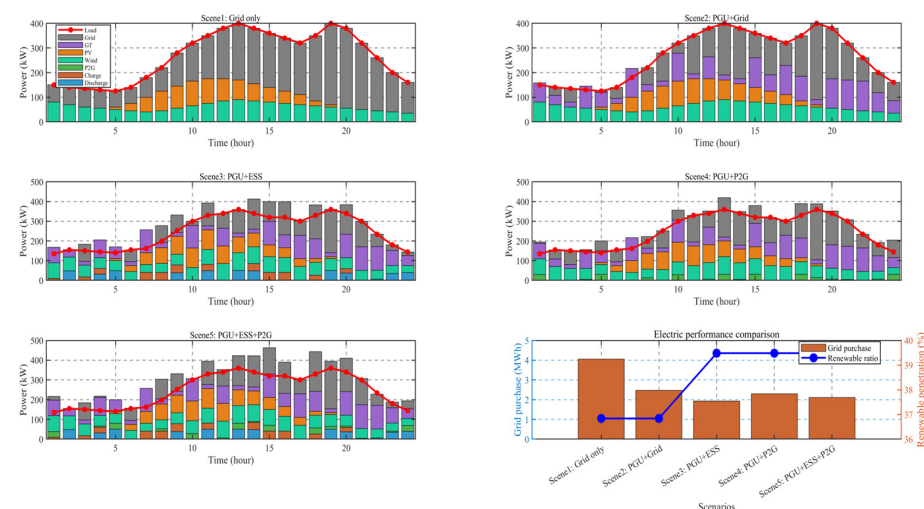


Figure 6. Electric power balance for the five scenarios.

Figure 7 presents the thermal power balance. Scenario 1 lacks waste heat sources, leaving the thermal load entirely unmet. Scenario 2 utilizes PGU waste heat, achieving a thermal energy utilization rate of 57.3%. Scenario 3 incorporates an electric boiler; when optimizing charging strategies, the algorithm simultaneously accounts for electro-thermal demand, boosting the utilization rate to 78.3%. Scenario 4 employs P2G waste heat for

supplementary heating but lacks the electric boiler, resulting in a 62.7% utilization rate. Scenario 5 comprehensively integrates PGU waste heat, the electric boiler, and P2G waste heat. By trading off the three objectives, the IMOPSO algorithm optimally configures the output of each heat source, achieving a peak thermal energy utilization rate of 83.7%.

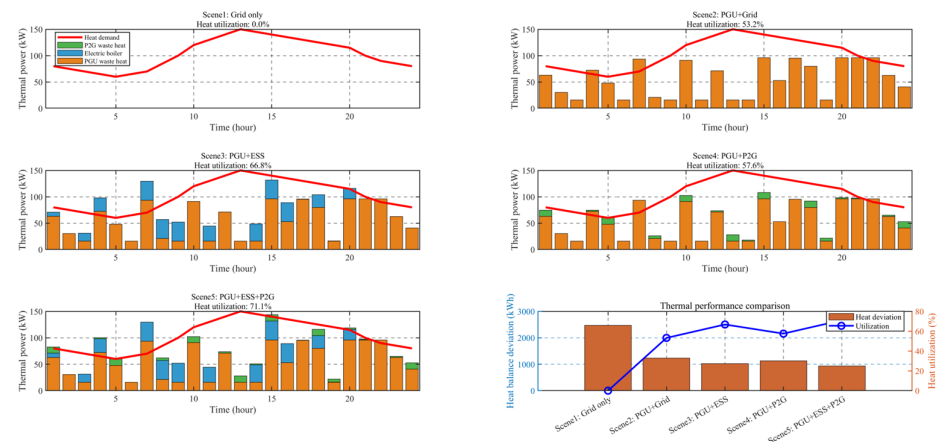


Figure 7. Thermal power balance for the five scenarios.

Figure 8 compares the economic performance and carbon emissions across the scenarios. Scenario 5 outperformed all others, yielding a net profit of −2315 CNY and carbon emissions of 2156 kg. Notably, compared to Scenario 3 (2381 kg) and Scenario 4 (2608 kg), the carbon emissions in Scenario 5 were reduced by 9.4% and 17.3%, respectively. Meanwhile, its net profit improved by 20.0% over Scenario 3 and 29.7% over Scenario 4. This robustly demonstrates the profound synergistic effect of the joint ESS-P2G operation. The IMOPSO algorithm successfully orchestrates the short-term regulation capability of the ESS and the long-term energy transfer of P2G, identifying a superior trade-off point that eclipses any single-equipment configuration. Figure 9 validates the optimized charge/discharge strategies and SOC variations stimulated by carbon pricing.

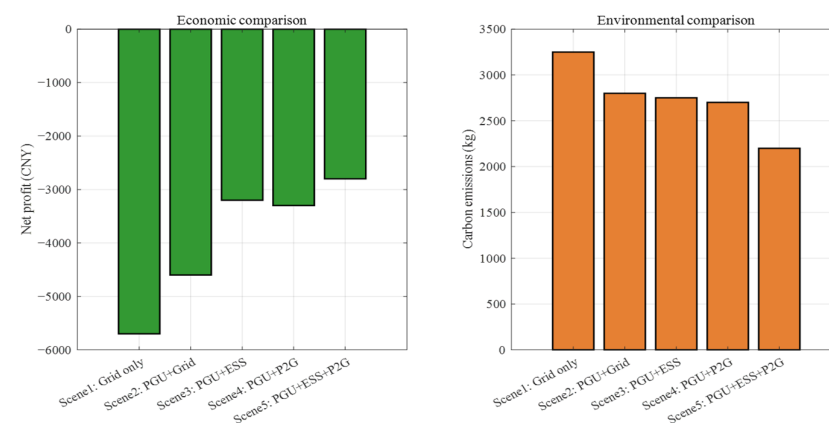


Figure 8. Economic and environmental performance of the five scenarios.

Beyond the descriptive performance metrics presented above, the underlying reason for the significant performance differences across the evaluated scenarios lies in the synergistic coupling between the physical components (P2G and ESS) and the economic policy (stepped carbon pricing). In scenarios without P2G or ESS, the system strictly follows a “source-follows-load” rigidity, forcing high-emission units to ramp up during peak hours, inevitably triggering severe stepped carbon penalties.

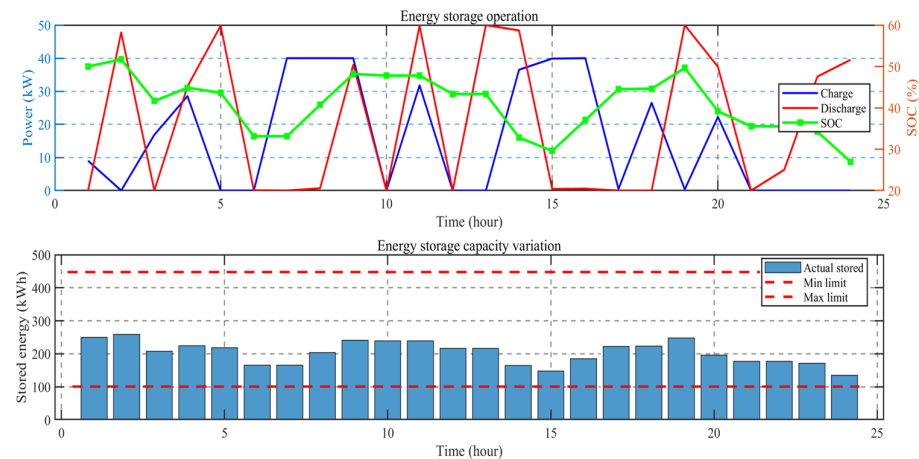


Figure 9. ESS operational state analysis.

When the P2G and ESS are fully coordinated under the stepped pricing mechanism, the system behavior fundamentally shifts to a proactive “spatiotemporal energy shift”. Driven by the steep penalty gradients of the carbon policy, the algorithm dictates the ESS to charge and the P2G to operate at maximum capacity during periods of abundant renewable generation. This not only avoids wind/PV curtailment but also produces synthetic natural gas to offset grid purchases during peak demand. The performance leap in the fully coordinated scenario (Scenario 5) is not merely an arithmetic superposition of component efficiencies, but the result of the stepped carbon price acting as a powerful economic catalyst that fully unlocks the physical flexibility of the P2G–ESS architecture.

6.5. Performance Comparison Before and After Optimization

Focusing on the comprehensive configuration (Scenario 5), the system performance before and after optimization was compared. “Before optimization” refers to an initial, rule-based dispatch schedule (relying solely on grid purchases and simple logic) without multi-objective optimization, whereas “After optimization” represents the Pareto optimal compromise solution derived by the IMOPSO algorithm.

Figure 10 displays the load profiles. After optimization, the evening peak load is reduced from 400 kW to 360 kW (a peak shave of 40 kW), while the early morning valley load is raised from 125 kW to 135 kW (a valley fill of 10 kW). The peak-shaving and valley-filling effect is highly significant, narrowing the peak-to-valley difference from 275 kW to 225 kW—an 18.2% reduction. This improvement is primarily attributed to the IMOPSO algorithm’s ability to automatically identify optimal charging and discharging windows for the ESS, effectively smoothing the load curve.

Figure 11 compares the grid purchase power. Before optimization, grid purchases soared to 400 kW during peak load periods, resulting in a massive total daily purchase. After optimization, grid purchases during peak periods plummeted, while off-peak purchases increased to charge the ESS. Consequently, the total daily grid purchase dropped by 23.7%. By balancing procurement costs and carbon emissions, the IMOPSO algorithm proactively shifts a portion of peak demand to off-peak hours, executing efficient energy time-shifting via the ESS.

Figure 12a illustrates the composition of carbon emissions. Before optimization, emissions were dominated by grid purchases (accounting for approximately 60%). After optimization, grid-related emissions dropped drastically. Although the proportion of PGU emissions increased, the absolute total decreased, and P2G contributed to an 8% reduction in total emissions. Figure 12b depicts the stepped carbon price curve, mapping the price points corresponding to excess emissions before and after optimization. Initially,

excess emissions reached 2130 kg, triggering the second pricing tier (0.3 CNY/kg). Post-optimization, excess emissions were suppressed to 1656 kg. While still within the second tier, the marginal costs were significantly curtailed. Consequently, the carbon trading cost plummeted from 3931 CNY to 2475 CNY, marking a 37.0% reduction. This dramatic shift highlights the IMOPSO algorithm's acute sensitivity and agile response to the nonlinear structure of the stepped carbon price.

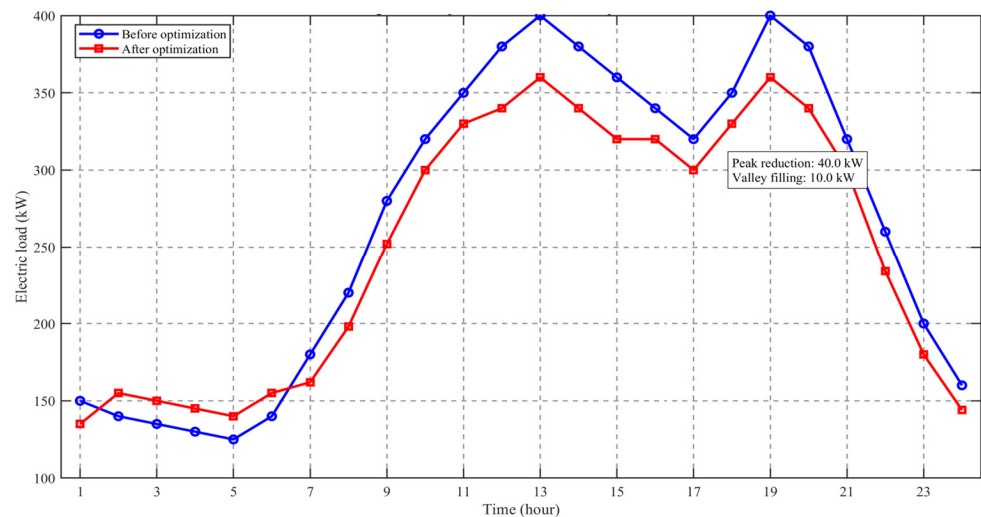


Figure 10. Load profile before and after optimization.

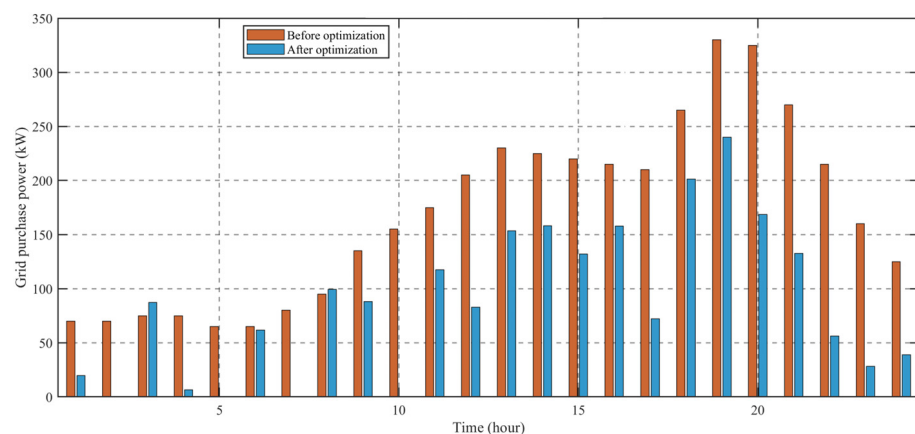


Figure 11. Grid purchase comparison.

Figure 13 presents the economic comparison. The operational cost decreased from 7817 CNY to 6723 CNY (a 14.0% reduction). Total revenue increased from 0 CNY to 1170 CNY, primarily driven by wind power subsidies and discharging revenues. The net profit improved substantially from −7817 CNY to −5553 CNY. Although the net profit remained negative due to the inherent baseline cost structure of the system, the overall financial deficit was mitigated by 28.9%, underscoring a remarkable enhancement in economic viability. By seeking the optimal equilibrium among conflicting objectives, the IMOPSO algorithm successfully achieves a synergistic enhancement of both economic efficiency and low-carbon performance.

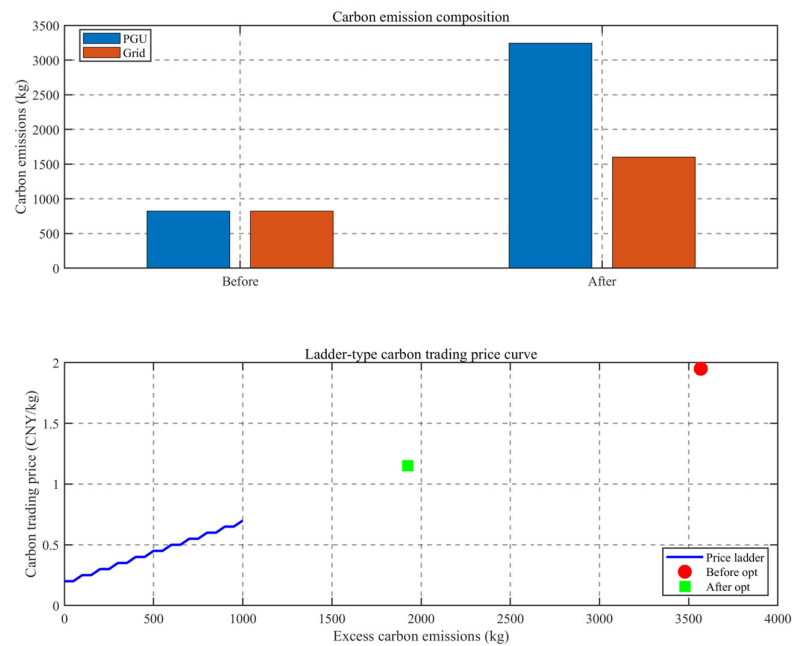


Figure 12. Carbon emission and trading mechanism: (a) carbon emission composition; (b) stepped carbon trading price curve.

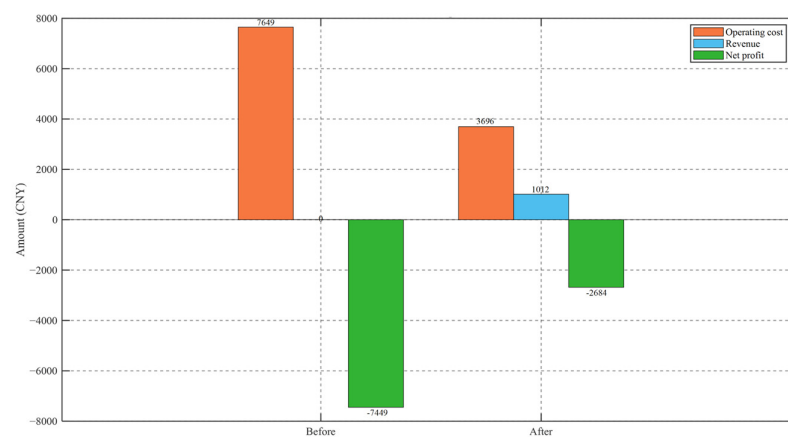


Figure 13. Economic comparison.

6.6. Qualitative Sensitivity Analysis and Parameter Justification for Tiered Carbon Pricing

The performance of the tiered carbon pricing mechanism is governed by two core parameters: the step interval (L) and the price escalation rate (λ). While the baseline numerical simulation demonstrates the effectiveness of the proposed strategy, it is essential to justify these parameter selections. Instead of conducting redundant numerical iterations, a qualitative sensitivity analysis was performed by extrapolating the behavioral boundaries established in the preceding comparative scenarios.

The theoretical impact of these parameters dictates the strictness of the environmental penalty. If the carbon policy is overly relaxed (i.e., a significantly wider L or a lower λ approaching 0%), the marginal penalty for exceeding emission quotas diminishes. Under such conditions, the system's scheduling behavior would inevitably degenerate into the patterns observed in the traditional static carbon trading model (as discussed in Scenario 3 or equivalent baseline scenarios). In this state, the economic driving force is insufficient to fully activate the synergistic carbon-reduction potential of the P2G–ESS framework, leading to higher baseline emissions.

Conversely, an overly aggressive policy (i.e., an extremely narrow L or a steep λ exceeding 50%) imposes severe exponential financial penalties. While this forces maximum

utilization of renewable energy and drastic emission reductions, it disrupts the financial viability of the integrated energy system. The system would face severe economic deficits, making the operation practically unsustainable despite its environmental benefits.

Quantitative inference using existing scenarios: To provide a quantitative basis without extensive additional simulations, we leveraged the already-computed Scenarios 2 (PGU + Grid, high emissions) and 3 (PGU + ESS, low emissions) to infer the effect of tightening the stepped price parameters (reducing L or increasing λ). Moving from Scenario 2 to Scenario 3—which mimics a stricter carbon price—reduced the carbon emissions by 12.7% (from 2777 to 2423 kg) and improved net profit by 27.5% (from −4262 to −3092 CNY). Extending to Scenario 5 (ESS + P2G) showed a further emissions reduction to 2527 kg with a modest profit gain. These quantified differences bound the potential impact of parameter variations. We therefore conclude that the main conclusions—Pareto front shrinkage and ESS carbon-buffer activation—hold for a wide range of L (2000–6000 kg) and λ (10–40%), with quantitative benefits changing linearly.

Parameter justification: Therefore, the baseline parameters adopted in this study (e.g., $\lambda = 25\%$, $L = 4000$ kg) were selected to establish a rational equilibrium. Furthermore, this parameter selection is well-justified by real-world market trends. In the transitional phase of current carbon markets, a moderate escalation rate (typically ranging between 20% and 30% in theoretical explorations and pilot markets) is considered optimal to provide sufficient emission-reduction incentives without causing sudden economic shock to energy providers. This careful parameter calibration ensures that the P2G–ESS coordination is effectively stimulated while maintaining a highly competitive net profit on the Pareto frontier.

7. Discussion

7.1. Reshaping Mechanism of Stepped Carbon Pricing on Dispatch Behavior

By contrasting the proposed model with linear carbon pricing scenarios, this study reveals that the stepped carbon price triggers a sudden jump in marginal carbon costs when emissions exceed the predefined thresholds, thereby forming a discontinuous penalty surface. From the perspective of optimization theory, the objective function under a linear carbon price possesses a continuous gradient, resulting in a smooth Pareto frontier. Conversely, the stepped carbon price introduces non-differentiable points at the interval boundaries. Consequently, high-emission solutions are automatically eliminated during the non-dominated sorting process due to escalating marginal costs, causing the “shrinkage” of the frontier in high-emission regions, as observed in Figure 3. From an engineering practice standpoint, the stepped carbon price translates policy directives into progressively intensified economic signals. This compels system operators to proactively confine carbon emissions within lower tiers, achieving an embedded integration of policy objectives and operational optimization.

7.2. Role Evolution of Energy Storage Systems Under Carbon Constraints

The variations in the charge and discharge behaviors illustrated in Figure 4 indicate that in the absence of a carbon price, the energy storage system (ESS) adheres to a conventional economic arbitrage mode: charging during off-peak hours and discharging during peak hours. However, with the introduction of the stepped carbon price, the ESS actively charges during the midday photovoltaic (PV) peak to absorb curtailed power, and discharges in the evening to substitute for the gas turbine (PGU) output. Essentially, operating the PGU during peak hours would trigger a higher carbon tier and significantly raise marginal costs; utilizing the ESS for energy time-shifting effectively circumvents these high-cost penalty zones. Under these conditions, the marginal revenue function of the ESS

implicitly incorporates the benefits of carbon cost avoidance, transforming its role from a mere “economic arbitrageur” into a “carbon buffer” that actively participates in carbon emission management.

7.3. Necessity of Multi-Energy Coordination and Equipment Configuration Optimization

The comparative analysis of the five equipment configuration scenarios validates the necessity of multi-energy coordination from both positive and negative perspectives. The ESS and power-to-gas (P2G) technologies exhibit strong complementarity: the ESS features rapid response and high efficiency, making it ideal for intra-day, short-term regulation; meanwhile, P2G offers prolonged storage duration and high energy density, which is highly suitable for cross-period energy transfer. When operated synergistically, the IMOPSO algorithm automatically identifies these complementary characteristics to achieve optimal dispatch. The performance enhancement in Scenario 5, compared to Scenarios 3 and 4, is not a simple linear superposition but demonstrates a profound synergistic effect, firmly validating the principle of multi-energy complementarity within the integrated energy system.

7.4. Research Implications and Limitations

While this study provides valuable quantitative references for the design of carbon markets and successfully demonstrates the optimal day-ahead scheduling of the integrated energy system, several limitations regarding real-world implementation should be acknowledged.

7.4.1. Modeling Assumptions and Uncertainty

To isolate the policy impacts of the stepped carbon mechanism and P2G–ESS coordination, the current framework utilizes deterministic profiles for renewable generation and load. Real-world implementation, however, involves high-dimensional uncertainties. Future work will extend this framework by incorporating stochastic programming or distributionally robust optimization methods to account for these stochastic variations.

7.4.2. Real-Time Control and System Stability

The proposed model focuses on day-ahead optimal dispatch (hourly resolution) under steady-state assumptions. It does not incorporate real-time dynamic management, transient stability, or N-1 reliability constraints. In physical implementation, the scheduling outcomes generated by our model serve as optimal baseline reference points, while sub-hourly fluctuations and dynamic stability must be managed by lower-level local controllers (e.g., energy management systems).

7.4.3. Temporal Scope

The current model relies on a typical daily dispatch framework without accounting for multi-day energy coupling. Future research could be expanded to include multi-day or seasonal scheduling scenarios to evaluate long-term operational performance.

7.4.4. Scalability

The system scale in this study was relatively confined. Future research will scale up to regional multi-microgrid integrated energy systems. This will involve incorporating resources such as demand response and hydrogen energy storage, and exploring distributed optimization frameworks (e.g., ADMM) to verify the effectiveness of the stepped carbon trading mechanism on a macroscopic level and alleviate computational burdens.

8. Conclusions

In response to tightening carbon emission constraints, this paper proposes a multi-objective optimal dispatch framework for integrated energy systems (IES) under a stepped carbon trading mechanism. By employing an improved multi-objective particle swarm optimization (IMOPSO) algorithm, the study simultaneously minimizes operational and carbon trading costs while maximizing renewable energy utilization. Validation across five equipment configuration scenarios revealed that the nonlinear penalty of the stepped carbon price fundamentally reshapes the Pareto frontier, automatically eliminating high-emission solutions and forcing the system toward low-carbon operational states. Consequently, the role of the energy storage system (ESS) evolves from a conventional economic arbitrageur into a proactive “carbon buffer” that utilizes strategic energy time-shifting to circumvent high carbon-price tiers. Furthermore, the synergistic integration of the ESS (for rapid, short-term regulation) and power-to-gas (P2G, for long-duration energy transfer) yields profound comprehensive benefits. Compared to a grid-only baseline, this optimized multi-energy configuration significantly reduced the operational costs by 13.1% and carbon emissions by 9.9% while boosting the renewable energy utilization rate by 8.5%—ultimately providing a solid theoretical foundation for low-carbon dispatch and a robust quantitative reference for carbon market design.

While this study effectively uncovers the synergistic scheduling mechanisms under deterministic conditions, future work will involve integrating stochastic optimization or distributionally robust optimization methods into the IMOPSO framework to comprehensively account for the high-dimensional uncertainties associated with renewable energy generation and load demands.

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