

Article

Multi-Objective Dynamic Economic Emission Dispatch with Wind-Photovoltaic-Biomass-Electric Vehicles Interaction System Using Self-Adaptive MOEA/D

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Abstract

The rapid use of renewables like wind power (WP) and photovoltaic (PV) power is essential for a sustainable energy future, yet their volatility poses a threat to grid stability. Electric vehicles (EVs) contribute to the solution by providing storage, while biomass energy (BE) ensures a reliable and sustainable power supply, solidifying its critical role in the stable operation and sustainable development of the power system. Therefore, a dynamic economic emission dispatch (DEED) model based on WP–PV–BE–EVs (DEED_{WPBEV}) is proposed. The DEED_{WPBEV} model is designed to simultaneously minimize operating costs and environmental emissions. The model formulation incorporates several practical constraints, such as those related to power balance, the travel needs of EV owners, and spinning reserve. To obtain a satisfactory dispatch solution, an adaptive improved multi-objective evolutionary algorithm based on decomposition with differential evolution (IMOEA/D-DE) is further proposed. In IMOEA/D-DE, the initialization of the population is achieved through an iterative chaotic map with infinite collapses, and the differential evolution mutation operator is adaptively adjusted. Finally, the feasibility and effectiveness of the proposed model and algorithm are verified on the ten-units system. The experimental results show that the proposed model and algorithm can effectively mitigate renewable energy uncertainty, reduce system costs, and lessen environmental impact.

Keywords: dynamic economic emission dispatch; electric vehicles; biomass energy; multi-objective optimization; renewable energy; sustainability



Academic Editor: Carlos Llopis-Albert

Received: 29 September 2025

Revised: 21 October 2025

Accepted: 4 November 2025

Published: 7 November 2025

Citation: Qiao, B.; Ye, J.; Hu, H.; Wen, P. Multi-Objective Dynamic Economic Emission Dispatch with Wind-Photovoltaic-Biomass-Electric Vehicles Interaction System Using Self-Adaptive MOEA/D. *Sustainability* **2025**, *17*, 9949. <https://doi.org/10.3390/su17229949>

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1. Introduction

Driven by the growing imperatives for environmental sustainability, the use of renewable energy sources, particularly wind power (WP) and photovoltaic (PV), has seen a significant rise in power systems. However, the inherent intermittency and volatility of these renewables may lead to power imbalances, frequency deviations, and even cascading failures, which severely restrict their large-scale grid integration and utilization, and pose major challenges to the stability, security, and economic operation of power systems [1,2]. Therefore, there is an urgent need to develop effective strategies to mitigate renewable energy fluctuations and achieve efficient, economical, and stable grid operation, making the management of WP and PV uncertainty a critical priority in smart grid research.

To address these challenges, the multi-energy complementary power system (MCPS) has emerged as a promising solution. Extensive research has been dedicated to integrating WP, PV, and other flexible resources to improve overall system reliability by mitigating renewable energy uncertainty. For instance, Dong et al. [3] designed a multi-energy complementary system in which the integrated energy storage system supplements power, alleviates the volatility of renewable energy, and enhances system stability. Lin et al. [4] developed an integrated energy system with WP, PV, and energy storage to smooth fluctuations. Other approaches include using hydropower regulation [5] or combining PV with battery and thermal systems [6]. Notably, electric vehicles (EVs) serve not only as controllable loads but also, through vehicle-to-grid (V2G) technology, provide grid services like peak shaving and frequency regulation. This capability has been leveraged to stabilize large-scale PV fluctuations [7], enhance system stability and user revenue in dispatching models [8], alleviate PV uncertainty through grid-connected EVs [9], and maximize renewable utilization in systems with EVs and storage capacity [10]. Similarly, Wang et al. [11] used large-scale EVs integration to smooth WP. In summary, existing research primarily focuses on mitigating renewable uncertainty through MCPS and flexible EVs dispatch. However, a significant gap remains: the power generation potential of urban biomass, particularly urban solid waste (USW), has been largely overlooked in MCPS frameworks.

As a dispatching and stable energy source, biomass energy (BE) effectively compensates for the intermittency of WP and PV, thereby enhancing the reliability of the energy supply. However, the current utilization efficiency of biomass remains unsatisfactory, leading to considerable resource waste. Globally, about 33% of USW is not recycled, indicating significant untapped potential [12]. In Europe, up to 90% of USW is directly landfilled without treatment, contributing to both resource depletion and environmental pollution [13]. Studies suggest that the efficient use of municipal waste could offset approximately 65% of Europe's oil consumption [14]. Internationally, the energy potential of biomass derived from MSW is recognized, with projections indicating it could supply up to 76% of Pakistan's energy needs [15]. Quantitatively, the energy currently wasted through landfilling represents 260 petajoules, equivalent to 20.7% of urban residential electricity demand [16]. Consequently, researchers are exploring the integration of BE into MCPS to improve its efficiency and environmental benefits. For example, Zheng et al. [17] incorporated a BE system with energy storage into a microgrid, effectively reducing overall operating costs. Wu [18] developed a rural integrated energy system combining WP, PV, BE, and biogas generation, significantly increasing user income. Wang et al. [19] established a complementary power generation model with PV and BE, considerably lowering comprehensive operating costs. Jayarathna et al. [20] enhanced sustainability by leveraging diversified BE resources for large-scale power generation. Li et al. [21] proposed an MCPS framework integrating renewables and BE in agricultural areas, substantially cutting operating costs. While converging evidence underscores dual contributions of BE to enhanced energy sustainability and reduced dispatch costs, a systematic architecture for the co-optimization of WP, PV, BE, and EVs clusters remains underdeveloped. Further research is thus required to fully exploit the complementary potential between the distributed, mobile storage of EVs and the stable, dispatching generation of BE.

Power system dispatch is a typical high-dimensional, strongly constrained, and multi-objective optimization problem, for which conventional optimization algorithms are often not directly applicable. Dai et al. [22] developed a multi-form evolutionary algorithm framework to address strongly constrained multi-objective optimization in integrated coal energy systems. Li et al. [23] tackled multi-constraint and strong-coupling issues in electrical-thermal integrated energy systems by hybridizing the non-dominated sorting genetic algorithm with multi-objective particle swarm optimization. Zio et al. [24]

applied a multi-objective genetic algorithm guided by Pareto optimality to resolve non-linear, constrained power dispatch problems. Ji et al. [25] proposed an environmentally featured PSO to address ocean current influences on autonomous underwater vehicles, achieving time-optimal path planning through the integration of current characteristics. Li et al. [26] introduced an adaptive decomposition strategy and an enhanced solution assignment mechanism into the multi-objective evolutionary algorithm based on decomposition (MOEA/D), significantly improving computational efficiency. Zhang et al. [27] incorporated a penalty-based boundary intersection method into MOEA/D to handle uncertainties from intermittent sources in hybrid energy systems while reducing operational costs. Shao et al. [28] integrated Lévy flight into MOEA/D, markedly boosting its performance in solving multi-objective optimization problems for grid-connected EVs in power systems. Despite these advances, most enhanced MOEA/D variants still suffer from limited distribution diversity and insufficient convergence performance when applied to high-dimensional, dynamic-constrained multi-objective dispatch problems.

Significant progress has been made in existing research on multi-energy complementary systems for mitigating renewable energy uncertainty. However, two critical limitations persist. First, while multi-energy coordination has been explored, the potential of EVs as a distributed, rapid-response storage resource for real-time fluctuation absorption remains under-used in dispatch models. Second, BE continues to be under-used in current research. Its potential as a scalable, stable power source for system-wide emission reduction and cost efficiency has yet to be fully leveraged within coordinated dispatch frameworks. To overcome these limitations, this paper proposes a novel multi-objective dynamic economic emission dispatching $DEED_{WPBEV}$ integrated power system model. The uniqueness of this model is primarily manifested in the establishment of a unified framework, within which systematic collaborative optimization of high-penetration renewable energy, distributed electric vehicle energy storage, dispatching biomass power generation, and large-scale thermal power generation is realized. Compared to traditional multi-energy dispatching methods, the dynamic coupling relationship between the distributed energy storage characteristics of EVs and WP, and PV is fully leveraged by the $DEED_{WPBEV}$ model, resulting in a significant improvement in renewable energy consumption efficiency. Meanwhile, the BE is innovatively introduced by this model as a partially dispatching alternative energy source, effectively alleviating the emission control and fuel cost pressures faced by traditional thermal power generation. And to solve the $DEED_{WPBEV}$ model, an adaptive multi-objective evolutionary algorithm based on decomposition with differential evolution (IMOEA/D-DE) multi-objective optimal dispatching method is developed.

The main contributions are summarized as follows: (1) A multi-energy complementary dynamic economic emission dispatch ($DEED_{WPBEV}$) model is proposed based on WP-PV-BE-EVs ($DEED_{WPBEV}$). (2) An improved IMOEA/D-DE algorithm is proposed to optimize the $DEED_{WPBEV}$ model. Compared with the MOEA/D algorithm, the iterative chaotic map with infinite collapses (ICMIC) was employed in IMOEA/D-DE for population initialization, while a DE mutation strategy was introduced, and a new adaptive adjustment mechanism was proposed, which can automatically select different mutation operators through different iteration stages to enhance the search capability. (3) The effectiveness of the proposed $DEED_{WPBEV}$ and IMOEA/D-DE was verified on a ten-units system. The results show that the proposed model and algorithm provide a good framework and method for addressing new energy uncertainty and biomass energy grid integration.

The remainder of this paper is organized as follows: Section 2 the $DEED$ with the $WPBEV$ is proposed. Section 3 elaborates on the proposed IMOEA/D-DE. Section 4 presents the experimental setup, results, and corresponding discussion. Finally, Section 5 concludes the work.

2. Modeling of DEED Based on WPBEV

2.1. Dispatch Model of Electric Vehicles

EVs can be categorized based on their primary functions into public transport, private transport, and commercial applications. Among these, commercial vehicles are less suitable for participation in V2G enabled grid services due to their high daily utilization rates. In contrast, privately owned EVs remain stationary and connected to the grid for extended periods, particularly after daily commutes, making them highly amenable to integration into grid dispatching via V2G. Therefore, this research primarily focuses on privately owned passenger EVs. This work adopts a hierarchical dispatching framework rather than directly controlling the charging and discharging processes of individual EVs. Specifically, all EVs within a designated area are grouped into several aggregates, with the charging and discharging behavior of each aggregate managed centrally by an aggregator. Under this structure, the aggregator participates in grid dispatching as a single entity, thereby eliminating the need to monitor or manage the behavior of each EV [29].

The operational mode of electric vehicles during each dispatching interval is defined by a sign function, with specific operational cases specified in Table 1. The function is formally defined as follows:

$$\begin{cases} p_t^{\text{ch}} = \text{sign}(x) \sum_{n=1}^{N_{\text{EV}}} p_n^{\text{EV}}, & x < 0 \\ p_t^{\text{dch}} = \text{sign}(x) \sum_{n=1}^{N_{\text{EV}}} p_n^{\text{EV}}, & x > 0 \\ p_t^{\text{ch}} \text{ and } p_t^{\text{dch}} = 0, & x = 0 \end{cases} \quad (1)$$

Table 1. The description of EV charging and discharging states.

State	Description
Charging	$x < 0$, $\text{sign}(x) = -1$, and $p_t^{\text{ch}} < 0$, describe that EVs are in the charging stage.
Discharging	$x > 0$, $\text{sign}(x) = 1$, and $p_t^{\text{dch}} > 0$, describe that EVs are in the discharging stage.
No charging/discharging	$x = 0$, EVs are not in the dispatch phase.

2.2. Modeling of Biomass Energy

In 2025, renewable energy is projected to contribute 14.9% of the global energy [30]. Within this share, BE accounts for 22.8% and demonstrates a steady year-on-year growth trajectory, as shown in Figure 1. Nevertheless, the integration of BE into power system dispatch remains relatively limited at present. Particularly in urban areas, substantial quantities of raw materials suitable for biomass power generation are discarded, resulting in considerable resource waste. The full utilization of these discarded biomass resources could not only mitigate environmental pollution but also enhance overall energy efficiency. This paper focuses on the coordinated operation of BE within a WP-PV-EVs system. Through multi-energy complementation, the proposed approach effectively alleviates environmental pollution and reduces operational stresses on power systems caused by conventional fossil-based energy sources.

As a renewable energy source, organic matter is employed as fuel in BE and is converted into thermal energy or combustible gases through combustion or conversion technologies, which are subsequently used to power generation equipment for electricity generation. Fundamentally, this technology achieves clean power production by converting energy from biomass resources. Ref. [31] indicates that there are two primary models for biomass power generation, one of which is the biomass steam turbine generation model, described as follows:

$$p^{\text{BE}} = k_r Q \zeta_{tb} o_{gt} \quad (2)$$

where P^{BE} represents biomass power. Q stands for steam passing through the steam turbine in unit time. ζ_{tb} stands for the efficiency of a biomass energy turbine, which represents the ability of a biomass energy turbine to convert steam heat energy into mechanical energy. o_{gt} denotes the thermal energy conversion efficiency of biomass materials. k_r is a constant, depending on the pressure and temperature of the steam.

Biomass boilers are as follows:

$$P^{BE} = H_V R_{fuel} \chi_{bu} \quad (3)$$

where H_V represents boiler efficiency. R_{fuel} denotes the fuel consumption rate. χ_{bu} is the efficiency of biomass heating equipment. It is especially noted that this article only conducts macro-level control of BE.

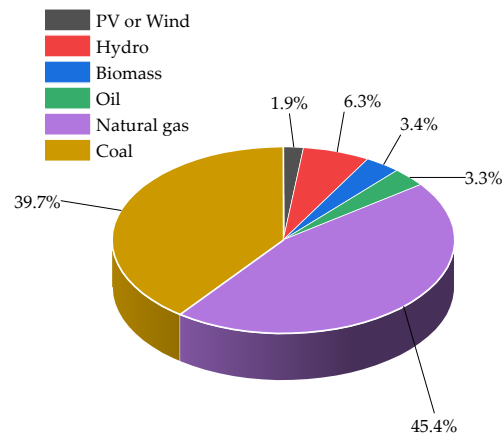


Figure 1. The total annual power generation of each energy in 2025.

2.3. Modeling of WP and PV

WP and PV power output exhibit significant intermittency and stochasticity, fundamentally due to their high dependence on natural conditions such as wind speed and solar radiation intensity. To accurately model the uncertainty of renewable power generation, this paper first employs QRF to generate probabilistic forecasts of key natural factors [32] and subsequently derives the final power output of WP and PV generation using a physical power curve model [33]. The physical model of dispatching active power $P_t^{w,rate}$ and wind speed $v_{i,t}$ of WP is the following:

$$P_t^{w,dis} = \begin{cases} 0, & v_{i,t} \leq v_{in} \text{ or } v_{out} \leq v_{i,t} \\ P_t^{w,rate} \frac{v_{i,t} - v_{in}}{v_r - v_{in}}, & v_{in} \leq v_{i,t} \leq v_r \\ P_t^{w,rate}, & v_r \leq v_{i,t} \leq v_{out} \end{cases} \quad (4)$$

where $P_t^{w,dis}$ represents the dispatching power of the WP; $v_{i,t}$ denotes the wind speed of the i th wind turbine at time t .

The physical model of PV dispatches active power $P_t^{s,dis}$ and solar radiation intensity $R_{n,t}$ is as the following:

$$P_t^{s,dis} = \sum_{t=1}^T \sum_{n=1}^{N_s} \frac{1}{G_{stc}} (P_s^{stc,max} R_{n,t} \times [1 + k(S_{n,t} - S_{stc})]) \quad (5)$$

where $P_t^{s,dis}$ denotes the dispatch power of PV. $P_s^{stc,max}$ is the maximum output power under standard conditions. $S_{n,t}$ and S_{stc} represent the solar radiation intensity and temperature of the n th photovoltaic power generation unit at time t , respectively.

2.4. Modeling of DEED with WPBEV

A new DEED_{WPBEV} model is proposed in this work to mitigate the impact of WP and PV uncertainty on the grid, with a structure presented in Figure 2. In this model, a portion of the power for EVs charging is sourced directly from renewable generation, while the remainder is supplied through the unified dispatch of the power grid control center. When renewable energy generation is insufficient, energy discharged from EVs is used to compensate for the shortfall. Conversely, EVs charging is used to absorb excess generation, thereby mitigating renewable curtailment. If the combined discharge from EVs and renewable energy is insufficient to meet the load demand, BE is dispatched to cover the deficit. If the BE power supply remains inadequate, conventional thermal power is activated to compensate for the remaining shortfall.

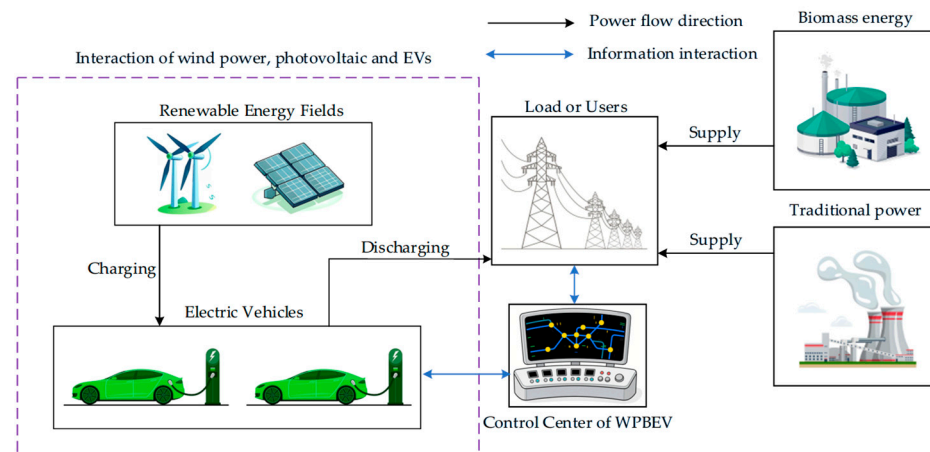


Figure 2. The DEED_{WPBEV} system.

2.5. Objective Functions

The DEED_{WPBEV} model proposed in this paper incorporates two objective functions: the total system cost and the emission cost. The total system cost encompasses the integration costs associated with coordinating WP, PV, and EVs. Within the considered system, WP, PV, and EVs are treated as zero-emission resources. Consequently, operational emissions, and thus the associated emission costs, are primarily attributable to thermal power generation. The objective function for minimizing total emission cost is formulated as follows:

$$\min F_M = \sum_{t=1}^T \sum_{n=1}^{N_p} \alpha_n (P_t^n)^2 + \beta_n (P_t^n) + \delta_n + \gamma_n \exp(\varepsilon_n P_t^n) \quad (6)$$

The uncertainty in WP and PV leads to forecasting errors, which incur imbalance costs for both overestimation and underestimation. In contrast, EVs participating in V2G services primarily incur operational costs related to charging and discharging cycles. Therefore, the total cost objective function comprises the following components: (1) the fuel cost of traditional thermal power units and BE; (2) the operating costs of EVs providing V2G services; (3) the imbalance costs (for both over- and under-estimation) of renewable generation; and (4) the net cost of WP and PV. The objective function is formulated as follows:

$$\min F_C = f_{WP} + f_{PV} + f_{V2G} + f_{new} + f_p + f_{BE} \quad (7)$$

where the WP operational cost is obtained from the following equation:

$$f_{WP} = \sum_{t=1}^T \sum_{n=1}^{N_w} \sigma_n^w P_{n,t}^{w,dis} \quad (8)$$

where $P_{n,t}^{w,dis}$ represents the dispatching active power from the n th wind turbine at time t . σ_n^w denotes the operating cost of the unit active power of WP. The PV operational cost is defined as the following:

$$f_{PV} = \sum_{t=1}^T \sum_{n=1}^{N_s} \sigma_n^s P_{n,t}^{s,dis} \quad (9)$$

where $P_{n,t}^{s,dis}$ represents the dispatching active power from the n th solar turbine at time t . σ_n^s denotes the operating cost of the unit active power of PV. The charging and discharging cost of EVs is defined as the following:

$$f_{V2G} = \sum_{t=1}^T \sum_{n=1}^{N_{EV}} (\partial_t^{ch} P_{n,t}^{ch} + \partial_t^{dch} P_{n,t}^{dch}) \quad (10)$$

where $P_{n,t}^{ch}$ represents the charging power and $P_{n,t}^{dch}$ the discharging power at time t . ∂_t^{ch} , ∂_t^{dch} are charging price and discharging price at time t . The interactive cost of WP-PV-EVs is defined as the following:

$$f_{new} = \sum_{t=1}^T \sum_{n=1}^{N_{new}} c_{rej}^{new} P_{n,t}^{new} + \sum_{t=1}^T \sum_{n=1}^{N_{new}} c_{res}^{new} P_{n,t}^{res} \quad (11)$$

In the DEED_{WPBEV} model, there are two main operating scenarios. Firstly, when the combined output of WP and PV is high, it may exceed demand of the system even after dispatching, resulting in the curtailment of renewable generation and incurring a corresponding cost, as shown in Equation (13). Secondly, when the output from WP and PV is insufficient, the system may still be unable to meet the load demand even after EVs dispatching is implemented, leading to a load loss cost, as quantified in Equation (14). These two costs, curtailment cost and load loss cost, are collectively termed the interactive cost WP-PV-EVs within the system, where $P_{n,t}^{new}$ is the new energy curtailment given by Equation (12) and $P_{n,t}^{res}$ is the new energy shortage given by Equation (15) as the following:

$$P_{n,t}^{new} = \sum_{t=1}^T \sum_{n=1}^{N_w} e_{rej}^w (P_{n,t}^w - \frac{1}{2} P_t^{ch} - P_{n,t}^{w,dis}) + \sum_{t=1}^T \sum_{n=1}^{N_s} e_{rej}^s (P_{n,t}^s - \frac{1}{2} P_t^{ch} - P_{n,t}^{s,dis}) \quad (12)$$

where $P_{n,t}^{new}$ represents the available power from all WP and PV at time t . $P_{n,t}^{new,dis}$ stands for the dispatched power for all WP and PV at time t . e_{rej}^w and e_{rej}^s represent the cost coefficients for WP and PV curtailment. The constraint for the first operational scenario is given by the following:

$$\sum_{t=1}^T \sum_{n=1}^{N_w} P_{n,t}^w + \sum_{t=1}^T \sum_{n=1}^{N_s} P_{n,t}^s > \sum_{t=1}^T \sum_{n=1}^{N_{ch}} P_{n,t}^{ch} + \sum_{t=1}^T \sum_{n=1}^{N_w} P_{n,t}^{w,dis} + \sum_{t=1}^T \sum_{n=1}^{N_s} P_{n,t}^{s,dis} \quad (13)$$

The constraint for the second operational scenario is given by the following:

$$\sum_{t=1}^T \sum_{n=1}^{N_w} P_{n,t}^{w,dis} + \sum_{t=1}^T \sum_{n=1}^{N_s} P_{n,t}^{s,dis} > \sum_{t=1}^T \sum_{n=1}^{N_{EV}} P_{n,t}^{dch} + \sum_{t=1}^T \sum_{n=1}^{N_w} P_{n,t}^w + \sum_{t=1}^T \sum_{n=1}^{N_s} P_{n,t}^s \quad (14)$$

New energy power shortage $P_{n,t}^{res}$ as follows:

$$P_{n,t}^{res} = \sum_{t=1}^T \sum_{n=1}^{N_w} e_{nrej}^w (P_{n,t}^{w,dis} - \frac{1}{2} P_t^{dch} - P_{n,t}^w) + \sum_{t=1}^T \sum_{n=1}^{N_s} e_{nrej}^s (P_{n,t}^{s,dis} - \frac{1}{2} P_t^{dch} - P_{n,t}^s) \quad (15)$$

where $P_{n,t}^{\text{res}}$ denotes the available power from all WP and PV at time t . $e_{\text{nrej}}^{\text{w}}$ and $e_{\text{nrej}}^{\text{s}}$ represent the cost coefficients for WP and PV uncurtail, respectively. The operation cost of thermal power units is defined as the following:

$$f_{\text{p}} = \sum_{t=1}^T \sum_{n=1}^{N_{\text{p}}} a_n (P_t^n)^2 + b_n (P_t^n) + c_n \quad (16)$$

The operation cost of BE units is defined as follows:

$$f_{\text{BE}} = \sum_{t=1}^T \sum_{n=1}^{N_{\text{BE}}} \sigma_n^{\text{BE}} P_{n,t}^{\text{BE,dis}} \quad (17)$$

where σ_n^{BE} is the cost per unit active power of the n th BE unit.

2.6. Constraints

The equality and inequality constraints of the DEED_{WPBEV} model are as follows:

Power balance constraints: In each interval, the sum of the total active power of thermal power units, the EVs charging or discharging power, WP, PV, and BE should satisfy the sum of system loss and load demands as the following:

$$\sum_{t=1}^T \sum_{n=1}^{N_{\text{w}}} P_{n,t}^{\text{w,dis}} + \sum_{t=1}^T \sum_{n=1}^{N_{\text{s}}} P_{n,t}^{\text{s,dis}} + \sum_{t=1}^T \sum_{n=1}^{N_{\text{p}}} P_{n,t} + \sum_{t=1}^T \sum_{n=1}^{N_{\text{BE}}} P_{n,t}^{\text{BE,dis}} + \sum_{t=1}^T \sum_{n=1}^{N_{\text{EV}}} P_{n,t}^{\text{dch}} = P_t^{\text{D}} + \sum_{t=1}^T \sum_{n=1}^{N_{\text{EV}}} P_{n,t}^{\text{ch}} + P_t^{\text{L}} \quad (18)$$

where P_t^{D} represents the load demand of the system at time t . P_t^{L} represents the network loss of the system at time t , which is calculated by the B-coefficient method [34].

$$P_t^{\text{L}} = \sum_{j=1}^N \sum_{n=1}^{N_{\text{p}}} P_{n,t} B_{nj} P_{n,t} + \sum_{n=1}^{N_{\text{p}}} P_{n,t} B_{n0} + B_{00} \quad (19)$$

EVs constraints: The main purpose of EVs is the daily travel of users, so the travel constraints of EVs owners in a dispatching period are shown in Equation (20) as the following:

$$\sum_{t=1}^T E_{\text{con}} = \sum_{t=1}^T \theta^{\text{ch}} P_t^{\text{ch}} \Delta t - \sum_{t=1}^T \frac{1}{\theta^{\text{dch}}} P_t^{\text{dch}} \Delta t \quad (20)$$

where θ^{ch} , θ^{dch} are charging and discharging power coefficient. E_{con} is power consumption of EVs when driving, which can be calculated by Equation (22), when the EVs are connected to the grid through the V2G system, at the t time the remaining power constraint of the EVs is shown in Equation (21) as the following:

$$E_t = E_{t-1} + \theta^{\text{ch}} P_t^{\text{ch}} \Delta t - \frac{1}{\theta^{\text{dch}}} P_t^{\text{dch}} \Delta t - E_{\text{con}} \quad (21)$$

where ΔE is the power consumed per unit distance of the EVs, and L is the distance driven.

$$E_{\text{con}} = \Delta E L \quad (22)$$

The remaining battery capacity of the EVs in Equation (23) should also meet the limit of the maximum and minimum values in each dispatching cycle as follows:

$$E_{\text{min}} \leq E_t \leq E_{\text{max}} \quad (23)$$

For the sake of safety, EVs must also meet the rated power of EVs when charging and discharging through V2G as follows:

$$\begin{cases} 0 \leq P_t^{\text{ch}} \leq P_{\max}^{\text{ch}} \\ 0 \leq P_t^{\text{dch}} \leq P_{\max}^{\text{dch}} \end{cases} \quad (24)$$

where $P_{\max}^{\text{ch}}$ and $P_{\max}^{\text{dch}}$ are the maximum power of EVs charging and discharging, respectively. WP, PV, and BE constraints are defined as the following:

$$\begin{cases} 0 \leq P_{n,t}^{\text{w,dis}} \leq P_{n,t}^{\text{w,rate}} \\ 0 \leq P_{n,t}^{\text{s,dis}} \leq P_{n,t}^{\text{s,rate}} \\ 0 \leq P_{n,t}^{\text{BE,dis}} \leq P_{n,t}^{\text{BE,rate}} \end{cases} \quad (25)$$

The WP, PV, and BE in the system should satisfy the upper and lower limits.

Spinning reserve constraints: The uncertainty in WP and PV requires the model to incorporate spinning reserves to maintain system reliability. Therefore, upward and downward spinning reserve constraints are formulated using chance constraints [35] as follows:

$$\Pr \left\{ \sum_{n=1}^N \min(P_{n,t}^{\max} - P_{n,t}, \frac{U_{Rt}}{6}) + \omega_u^{EV} (P_t^{\text{dch}} + P_t^{\text{ch}}) + \omega_u^{\text{BE}} P_t^{\text{BE}} \geq \omega_u^{\text{w}} P_t^{\text{w}} + \omega_u^{\text{s}} P_t^{\text{s}} + S_{R,T}^t \right\} \geq \eta_1 \quad (26)$$

$$\Pr \left\{ \sum_{n=1}^N \min(P_{n,t} - P_{n,t}^{\min}, \frac{D_{Rt}}{6}) + \omega_d^{EV} (P_t^{\text{dch}} + P_t^{\text{ch}}) + \omega_d^{\text{BE}} P_t^{\text{BE}} \geq \omega_d^{\text{w}} (P_t^{\text{w,rate}} - P_t^{\text{w}}) + \omega_d^{\text{s}} (P_t^{\text{s,rate}} - P_t^{\text{s}}) \right\} \geq \eta_2 \quad (27)$$

The amounts of upper and lower spinning reserve are given by Equations (26) and (27), respectively. ω_u^{w} and ω_d^{w} respectively denotes the spinning reserve capacity coefficients of WP. ω_u^{s} and ω_d^{s} respectively denotes the spinning reserve capacity coefficients of PV. Similarly, ω_u^{BE} and ω_d^{BE} represent the spinning reserve capacity coefficients of BE, respectively. ω_u^{EV} and ω_d^{EV} represent the spinning reserve capacity coefficients of EVs, respectively. η_1 and η_2 are two pre-specified confidence levels, which are used to represent the spinning reserve capacity range, when dispatching new energy power generation is insufficient. $S_{R,T}^t$ stands for the spinning reserve capacity demand for time t , usually 5–10% of the load demand, this is mentioned in [33]. $P_{n,t}^{\max}$ and $P_{n,t}^{\min}$ are calculated as follows:

$$\begin{cases} P_{n,t}^{\max} = \min(P_n^{\max}, P_{n,t-1} + U_{Rt} \Delta t) \\ P_{n,t}^{\min} = \max(P_n^{\min}, P_{n,t-1} - D_{Rt} \Delta t) \end{cases} \quad (28)$$

3. Adaptive IMOEA/D-DE with ICMIC

This section focuses on the improved IMOEA/D-DE proposed in this paper, with detailed explanations of both its algorithmic flow and implementation for model solving.

3.1. The Proposed IMOEA/D-DE

The DEED_{WPBEV} dispatching problem is a high-dimensional, strongly constrained, multi-objective optimization that necessitates the use of efficient solution algorithms. MOEA/D, which employs a cooperative optimization strategy, has been shown to achieve high computational efficiency and rapid convergence when solving such multi-period problems with complex constraints [36].

In evolutionary algorithms, the quality of the initial population plays a critical role in overall performance. A well-distributed and diverse initial population not only improves convergence speed and robustness during optimization but also fundamentally shapes the distribution and convergence characteristics of the final Pareto fronts (PFs). To

address this problem, a chaotic mapping method is introduced to enhance the population initialization process in MOEA/D, thereby effectively increasing population diversity. Additionally, a differential mutation strategy derived from differential evolution (DE) is integrated to strengthen the algorithm's search capability and convergence performance during optimization.

The ICMIC, an iterative chaotic map characterized by infinite folding properties, is known to possess an infinite number of fixed points. It is indicated by these features that the ICMIC chaotic map exhibits strong sensitivity to initial conditions, which allows it to be used effectively in enhancing the global exploration capability of algorithms with exceptional performance [37] as follows:

$$x_{n+1} = f(\tau, x_n) = \sin\left(\frac{\tau}{x_n}\right), -1 \leq x_n \leq 1, x_0 \neq 0, \tau \in (0, +\infty) \quad (29)$$

where τ is the adjustable parameter.

In the DE, a new individual is generated for each existing individual by leveraging the vector differences between other individuals in the current population [38]. Five common mutation strategies are listed in Equation (30) as follows:

$$\begin{cases} x_{r1} + F(x_{r2} - x_{r3}) \\ x_{\text{best}} + F(x_{r1} - x_{r2}) \\ x_i + F(x_{r1} - x_i) + F(x_{r2} - x_{r3}) \\ x_i + F(x_{r1} - x_{r2}) + F(x_{r3} - x_{r4}) \\ x_{r1} + F(x_{r2} - x_{r3}) + F(x_{r4} - x_{r5}) \end{cases} \quad (30)$$

where x_{r1} , x_{r2} , x_{r3} , x_{r4} , and x_{r5} represent five distinct individuals randomly selected from the population, x_{best} denotes the current best individual, and F is the mutation factor. This paper integrates these five strategies and proposes a novel stage-adaptive dynamic mutation strategy.

3.2. Adaptive Dynamic Mutation Strategy

In the conventional MOEA/D framework, mutation is performed using the polynomial mutation operator. While this approach promotes some diversity, its performance degrades when handling high-dimensional multi-objective problems, making it ill-suited for application to the DEED_{WPBEV} model introduced in this work. To address this limitation, the mutation mechanism is enhanced by integrating DE strategies.

In IMOEA/D-DE, the mutation strategy is adaptively adjusted based on the evolutionary stage. During the early iterations, mutation strategies biased toward global exploration are preferentially employed to broadly probe the solution space and mitigate premature convergence. As the algorithm progresses to the middle stage, exploration and exploitation capabilities are gradually balanced, with population diversity preserved while individuals are guided toward the PFs. In the later stages of evolution, the focus of the strategy is shifted to local exploitation, with fine-grained searches conducted in the optimal solution region to enhance convergence precision.

The improved algorithm is particularly well-suited for the complex DEED_{WPBEV} model. The overall flowchart is presented in Figure 3, and the pseudocode of the adaptive mutation strategy is provided in Algorithm 1. The enhanced MOEA/D is evaluated using the hypervolume (HV) metric [39], a comprehensive performance indicator that quantifies both the convergence and distribution diversity of solutions. The HV results from a comparative work with several state-of-the-art algorithms are presented in Table 2, where a higher value indicates superior overall performance.

Algorithm 1. Adaptive dynamic mutation strategy

Input:

itrCounter: Represents the number of iterations
itrCounter_{ratio}: The running progress of the current algorithm
j_n: The stage represents the coefficient
x_n: Mutation parameter
mut_{prob}: Select mutation Indicators
p_{iter}: Current number of iterations

Output:

newpoint: The generated new individual

```

for i = 1 to itrCounter do
    % Calculate the proportion of iteration progress
    itrCounterratio = piter / itrCounter
    % Three-stage adaptive strategy selection
    if itrCounterratio ≤ jn then % Early stage
        mutprob = xn
    else if itrCounterratio ≤ jn
        mutprob = xn % Middle stage
    else mutprob = xn % Late stage
    end else
end if
end if
if rand() < mutprob then
    % MOEA/D mutation strategy
    else rand() ≥ mutprob % DE multi-strategy variation
    % DE mutation strategy
end else
end if
end

```

Table 2. Comparison of the hypervolume index.

	MODA	MOAHA	MODE	MOPSO	MOEA/D	IMOE/D-DE
HV	3.20×10^{-3}	1.46×10^{-2}	2.02×10^{-2}	1.49×10^{-2}	2.97×10^{-2}	3.01×10^{-2}

The superior overall performance of IMOE/D-DE in both convergence and diversity is confirmed by the experimental results in Table 2, which demonstrate a significantly higher HV value compared to traditional algorithms. In the table, the bolded data represent the best performance.

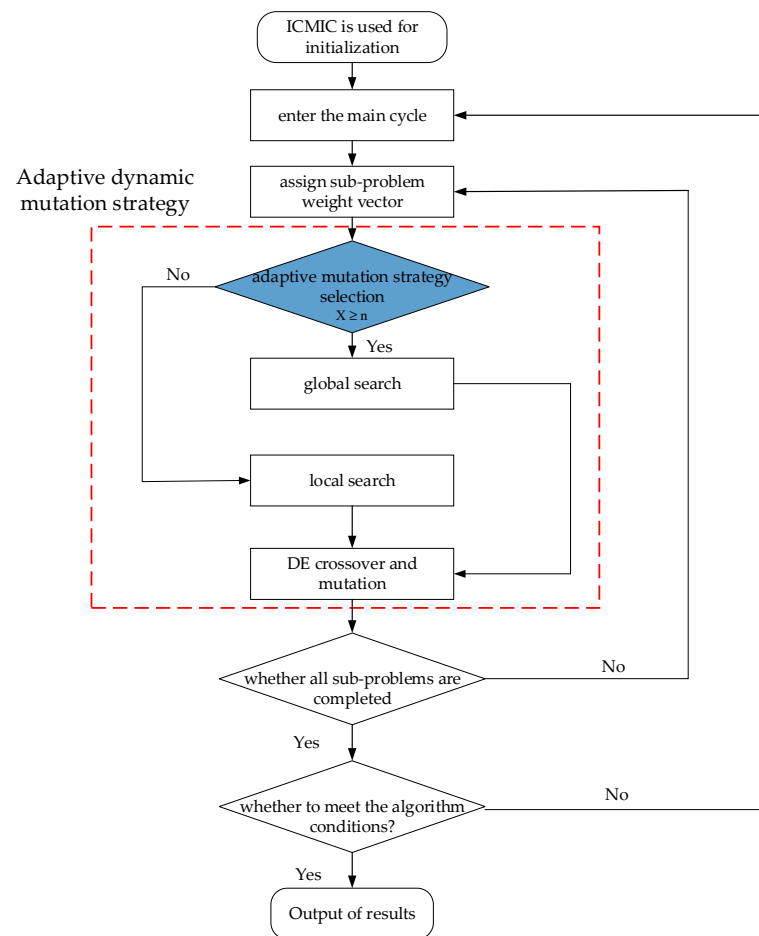


Figure 3. The flowchart of IMOEA/D-DE.

4. Experimental Results and Analysis

4.1. Test System and Algorithm Parameters

The performance of the proposed DEED_{WPBEV} model and IMOEA/D-E was evaluated using multiple test scenarios. For demonstration purposes, a ten-units system was simulated, with its load demand and parameters referenced from [40], which are given in Tables 3 and 4.

Table 3. The load demand of the system.

t	1	2	3	4	5	6	7	8	9	10	11	12
Load/MW	1184	1036	1110	1258	1406	1480	1628	1702	1776	1924	2022	2106
t	13	14	15	16	17	18	19	20	21	22	23	24
Load/MW	2127	2072	1924	1776	1554	1480	1628	1776	1972	1924	1628	1332

Table 4. Ten-units system parameters.

Unit	$p_i^{\max}$	$p_i^{\min}$ MW	U_R MW/h	D_R	a_n USD/h	b_n USD/MW/h	c_n USD/(MW) ² /h	α_n lb/h	β_n lb/MW/h	δ_n lb/(MW) ² /h	γ_n lb/h	ε_n 1/MW
P_1	470	150	80	80	786.7988	38.5379	0.1524	103.3908	−2.4444	0.0312	0.5035	0.0207
P_2	470	135	80	80	451.3251	46.1591	0.1058	103.3908	−2.4444	0.0312	0.5035	0.0207
P_3	340	73	80	80	1049.9977	40.3965	0.0280	300.3910	−4.0695	0.0509	0.4968	0.0202
P_4	300	60	50	50	1243.5311	38.3055	0.0354	300.3910	−4.0695	0.0509	0.4968	0.0202
P_5	243	73	50	50	1658.5696	36.3278	0.0211	320.0006	−3.8132	0.0344	0.4972	0.0200
P_6	160	57	50	50	1356.6592	38.2704	0.0179	320.0006	−3.8132	0.0344	0.4972	0.0200
P_7	130	20	30	30	1450.7045	36.5104	0.0121	330.0056	−3.9023	0.0465	0.5163	0.0214
P_8	120	47	30	30	1450.7045	36.5104	0.0121	330.0056	−3.9023	0.0465	0.5163	0.0214
P_9	80	20	30	30	1455.6056	39.5804	0.1090	350.0056	−3.9524	0.0465	0.5475	0.0234
P_{10}	55	10	30	30	1469.4026	40.5407	0.1295	360.0012	−3.9864	0.0470	0.5475	0.0234

All simulations were performed in the MATLAB R2024b environment on a computational platform equipped with an Intel Core i7-12700 CPU and 32 GB of RAM. In each test system, the key algorithm parameters were configured as follows: NP was 100, and the Max_Fes were 3000. The EVs data corresponded to the Nissan Leaf model [41], while the BE parameters were adopted from [31]. A complete list of EVs parameters is presented in Table 5.

The DEED_{WPBEV} model comprises 20,000 EVs, 50 wind turbines, 50 photovoltaic units, and two biomass generators (each with a rated capacity of 100 MW). The experiment used historical wind speed, solar irradiance, and temperature data from a renewable energy power station in northwest China. The data spans from 1 September 2019 to 31 December 2019 with a sampling interval of 15 min. Detailed parameters of the wind turbines and photovoltaic units are provided in Table 6.

Table 5. The parameters of EVs.

Parameters	Value
Battery capacity	24 kWh
ΔE	0.15 kWh/km
L	50 km
Commuting period	07:00–08:00 and 18:00–19:00
The initial state of SOC	100% of the battery capacity
Minimum SOC	20% of the battery capacity
Charge discharge efficiency	0.85

Table 6. Parameters of new energy.

Parameters of the Wind Turbines	Value	Photovoltaic Parameters	Value
$p^{w,rate}$	2 MW	$p^{s,rate}$	1 MW
v_r	13 m/s	T_{stc}	25 °C
v_{in}	3 m/s	G_{stc}	1357 W/m ²
v_{out}	22 m/s	a	0.38

4.2. Verify the Proposed IMOEAD-DE

The performance of the proposed IMOEAD-DE was evaluated through comparative experiments with several state-of-the-art algorithms, including MOEA/D, MOPSO [42], MODE [43], MODA [44], MOAHA [45], NSGA-II [46], and NSGA-III [47]. To ensure statistical significance, each algorithm was independently executed 30 times.

PFs represent the set of non-dominated solutions obtained by each algorithm in the objective space. As illustrated in Figure 4, the PFs achieved by the proposed IMOEAD-DE demonstrate superior performance in both convergence and diversity compared to all other algorithms. Specifically, the PF of IMOEAD-DE is positioned closer to the bottom-left corner of the objective space, indicating enhanced convergence, while also exhibiting a more uniform distribution of solutions. The inferior performance of NSGA-III, as evident from its PFs, serves as a benchmark for comparison. The marked superiority of IMOEAD-DE can be attributed to its effective global search mechanism, facilitated by the incorporated differential evolution mutation strategy, which effectively prevents premature convergence. The extreme and compromise solutions obtained by each algorithm are summarized in Table 7, where the extreme solutions comprise the optimal cost solution and the optimal emission solution, with superior solutions highlighted in bold.

As shown in Table 7, both the best cost and the best emission were obtained by the proposed IMOEAD-DE, reaching 2.4326×10^6 USD and 1.9967×10^5 lb, respectively. This indicates that the proposed IMOEAD-DE provides the optimal solution in terms of both system cost and emission objectives. In addition, the best compromise solution was also achieved by IMOEAD-DE among all compared algorithms. Overall, the proposed

algorithm demonstrates superior performance in minimizing the total system cost and total emission. Compared with the traditional MOEA/D, the proposed IMOEA/D-DE exhibits reductions of 3.39% in F_M and 0.02% in F_C . Overall, the proposed algorithm demonstrates superior performance in minimizing the total system cost and total emission.

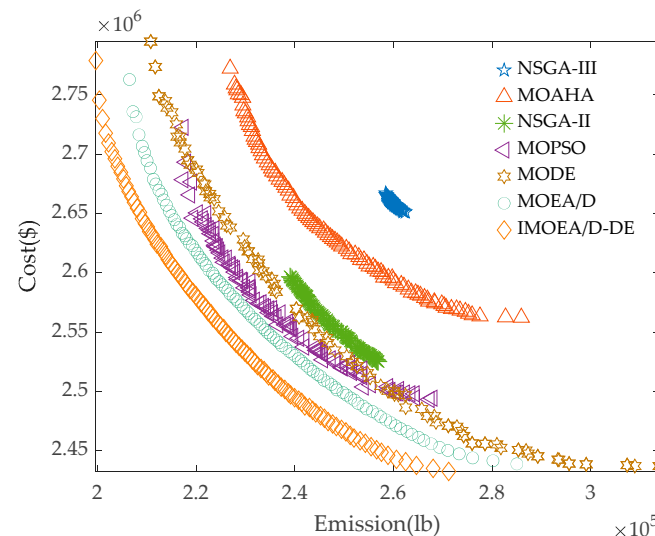


Figure 4. The PFs obtained by different algorithms.

Table 7. The solution of different algorithms.

Algorithms		F_M (lb)	F_C (USD)
MOAHA	Best cost	2.8592×10^5	2.5624×10^6
	Best emission	2.2689×10^5	2.7724×10^6
	Best compromise solutions	2.4406×10^5	2.6412×10^6
NSGA-II	Best cost	2.5659×10^5	2.5267×10^6
	Best emission	2.3834×10^5	2.6753×10^6
	Best compromise solutions	2.4717×10^5	2.5559×10^6
NSGA-III	Best cost	2.5843×10^5	2.6673×10^6
	Best emission	2.6239×10^5	2.6513×10^6
	Best compromise solutions	2.6017×10^5	2.6575×10^6
MOPSO	Best cost	2.6787×10^5	2.4944×10^6
	Best emission	2.1741×10^5	2.7228×10^6
	Best compromise solutions	2.3186×10^5	2.5769×10^6
MODE	Best cost	3.1387×10^5	2.4372×10^6
	Best emission	2.1078×10^5	2.7950×10^6
	Best compromise solutions	2.4811×10^5	2.5346×10^6
MOEA/D	Best cost	2.8501×10^5	2.4389×10^6
	Best emission	2.0649×10^5	2.7631×10^6
	Best compromise solutions	2.3125×10^5	2.5628×10^6
IMOEA/D-DE	Best cost	2.7120×10^5	2.4326×10^6
	Best emission	1.9967×10^5	2.7790×10^6
	Best compromise solutions	2.2341×10^5	2.5622×10^6

The convergence behaviors of the six algorithms with respect to cost and emission objectives are depicted in Figures 5 and 6, respectively. As observed in Figure 5, the proposed IMOEA/D-DE exhibits significantly superior convergence performance compared to the other five algorithms. Figure 6 further illustrates that although IMOEA/D-DE demonstrates a higher convergence rate than MOEA/D in the early iteration phase, it is temporarily surpassed by MOEA/D during the mid-iteration stage. Nevertheless, IMOEA/D-DE regains a faster convergence trend in the later iterations. Overall, IMOEA/D-DE maintains the best

comprehensive convergence speed and performance throughout the entire iterative process. This advantage can be attributed to two main factors. The adaptive DE mutation operator embedded in IMOEA/D-DE enables dynamic switching of operator types at different iteration stages, thereby enhancing global optimization capability. Second, the initial population generated by ICMIC improves population diversity, providing a favorable foundation for accelerated convergence and high-quality solution attainment.

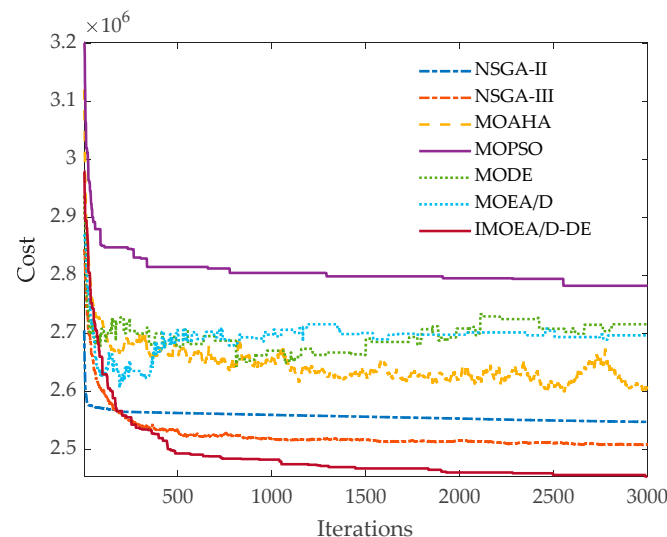


Figure 5. The convergence of cost by different algorithms.

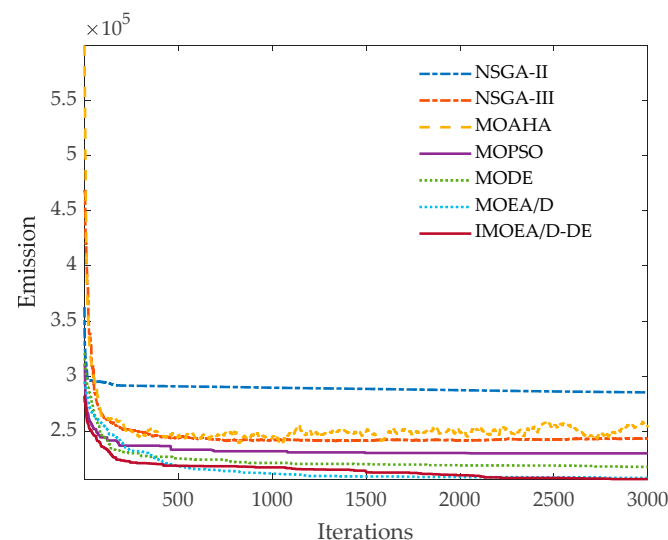


Figure 6. The convergence of emission by different algorithms.

The best compromise solution obtained by IMOEA/D-DE is presented in Table 8. It can be observed that V2G charging events were concentrated during predefined electric vehicle travel periods, while discharging primarily occurred during peak load hours from 10:00–14:00 to 20:00–24:00, which is consistent with the experimental design. Additionally, photovoltaic power generation was active only between 13:00 and 17:00, corresponding to the period of maximum solar irradiance. The power balance constraint condition can be checked for each interval in Figure 7. In the Figure 7 demonstrates that power balance is maintained across all time periods, meeting the system constraints.

Table 8. The best compromise solution obtained by IMOEA/D-DE.

<i>t</i>	<i>P</i> ₁	<i>P</i> ₂	<i>P</i> ₃	<i>P</i> ₄	<i>P</i> ₅	<i>P</i> ₆	<i>P</i> ₇	<i>P</i> ₈	<i>P</i> ₉	<i>P</i> ₁₀	<i>P</i> ^{V2G}	<i>P</i> ^{BE}	<i>P</i> ^w	<i>P</i> ^s	<i>P</i> ^L	<i>P</i> ^D
1	134.52	133.35	94.01	71.47	130.20	129.68	111.34	106.17	61.22	47.86	72.71	0.22	27.29	0.00	84.05	1036
2	150.07	138.97	97.17	89.74	143.06	138.51	115.21	113.40	64.73	45.27	9.10	2.85	34.23	0.00	32.31	1110
3	152.74	145.64	141.08	125.97	183.03	138.33	123.72	112.33	77.78	52.21	1.82	0.00	27.29	0.00	23.93	1258
4	157.01	143.90	174.94	151.33	231.46	154.32	128.58	119.10	79.20	53.67	−11.67	0.00	27.29	0.00	3.13	1406
5	177.74	170.77	174.76	170.50	233.55	160.00	130.00	116.38	80.00	55.00	1.08	1.55	27.29	0.00	18.61	1480
6	201.08	240.05	204.42	220.00	241.96	158.80	128.90	118.90	78.37	53.73	12.01	0.00	55.19	0.00	85.41	1628
7	212.96	235.41	221.78	195.13	241.35	159.83	130.00	120.00	79.16	54.80	0.00	58.11	55.19	0.00	61.73	1702
8	199.08	247.35	213.58	229.28	243.00	160.00	130.00	120.00	80.00	55.00	12.66	140.31	28.19	0.00	82.44	1776
9	226.79	247.42	235.02	248.63	242.66	159.56	129.94	119.90	79.43	54.94	0.26	192.13	62.14	0.00	74.81	1924
10	242.34	279.78	265.76	249.83	242.87	159.78	129.67	119.99	79.86	54.79	−16.45	198.45	41.24	0.00	25.93	2022
11	258.63	299.11	302.24	289.24	242.44	159.80	129.78	119.77	79.91	54.85	−17.38	198.97	41.24	0.00	52.62	2106
12	259.65	325.50	285.26	268.68	243.00	160.00	130.00	120.00	80.00	55.00	−40.47	195.65	47.29	0.00	2.56	2127
13	264.47	276.03	247.63	277.89	243.00	160.00	130.00	120.00	80.00	55.00	−13.18	200.00	55.19	20.17	44.21	2072
14	225.96	225.48	240.48	244.73	243.00	160.00	130.00	119.58	80.00	55.00	−3.36	200.00	48.19	50.00	95.06	1924
15	226.24	230.88	204.25	229.48	242.91	159.94	129.91	119.91	79.72	54.85	5.41	47.55	34.23	50.00	39.27	1776
16	183.93	189.29	174.95	180.64	239.78	160.00	129.92	119.94	80.00	54.76	90.41	23.33	20.28	0.24	93.48	1554
17	170.05	153.38	150.32	174.63	238.69	159.47	129.65	119.13	79.90	54.98	0.00	4.25	76.09	0.26	30.80	1480
18	192.04	187.55	211.57	196.07	243.00	158.99	129.34	119.42	79.79	54.97	47.17	51.04	34.23	0.00	77.20	1628
19	218.19	235.51	216.68	215.31	243.00	160.00	130.00	120.00	80.00	55.00	31.98	116.46	34.23	0.00	80.36	1776
20	229.85	251.62	259.66	265.07	242.85	159.78	129.99	119.99	79.90	54.99	−1.35	199.15	27.29	0.00	46.80	1972
21	226.27	248.21	236.39	246.37	240.33	158.68	128.67	118.90	78.90	53.90	−1.42	197.67	27.29	0.00	36.15	1924
22	191.89	203.38	204.88	232.67	242.93	159.96	129.96	119.89	79.88	54.96	36.40	22.65	41.24	0.00	92.70	1628
23	160.32	145.20	158.15	185.06	231.25	147.80	129.94	119.89	79.26	54.94	−93.70	30.78	34.23	0.00	51.13	1332
24	154.69	141.00	140.49	109.77	121.58	142.70	121.73	118.07	79.94	47.92	−66.84	51.00	40.28	0.00	18.32	1184

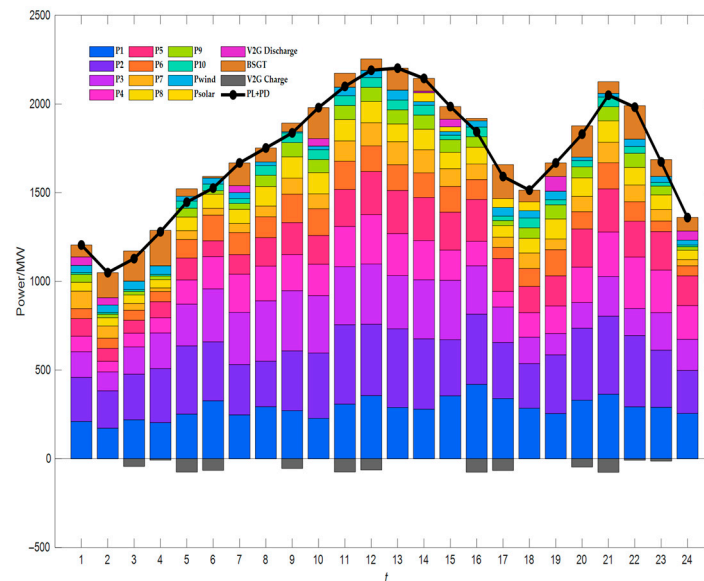


Figure 7. Constraints checked IMOEA/D-DE for the best compromise solution.

4.3. Verify the $DEED_{WPBEV}$ Model

The reliability of the $DEED_{WPBEV}$ model was tested through a sensitivity analysis across the following five scenarios:

Scenario 1: Combines QRF for renewable uncertainty forecasting, WP-PV-EVs interaction for curtailment reduction, and BE for emission or fuel cost abatement.

Scenario 2: Replaces QRF with fixed forecasts, keeping other components identical to Scenario 1.

Scenario 3: Removes the WP-PV-EVs interaction component.

Scenario 4: Eliminates the BE component, requiring thermal generators to meet all demands.

Scenario 5: Only a ten-unit system is used to meet the load demand.

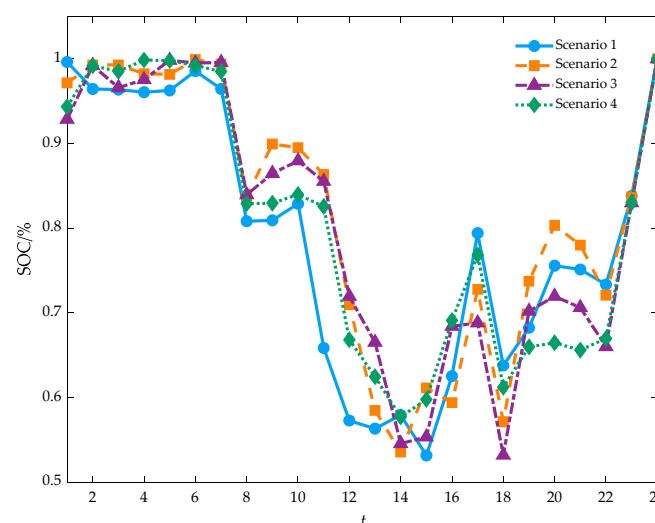
The extreme and best compromise solutions for the five scenarios are displayed in Table 9, which including the optimal cost and emission values, with superior solutions highlighted in bold. The comparison between Scenario 1 and Scenario 2 indicates that the better performance of Scenario 1 demonstrates the superior capability of QRF in capturing the uncertainty associated with WP and PV generation compared to the use of fixed values. Comparing Scenario 1 with Scenario 3 reveals that removing the WP-PV-EVs interaction in Scenario 3 leads to a shift in both optimal cost and emission levels. When Scenario 1 is compared with Scenario 4, the incorporation of BE is shown to substantially reduce system emissions. Specifically, the best emission value in Scenario 1 is 28.48% lower than that in Scenario 4, attributable to the cleaner profile of BE relative to conventional thermal power. This environmental gain is accompanied by only a slight increase of 0.35% in the best cost. This demonstrates that the incorporation of BE is instrumental in promoting the system sustainable development. A comparison of Scenario 1 and Scenario 5 underscores that the $DEED_{WPBEV}$ model employed in Scenario 1 achieves considerable improvements in both cost and emission objectives over the traditional ten-units thermal system model used in Scenario 5. In summary, a substantial improvement in sustainability is demonstrated by the proposed $DEED_{WPBEV}$ model, as confirmed through a comparative analysis of extreme scenarios. The critical value of the model for advancing sustainable development is thereby underscored.

Table 9. Solutions under different scenarios.

Scenarios		F_M (lb)	F_C (USD)
1	Best cost	2.7120×10^5	2.4326×10^6
	Best emission	1.9967×10^5	2.7790×10^6
	Best compromise solutions	2.2341×10^5	2.5622×10^6
2	Best cost	2.4844×10^5	2.4760×10^6
	Best emission	2.0671×10^5	2.6828×10^6
	Best compromise solutions	2.3026×10^5	2.5784×10^6
3	Best cost	2.6237×10^5	2.4530×10^6
	Best emission	2.0206×10^5	2.7378×10^6
	Best compromise solutions	2.2352×10^5	2.5650×10^6
4	Best cost	3.0116×10^5	2.4240×10^6
	Best emission	2.7918×10^5	2.5148×10^6
	Best compromise solutions	2.8556×10^5	2.4539×10^6
5	Best cost	2.9793×10^5	2.4381×10^6
	Best emission	2.7737×10^5	2.5185×10^6
	Best compromise solutions	2.8340×10^5	2.4618×10^6

A comparative analysis of the optimal compromise solutions across various scenarios unveils the impact of each model component. When compared with Scenario 1, Scenario 2 demonstrates a 0.63% increment in the minimum cost and a 3.07% rise in the minimum emissions. Scenario 3 shows a 0.11% increase in the minimum cost and a 0.05% growth in the minimum emissions relative to Scenario 1.

Conversely, although Scenario 4 cuts the minimum cost by 4.23%, it brings about a substantial 27.82% surge in the minimum emissions. Similarly, Scenario 5 attains a 3.92% reduction in the minimum cost, yet it results in a 26.85% hike in the minimum emissions when compared to Scenario 1. Figure 8 depicts the state-of-charge profiles of electric vehicles at different time intervals in scenarios 1–4. In these profiles, downward trends indicate discharging, while upward trends signify charging. As illustrated in Figure 8, all EVs conduct charging and discharging operations under complete availability conditions (100%) while achieving full recharge by the conclusion of the dispatching period. Within scenario 1, the most distinct discharge behavior is evident, leading to the maximum cost reduction in the system model. In contrast, scenarios 2, 3, and 4 exhibit suboptimal utilization of EV dispatch capabilities, resulting in comparatively elevated operational costs.

**Figure 8.** The SOC of EVs in different scenarios.

The extreme and optimal compromise solutions for different EV scales are presented in Table 10, with the superior solutions highlighted in bold. The Pareto-optimal solution was achieved when the number of EVs reached 20,000. At this point, the minimum cost was 2.4792×10^6 USD, and the minimum emissions were 2.0712×10^5 lb. The analysis indicated that the number of EVs had a significant effect on the performance of the DEED_{WPBEV} model. Specifically, 20,000 EVs strike the optimal balance, resulting in the lowest total cost and emissions. This optimal state occurred because an insufficient number of EVs failed to fully use the model consumption capacity. Conversely, an excessive number of EVs imposed an operational burden on the system. Therefore, 20,000 EVs were identified as the most effective configuration for the proposed DEED_{WPBEV} model. The costs resulting from the interaction between EVs and the new energy system are depicted in Figure 9. As clearly illustrated in Figure 9, the highest interaction cost between EVs and the renewable energy system was observed at a fleet size of 60,000 EVs. When the EVs penetration level was 10,000 vehicles, the interaction cost was found to be lower than that with 20,000 EVs only during the hours of 7:00, 15:00, 16:00, and 19:00, while it was exceeded by the 20,000-EV benchmark during all other time periods. Furthermore, higher interaction costs were consistently demonstrated by systems with 30,000, 40,000, and 50,000 EVs when compared to the 20,000 EVs scenario across most operational intervals. In conclusion, an EV fleet size of 20,000 was identified as the optimal configuration for the proposed model.

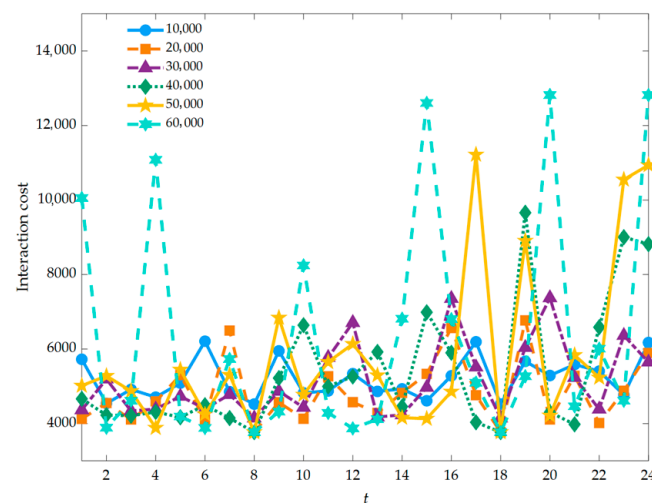


Figure 9. Interaction cost obtained with different scales of EVs.

Table 10. The solution under a different number of EVs.

EVs		F_M (lb)	F_C (USD)
10,000	Best cost	2.0929×10^5	2.7227×10^6
	Best emission	2.0780×10^5	2.7332×10^6
	Best compromise solutions	2.6437×10^5	2.4268×10^6
20,000	Best cost	2.0653×10^5	2.7082×10^6
	Best emission	2.0712×10^5	2.7048×10^6
	Best compromise solutions	2.4570×10^5	2.4792×10^6
30,000	Best cost	2.0684×10^5	2.7421×10^6
	Best emission	2.0936×10^5	2.6952×10^6
	Best compromise solutions	2.5679×10^5	2.4738×10^6
40,000	Best cost	2.0901×10^5	2.7467×10^6
	Best emission	2.1025×10^5	2.7075×10^6
	Best compromise solutions	2.6038×10^5	2.4702×10^6

Table 10. Cont.

EVs		F_M (lb)	F_C (USD)
50,000	Best cost	2.0480×10^5	2.7721×10^6
	Best emission	2.1611×10^5	2.6393×10^6
	Best compromise solutions	2.6642×10^5	2.4569×10^6
60,000	Best cost	2.1416×10^5	2.7501×10^6
	Best emission	2.2632×10^5	2.6289×10^6
	Best compromise solutions	2.5052×10^5	2.5314×10^6

4.4. Sensitivity Analysis for Parameters

Different Population Size and Number of Iterations

Two sets of comparative experiments were conducted to evaluate the impact of EVs and BE on system economics and operational costs, as well as to examine the influence of population size and iteration number on algorithmic efficiency. In the first experimental group, the population size was varied while the maximum number of iterations was fixed at 3000 to assess algorithm performance in identifying extreme-value and best compromise solutions. The corresponding results are presented in Table 11, with the superior solutions highlighted in bold. In the second group, the number of iterations was adjusted under a fixed population size to evaluate algorithmic performance, with results provided in Table 12, with the superior solutions highlighted in bold.

As summarized in Table 11. The best emission value of 1.9967×10^5 lb is achieved with a population size of 100, representing reductions of 1.49%, 1.01%, 2.46%, and 5.08% compared to populations of 200, 300, 400, and 500, respectively. The best cost of 2.4254×10^6 USD is obtained with a population size of 300, which is 0.29%, 0.64%, 0.83%, and 0.92% lower than when the population is 100, 200, 400, and 500. Regarding the best compromise solutions, the lowest emission of 2.2341×10^5 lb attained at a population size of 100, while the lowest cost of 2.5326×10^6 USD is observed at a population size of 200. In terms of computational efficiency, the shortest average computation time of 2103.2 s was recorded at a population size of 100 under the 3000-iteration limit. In summary, the experimental findings indicate that the algorithm achieves optimal performance when the population size is set to 100 and the maximum number of iterations is fixed at 3000.

As evidenced by the results in Table 12, the number of iterations influences solution quality to some extent. However, more iterations do not invariably lead to better solutions. Analysis of the compromise solutions in Table 12 reveals that the best cost and emission outcomes are achieved when the population size is 100 and the number of iterations is 3000. Therefore, considering the combined effects of population size on cost, emission, and computational time, the population size and iteration number were set to 100 and 3000, respectively, in this study.

Table 11. Different initial population extreme and optimal compromise schemes.

$Max_Fes = 3000$		F_M (lb)	F_C (USD)
NP = 100	Best cost	2.7120×10^5	2.4326×10^6
	Best emission	1.9967×10^5	2.7790×10^6
	Best compromise solutions	2.2341×10^5	2.5622×10^6
	Average times	2103.2 s	
NP = 200	Best cost	2.7819×10^5	2.4410×10^6
	Best emission	2.0269×10^5	2.7150×10^6
	Best compromise solutions	2.3122×10^5	2.5326×10^6
	Average times	2353.68 s	

Table 11. *Cont.*

<i>Max _Fes = 3000</i>		<i>F_M (lb)</i>	<i>F_C (USD)</i>
<i>NP = 300</i>	Best cost	2.8158×10^5	2.4254×10^6
	Best emission	2.0171×10^5	2.4244×10^6
	Best compromise solutions	2.3013×10^5	2.5569×10^6
	Average times	2581.89 s	
<i>NP = 400</i>	Best cost	2.8445×10^5	2.4458×10^6
	Best emission	2.0470×10^5	2.7333×10^6
	Best compromise solutions	2.3230×10^5	2.5502×10^6
	Average times	2956.5 s	
<i>NP = 500</i>	Best cost	2.8833×10^5	2.4478×10^6
	Best emission	2.1197×10^5	2.4008×10^6
	Best compromise solutions	2.2965×10^5	2.5426×10^6
	Average times	3301.21 s	

Table 12. Extreme and optimal compromise schemes with different iterations.

<i>NP = 100</i>		<i>F_M (lb)</i>	<i>F_C (USD)</i>
<i>Max _Fes = 1000</i>	Best cost	2.7483×10^5	2.4516×10^6
	Best emission	2.1012×10^5	2.7610×10^6
	Best Compromise Solutions	2.3483×10^5	2.5733×10^6
<i>Max _Fes = 2000</i>	Best cost	2.7222×10^5	2.4467×10^6
	Best emission	2.1060×10^5	2.7112×10^6
	Best Compromise Solutions	2.2840×10^5	2.5731×10^6
<i>Max _Fes = 3000</i>	Best cost	2.7120×10^5	2.4326×10^6
	Best emission	1.9967×10^5	2.7790×10^6
	Best Compromise Solutions	2.2341×10^5	2.5622×10^6
<i>Max _Fes = 4000</i>	Best cost	2.7213×10^5	2.4369×10^6
	Best emission	2.0430×10^5	2.7472×10^6
	Best Compromise Solutions	2.2439×10^5	2.5723×10^6
<i>Max _Fes = 5000</i>	Best cost	2.7448×10^5	2.4434×10^6
	Best emission	2.0754×10^5	2.7402×10^6
	Best Compromise Solutions	2.2401×10^5	2.5673×10^6

4.5. Verify Algorithm and Model Scalability

The ten-units model was extended to a forty-units large-scale energy system to evaluate the scalability of the proposed model and algorithm. Comparative evaluations were conducted against the IMOE/D-DE, NSGA-II, MODE, MOAHA, MOEA/D, and MOPSO algorithms, with cost and emission values employed as performance metrics. The experimental results are summarized in Table 13, with the superior solutions highlighted in bold.

Table 13 shows the extreme solutions and optimal compromise solutions obtained by the compared algorithms. Based on a comparative analysis of the algorithmic results, the following conclusions can be drawn. First, the proposed IMOE/D-DE achieves optimal performance in both cost and emission objectives, attaining a minimum emission value of 2.6831×10^6 lb and the lowest cost value of 2.9799×10^6 USD among all compromise solutions. These results confirm the effectiveness of IMOE/D-DE in balancing economic and environmental objectives, providing superior decision-making support. Furthermore, the forty-units experiment demonstrates that the algorithm can supply a wider range of high-quality solutions, confirming its applicability to large-scale energy systems.

Table 13. The comparison of different optimization methods for testing forty-units.

Algorithms		F_M (lb)	F_C (USD)
MOAHA	Best cost	5.2683×10^6	3.6661×10^6
	Best emission	4.6673×10^6	3.5259×10^6
	Best compromise solutions	5.0804×10^6	3.6766×10^6
NSGA-II	Best cost	4.7683×10^6	3.0226×10^6
	Best emission	4.6380×10^6	3.6267×10^6
	Best compromise solutions	4.6528×10^6	3.6528×10^6
MOPSO	Best cost	4.8410×10^6	3.5391×10^6
	Best emission	4.0167×10^6	3.4803×10^6
	Best compromise solutions	4.6954×10^6	3.5152×10^6
MODE	Best cost	4.2853×10^6	3.1253×10^6
	Best emission	3.8366×10^6	3.1784×10^6
	Best compromise solutions	4.1049×10^6	3.6766×10^6
MOEA/D	Best cost	2.8072×10^6	3.1065×10^6
	Best emission	3.0828×10^6	2.9403×10^6
	Best compromise solutions	2.9266×10^6	2.9976×10^6
IMOEA/D-DE	Best cost	2.9829×10^6	2.9036×10^6
	Best emission	2.6831×10^6	3.2150×10^6
	Best compromise solutions	2.8106×10^6	2.9799×10^6

5. Conclusions

In this paper, a new DEED_{WPBEV} model is proposed based on the multi-energy system. In DEED_{WPBEV}, the QRF method was employed to simulate the uncertainty of WP and PV. Additionally, an IMOEA/D-DE with ICMIC initialization population and adaptive adjustment mutation strategy was proposed to solve the DEED_{WPBEV} model. To verify the effectiveness of the proposed model and algorithm, simulation experiments were conducted on a ten-units system with different numbers of electric vehicles and different scenarios. The results show that, compared with other algorithms, the proposed IMOEA/D-DE algorithm can obtain the optimal solution. The DEED_{WPBEV} model is crucial in advancing the sustainability transition, effectively promoting renewable utilization while mitigating the ecological impact of conventional power generation. This study focuses on the grid-side influence of electric vehicle integration, omitting the effects of extreme weather, load fluctuation stability, user behavior uncertainty, and battery aging. Subsequent studies could incorporate these factors to improve the model practical applicability.

Author Contributions: Conceptualization, B.Q. and J.Y.; methodology, B.Q. and J.Y.; software, B.Q. and J.Y.; validation, B.Q., J.Y. and P.W.; formal analysis, P.W. and H.H.; investigation, J.Y.; resources, P.W. and H.H.; data curation, J.Y. and B.Q.; writing—original draft preparation, J.Y. and B.Q.; writing—review and editing, B.Q., P.W. and H.H.; visualization, B.Q., J.Y. and H.H.; supervision, B.Q. and P.W.; project administration, B.Q. and P.W.; funding acquisition, B.Q. and P.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported in part by the National Natural Science Foundation of China under Grant (62503513, 62373389, 62576372), in part by the Natural Science Foundation of Henan Province under Grant 252300421821, the Key Scientific Research Projects in Higher Education Institutions in Henan Province under Grant 24A120017, the Leading talents of science and technology in the Central Plain of China under Grant 254200510055, the Science and Technology Innovation Talents of Colleges and Universities in Henan Province under Grant 24HASTIT037, the Postgraduate Education Reform and Quality Improvement Project of Henan Province under Grant YJS2026YBGZZ20, the Key Research and Development Program of Henan under Grant 241111210100, the Discipline Strength Enhancement Plan of Zhongyuan University of Technology under Grant SD202418, and the Natural Science Foundation of Zhongyuan University of Technology under Grant K2025YB010.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors would like to thank the reviewers for their critical comments and valuable suggestions.

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

Abbreviations

The following abbreviations are used in this manuscript:

$P_t^{w,rate}$	WP rated power
v_{in}, v_{out}, v_r	Cut-in wind speed, cut-out wind speed, and rated wind speed
T_{stc}	Temperature under standard conditions
k	Temperature-power coefficient
G_{stc}	Light intensity under standard conditions
T	Dispatching cycle
N_p	Number of units
$\alpha_n, \beta_n, \delta_n, \gamma_n, \varepsilon_n$	Emission coefficients of the n th thermal generator
σ_n^w	Net operating cost of the unit, active power of WP
σ_n^s	Net operating cost of the unit, active power of PV
$\partial_t^{ch}, \partial_t^{dch}$	Charging price and discharging price
$c_{rej}^{new}, c_{res}^{new}$	New energy abandonment and the shortage cost coefficient
e_{rej}^w, e_{rej}^s	Abandoned wind and photovoltaic coefficient
a_n, b_n, c_n	Fuel cost coefficient of the j th thermal generator
p^L	Network loss at time t
$\theta^{ch}, \theta^{dch}$	Charging and discharging power coefficient
E_{con}	Power consumed by EVs during driving
L	The distance driven by EVs
B_{ij}, B_{i0}, B_{00}	Coefficients of the B-coefficient method
N_{new}	Number of new energy-generating units
p^{res}, p^{new}	Shortage of power and new energy waste power

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