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An Ordered Charging–Discharging Optimization Strategy for Electric Vehicles Considering Discharge Restraint and Carbon Emission Reduction

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Abstract

Uncoordinated charging and discharging of large-scale electric vehicles (EVs) exacerbates grid peak–valley fluctuations, while deep discharging accelerates battery degradation. To address these challenges, this study proposes a coordinated charging–discharging optimization strategy integrating dynamic discharge restraint and a three-dimensional weighted comprehensive objective covering electricity price signals, grid operational constraints and battery health state. First, an EV travel behavior model is established to characterize spatiotemporal availability. Subsequently, a coupled battery aging model is developed by combining a power-law-based cycle aging formulation with a square-root calendar aging model, based on which an adaptive linkage mechanism between the depth-of-discharge upper bound and a net-revenue threshold is introduced. Building on these components, this model is constructed to jointly optimize three sub-objectives: charging station revenue maximization, battery lifetime cost minimization, and load fluctuation suppression, thereby mitigating grid peak–valley differences while reducing battery degradation and discharge costs. Multi-scenario simulations demonstrate that the proposed strategy, by coupling discharge restraint with spatiotemporal dynamic pricing, enables precise peak shaving of discharge power. For a fleet of 50 EVs, the charging station revenue reaches 1073.7 CNY, the grid peak–valley difference is reduced by 9.8%, and the battery degradation cost decreases by 23.1% compared with conventional strategies, corresponding to a carbon emission reduction of 386.4 tCO₂. When scaled to 100 EVs, the revenue increases by 101.9%, while the peak–valley difference is further reduced by 0.6%, demonstrating the effectiveness of the proposed strategy in enhancing economic performance, extending battery lifetime, and supporting grid stability.



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Keywords: discharge restraint; carbon emission reduction; ordered charging and discharging; electric vehicles; peak–valley difference

1. Introduction

Driven by global carbon neutrality targets and the accelerating electrification of the transportation sector, electric vehicles (EVs) have experienced rapid growth worldwide. The large-scale integration of EVs not only reshapes the energy consumption structure of the transportation sector but also exerts profound impacts on power system operation [1,2]. Compared with conventional loads, EVs exhibit pronounced spatiotemporal flexibility

and inherent energy storage capabilities, enabling them to function as controllable loads or distributed energy storage resources in grid operation. Accordingly, the coordinated optimization of EV charging and discharging behaviors is widely recognized as a critical pathway to enhancing renewable energy integration, improving grid flexibility, and facilitating the transition toward low-carbon power systems [3,4]. For emerging economies, the large-scale deployment of EVs not only depends on technical optimization of grid interaction, but also requires coordinated support from policy incentives, charging infrastructure and market mechanisms [5].

However, in the absence of effective coordination mechanisms, EV users tend to concentrate charging activities during periods of low electricity prices or traditional off-peak hours, which may lead to load superposition and even the formation of secondary peaks, thereby exacerbating grid peak–valley disparities [6]. To address these challenges, vehicle-to-grid (V2G) technologies and electricity price-based incentive mechanisms, such as time-of-use (TOU) pricing, have been jointly explored from the perspectives of bidirectional energy interaction and demand response to support peak shaving, valley filling, and enhanced operational flexibility. A multi-timescale V2G coordinated scheduling and control framework was proposed in [7], enabling EVs to provide joint support for grid peak regulation and transient power balance. In [8], V2G energy interaction and TOU pricing were incorporated into the EV routing problem, where an EVRP optimization model considering multiple charging station options was developed and solved using an improved NSGA-II algorithm to achieve coordinated reductions in logistics costs and improvements in operational profitability. Furthermore, Ref. [9] proposed a multi-objective EV charging–discharging scheduling framework based on the integration of reinforcement learning and swarm intelligence algorithms, addressing comprehensive optimization challenges under electricity price volatility and renewable energy uncertainty.

Despite these advances in grid-side performance optimization, most existing studies primarily focus on macroscopic indicators such as peak–valley differences, load smoothing, or operating costs, while the degradation characteristics of traction batteries are often insufficiently represented. In practice, frequent charging and discharging, particularly under deep discharge conditions, significantly accelerates battery aging, manifesting as intensified capacity fade and shortened service life. This not only increases the total lifecycle cost of the system but also undermines the willingness of EV users and operators to participate in V2G scheduling schemes [10–12]. Experimental investigations in [13] revealed the impact of depth of discharge (DOD) on the degradation and safety of high-nickel batteries under different state-of-health (SOH) zones, based on which an optimal discharge depth control strategy was proposed. A low-parameter battery capacity fade model based on a two-step reaction kinetics approach was developed in [14], providing a concise and effective method for battery aging prediction under complex EV operating conditions. A comprehensive review of EV battery aging mechanisms and modeling approaches from both calendar and cycle aging perspectives was presented in [15], highlighting common characteristics and key research challenges across different models. In [16], a cycle aging model incorporating coupled aging effects was constructed using multivariate regression and validated under realistic EV operating conditions. Nevertheless, these studies largely concentrate on battery-level mechanisms or lifetime modeling, without fully considering the coupled interactions among electricity price signals, grid operating states, and battery health conditions. As a result, their applicability to system-level optimization for large-scale EV participation in grid operation remains limited [17,18].

To address the above gaps, this paper proposes a coordinated EV charging–discharging optimization strategy integrating a dynamic discharge restraint mechanism and a three-dimensional weighted multi-objective framework covering electricity price signals, power

grid operating conditions and battery health state. Specifically, an EV travel behavior model is developed to characterize vehicle availability and energy demand. A coupled battery aging model combining a power-law-based cycle aging formulation and a square-root calendar aging model is then established. On this basis, an adaptive linkage mechanism between the depth-of-discharge upper bound and the minimum net revenue threshold is introduced, enabling the dynamic regulation of discharging behavior in accordance with battery health status and economic feasibility.

The main contributions of this study are summarized as follows:

A dynamic discharge restraint decision-making model incorporating battery lifetime protection is proposed. To address battery degradation issues, a multi-stress coupled aging model is developed, integrating an Arrhenius–power-law formulation for cycle aging and a square-root-exponential model for calendar aging. Based on this model, a dual-parameter adaptive regulation mechanism linking the maximum allowable depth of discharge $D_{\max}(t)$ and the minimum net revenue threshold R_{basemin} is established.

A weighted multi-objective coordinated scheduling model integrating three dimensions of electricity price, power grid operation and battery health state is constructed. A spatiotemporal dynamic pricing strategy is designed and integrated with load fluctuation suppression objectives and discharge behavior constraints, thereby guiding discharge power to act precisely on grid peak periods.

The evolutionary characteristics of grid support provided by coordinated EV fleets of different scales are systematically revealed, demonstrating the impacts of EV penetration levels on economic performance, battery lifetime, and grid peak–valley regulation.

2. EV Mobility Model

2.1. EV Mobility Characteristics Modeling

Based on real-world vehicle operation data collected in Winnipeg, Canada [19], this study develops a mathematical model of electric vehicle travel characteristics. The proposed model establishes a probabilistic framework to describe the spatiotemporal behavior of EVs, with particular emphasis on the stochastic nature and interdependence of grid disconnection and reconnection times, travel distance, and state of charge (SOC). This framework provides a robust foundation for accurately characterizing the operational uncertainty of EVs in coordinated charging and discharging analysis.

2.1.1. Probabilistic Model of EV Grid Disconnection Time

The grid disconnection time t_{dep} is assumed to follow a modified chi-square χ^2 distribution, as given in Equation (1), where the probability density function and normalization factor are defined in Equation (2).

$$f_d(t_{dep,m}) = \kappa \cdot \frac{t_{dep,m}^{\lambda-1} e^{-t_{dep,m}/\tau}}{\Gamma(\lambda) \tau^\lambda} \quad (1)$$

$$t_{dep,m} = t_{dep} / \Delta t \quad (2)$$

where $f_d(t_{dep,m})$ denotes the probability density function of the grid disconnection time, $t_{dep,m}$ represents the discretized departure time, and λ and τ are the shape and scale parameters, respectively, calibrated using the maximum likelihood estimation method based on actual driving data from Winnipeg, Canada that $\lambda = 3.52$ and $\tau = 1.28$. The parameter κ is a normalization factor, t_{dep} denotes the actual continuous grid disconnection time, and $\Delta t = 1$ h is the discretization time step.

2.1.2. Conditional Probability Model of Grid Reconnection Time

The grid reconnection time t_{arr} , conditioned on the grid disconnection time t_{dep} , is assumed to follow a truncated normal distribution.

$$p_{arr}(t_{arr}|t_{dep,m}) = \frac{\phi\left(\frac{t_{arr}-\mu_m}{\sigma_m}\right)}{\Phi\left(\frac{T_{\max}-\mu_m}{\sigma_m}\right) - \Phi\left(\frac{T_{\min}-\mu_m}{\sigma_m}\right)} \quad (3)$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ denote the probability density function and cumulative distribution function of the standard normal distribution, respectively; $[T_{\min}, T_{\max}]$ represents the admissible grid reconnection time window; and $\mu_m = g(t_{dep,m})$, $\sigma_m = h(t_{dep,m})$ is a mapping function related to the grid disconnection time.

2.1.3. Probability Model of Daily Driving Distance

The daily driving distance is R_d assumed to follow a two-parameter Weibull distribution, as shown in Equation (4).

$$f_R(R_d) = \frac{\beta}{\alpha} \left(\frac{R_d}{\alpha}\right)^{\beta-1} \cdot \exp\left[-\left(\frac{R_d}{\alpha}\right)^{\beta}\right] \quad (4)$$

where $\alpha = 42.3$ km, $\beta = 1.8$.

2.1.4. Expected SOC Dynamic Equation

The target state of charge at grid disconnection, SOC_e , is jointly determined by the initial state of charge SOC_s and the energy consumption associated with the trip, as described in Equation (5).

$$SOC_e = SOC_s + \frac{R_d \cdot \epsilon_{km}}{E} + \zeta \quad (5)$$

where ϵ_{km} denotes the energy consumption per unit distance (kWh/km), with a typical range of 0.15–0.18, and $\zeta \sim \mathcal{N}(0, \sigma_{\zeta}^2)$ represents a stochastic disturbance term accounting for trip uncertainty, E denotes the rated capacity of the electric vehicle power battery (kWh).

2.1.5. Schedulable Time Window Constraints

Each EV is required to complete its energy replenishment within the grid-connected time window $[t_{arr}, t_{dep}]$, satisfying the inequality in Equation (6).

$$t_{dep} - t_{arr} \geq \frac{(SOC_e - SOC_s)E}{\eta_c P_{\max}^{EV}} \quad (6)$$

where η_c denotes the charging efficiency.

2.2. Battery Degradation Model

To characterize the aging behavior of EV traction batteries during charging and discharging processes, a degradation model incorporating multi-stress coupling effects is developed. By quantitatively capturing the synergistic impacts of cycle-induced degradation and calendar aging, the proposed model accurately describes battery lifetime decay dynamics, thereby providing a theoretical foundation for discharge restraint strategies in charging station operations.

2.2.1. Cycle Degradation Model

An Arrhenius–power-law coupled formulation is introduced to quantify the acceleration effect of temperature on cycle-induced degradation, whereas conventional models

typically account only for the depth of discharge (DoD). Accordingly, the per cycle battery degradation L_{cycle} is jointly determined by the depth of discharge (DoD) and the operating temperature T .

$$L_{cycle} = k_1 \cdot D_{DoD}^{k_2} \cdot e^{k_3/T} \quad (7)$$

where $D_{DoD} = S_{pre} - S_{post}$ denotes the depth of discharge, with S_{pre} and S_{post} representing the state of charge before and after discharge, respectively; k_1 , k_2 and k_3 denotes a set of material-dependent parameters, specified herein for LiFePO₄ batteries, k_1 is the baseline aging coefficient, which scales the overall magnitude of cycle-induced capacity degradation; k_2 denotes the sensitivity exponent of cycle aging with respect to depth of discharge, capturing the nonlinear growth trend of battery degradation as DoD rises; k_3 is the Arrhenius constant describing temperature dependence of aging rate, where T stands for absolute ambient temperature (K). The specific values adopted in this study are: $k_1 = 1.2 \times 10^{-2}$, $k_2 = 1.82$, $k_3 = -687.5$ [20].

This model's valid application ranges:

The operating temperature is from -10°C to 55°C . Beyond this range, parasitic side reactions inside the cell are intensified, and the aging rate will deviate from the power-law correlation.

The depth of discharge is 0 to 0.8. The model maintains high prediction accuracy within this interval. When DoD exceeds 0.8, capacity fade presents a nonlinear accelerating trend that is not covered by the current formulation.

In this work, the battery reference operating temperature is set to 25°C , and the maximum allowable DoD is limited to below 0.4 via the discharge restraint mechanism. All simulation conditions stay within the valid range of the model.

2.2.2. Calendar Aging Model

The capacity fade induced by static storage, denoted as L_{cal} , is assumed to follow a square-root-exponential hybrid model.

$$L_{cal} = \alpha \cdot \sqrt{t} + \beta \cdot e^{\gamma S_{avg}} \quad (8)$$

where t denotes the storage duration (in months), S_{avg} represents the average state of charge, α , β and γ are aging parameters, with typical values of $\alpha = 0.015$, $\beta = 0.12$, $\gamma = -2.5$.

2.2.3. Lifetime Degradation Cost Model

A degradation cost end-of-life threshold linkage mechanism is established to achieve a balanced optimization between economic performance and battery lifetime. Accordingly, the total battery degradation cost is determined by the cumulative number of charge–discharge cycles and the end-of-life threshold.

The total battery degradation cost is determined by the cumulative cycles and the end-of-life threshold, as expressed in Equation (9), with the inequality constraint in Equation (10) ensuring lifetime limits.

$$C_{loss} = C_{bat} \cdot \frac{\sum_{d=1}^D L_{cycle,d}}{L_{EOL}} + \frac{C_{bat}}{T_{life}} \cdot \int_0^t L_{cal}(\tau) d\tau \quad (9)$$

where C_{bat} denotes the unit capacity purchase cost of the battery; $L_{cycle,d}$ represents the degradation incurred during the cycle; L_{EOL} is the end-of-life threshold defined in terms of capacity fade ratio; D denotes the total number of charge–discharge cycles; T_{life} is the

designed calendar lifetime; $L_{cal}(\tau)$ represents the instantaneous calendar aging rate; and t denotes the battery operating time.

$$\sum_{N_{cycle}}^{i=1} L_{cycle,i} + \lambda \int_0^t L_{cal} dt \leq L_{EOL} \quad (10)$$

where λ denotes the weighting coefficient for calendar aging, which is set to 0.35, $L_{EOL} = 0.2$.

2.2.4. Discharge Restraint Mechanism

To coordinate battery lifetime protection and economic performance, a discharge restraint mechanism based on multi-constraint decision-making and dynamic thresholds is proposed. It dynamically regulates discharging through real-time evaluation of battery temperature, state of charge (SOC), cycling history, and electricity price signals.

2.2.5. Multi-Constraint Safety Boundaries

Discharging must comply with physical constraints and lifetime protection limits, as summarized in Equation (11).

$$\left\{ \begin{array}{l} P_c \left\{ \begin{array}{l} p_d^{\min} \leq P_d(t) \leq \min(P_{\max}^{EV}, 0.2C \cdot E) \\ S(t) \geq S_{\min} + \delta_S \end{array} \right. \\ L_c \left\{ \begin{array}{l} D_{DoD}(t) \leq D_{\max} \cdot f_T(T) \\ \sum_{N}^{i=1} L_{cycle,i} \leq \kappa L_{EOL} \\ T_{cell} \leq 45^\circ C \end{array} \right. \end{array} \right. \quad (11)$$

where $f_T(T)$ denotes the temperature derating function, δ_S represents the SOC safety margin, κ is the reserve coefficient for cycle-induced degradation, and $0.2C$ denotes the maximum allowable discharge rate.

2.2.6. Adaptive Threshold Adjustment Model

Dynamic adjustment of the maximum allowable depth of discharge:

$$D_{\max}(t) = D_{\max}^0 \cdot \left(1 - \alpha \cdot \frac{\sum_{N}^{i=1} L_{cycle,i}}{L_{EOL}} \right) \cdot \exp(-\gamma \cdot |T(t) - T_{opt}|) \quad (12)$$

where $D_{\max}^0$ denotes the initial design upper bound, $\alpha \cdot \frac{\sum_{N}^{i=1} L_{cycle,i}}{L_{EOL}}$ represents the compensation term for cycle-induced degradation, and T_{opt} is the optimal operating temperature.

Dynamic adjustment of the net revenue threshold:

$$R_{net}^{\min}(t) = R_{base}^{\min} \cdot \left[1 + \beta \cdot \left(\frac{L_{cal}(t)}{L_{cal}^{avg}} - 1 \right) \right] \quad (13)$$

where $R_{base}^{\min}$ denotes the baseline net revenue threshold, set to 0.25 CNY/kWh; β is the calendar aging sensitivity coefficient with a value of 0.18.

2.2.7. Optimization Scheduling Model

By integrating dynamic EV behavior, battery degradation, and the proposed discharge restraint strategy, a multi-objective scheduling model is developed to optimize economic performance, battery lifetime, and grid interaction.

2.3. Objective Functions

The multi-objective scheduling model optimizes the weighted sum of three sub-objectives, as defined in Equation (14).

$$\min \left(\begin{array}{l} \sum_{t=1}^{t=T} [c_g(t)P_{grid}(t) - c_c(t)P_c(t) + c_d(t)P_d(t)] \Delta t \\ + \lambda \cdot \sum_{t=1}^{t=T} \Gamma(t) \cdot |I_{bat}(t)| \Delta t \\ + \mu \cdot \sum_{t=2}^{t=T} |P_{grid}(t) - P_{grid}(t-1)| \end{array} \right) \quad (14)$$

where $c_g(t)$ denotes the electricity purchase price of the charging station (CNY/kWh); $c_c(t)$ and $c_d(t)$ represent the dynamic charging and discharging prices (CNY/kWh), respectively; $P_c(t)$ and $P_d(t)$ denote the total charging and discharging power (kW); $\Gamma(t)$ is the battery degradation rate (%/Ah) derived from the proposed degradation model; $I_{bat}(t)$ denotes the instantaneous operating current of the power battery at time t (A); λ and μ denote weighting coefficient used to balance economic performance and grid friendliness.

2.4. Constraints

2.4.1. EV Energy State Evolution and Discharge Restraint

The energy state evolution follows Equation (15), which accounts for discharge losses.

$$\begin{cases} \text{SOC}(t+1) = \text{SOC}_i(t) + \eta_c P_i^{ch}(t) \Delta t - \frac{1}{\eta_d} P_i^{dis}(t) \Delta t \\ \text{SOC}_i^{\min}(t) \leq \text{SOC}_i(t) \leq \text{SOC}_i^{\max}(t) \end{cases} \quad (15)$$

where $\frac{1}{\eta_d} P_i^{dis}(t)$ denotes the actual power consumed by the battery (kW), accounting for discharge losses.

2.4.2. EV Dispatchable Power Constraints

All EVs in this study are equipped with vehicle-to-grid (V2G) bidirectional power interfaces, and are matched with one-to-one bidirectional charging piles. All grid-connected vehicles support simultaneous charging or discharging within the rated power limit. The single-vehicle power constraint is expressed as:

$$\begin{cases} 0 \leq P_i^{ch}(t) \leq \delta_i(t) P_i^{ch,\max} \\ 0 \leq P_i^{dis}(t) \leq \delta_i(t) P_i^{dis,\max} \end{cases} \quad (16)$$

where $P_i^{ch}(t)$ denotes the charging power of the i -th EV at time t ; $\delta_i(t)$ represents the availability status of the i -th EV at time t ; $P_i^{ch,\max}$ stands for the maximum charging power of, and the analogous notation applies to discharging.

2.4.3. System Power Balance and Peak-Shaving Requirements

The system satisfies power balance at each time interval, while peak load fluctuations are mitigated through aggregated EV scheduling.

$$P_{grid}(t) + \sum_i (P_i^{dis}(t) - P_i^{ch}(t)) = P_{load}(t) \quad (17)$$

where $\sum_i (P_i^{dis}(t) - P_i^{ch}(t))$ represents the net power contribution of each EV to the system.

2.5. Influence Mechanism of the Proposed Algorithm on the Final State of Charge

It should be noted that the proposed algorithm does not alter the target value of the state of charge at the departure time, SOC_e , which is independently determined by the user's travel demand. Instead, it substantively affects the formation path and distribution characteristics of the final SOC through three mechanisms. First, the dynamically adjusted maximum depth of discharge $D_{max}(t)$ in Equation (12) directly limits the amount of energy that can be released during the grid-connected period, thereby indirectly changing the total energy that must be replenished during the charging phase. Second, the objective function in Equation (14) simultaneously incorporates charging or discharging costs and battery degradation costs, so that the algorithm, while satisfying the hard constraint on the final SOC given by Equation (6), preferentially allocates charging power to low-electricity-price periods and avoids additional degradation caused by deep cycling. Third, the dynamic pricing signal encourages concentrated discharging during peak hours, which lowers the initial SOC at the start of charging; however, the subsequent charging amount is automatically matched by the energy state evolution equation in Equation (15), ensuring that the SOC reaches or exceeds SOC_e at t_{dep} . In other words, the algorithm always optimizes the sequence of charging and discharging powers over the entire grid-connected window under the constraints of Equations (6) and (15); the feasibility of the final SOC is guaranteed by the hard constraints of the optimization problem, while its specific trajectory is dynamically regulated by the depth-of-discharge limits and the electricity price signals.

3. Model Solution

3.1. Particle Swarm Optimization Algorithm

PSO is a population-based optimization algorithm that iteratively updates particle positions and velocities to obtain optimal solutions [21]. The improved PSO introduces crossover and mutation to increase diversity and mitigate premature convergence in high-dimensional, multi-constraint problems [22].

The solution procedure is illustrated in Figure 1.

Step 1: Initialization

System parameters, electricity prices, and constraints are read. Particle positions and velocities are initialized, and algorithm parameters and maximum iterations are set.

Step 2: Fitness Evaluation

The initial fitness of each particle is calculated based on its charging–discharging scheme.

Step 3: Particle Update

Particles are updated using standard PSO rules, with crossover and mutation introduced to enhance diversity and global search capability.

Step 4: Constraint Handling

Updated schemes are checked against operational constraints. Infeasible solutions are iteratively adjusted until feasibility is achieved.

Step 5: Objective Calculation

For feasible solutions, operational metrics such as cost, revenue, or composite objective values are computed.

Step 6: Convergence Check

The algorithm checks termination criteria; otherwise, the iteration continues.

Step 7: Output

The optimal charging–discharging scheme is obtained and output.

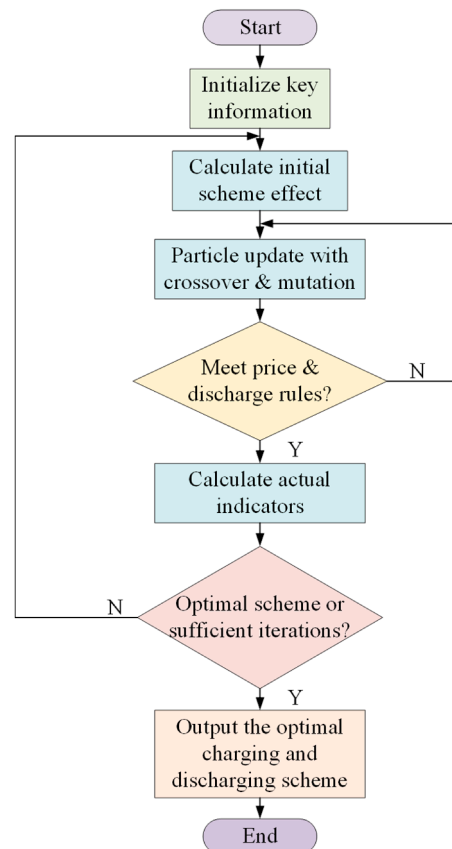


Figure 1. Flowchart of the improved particle swarm optimization algorithm.

3.2. Principle of the Improved PSO Algorithm

In this paper, each 24 h charging–discharging scheduling scheme of the EV fleet is abstracted as a particle in the D-dimensional solution space, where D is the total dimension of decision variables. The iterative update formulas of particle velocity and position in standard PSO are as follows:

$$\begin{cases} v_i^{k+1} = \omega v_i^k + c_1 r_1 (pbest_i^k - x_i^k) + c_2 r_2 (gbest^k - x_i^k) \\ x_i^{k+1} = x_i^k + v_i^{k+1} \end{cases} \quad (18)$$

where v_i^k is the velocity of the i -th particle at the k -th iteration; x_i^k is the position of the i -th particle, corresponding to a set of EV charging–discharging scheduling schemes; ω is the inertia weight; c_1 and c_2 are the individual learning factor and global learning factor, respectively; r_1 and r_2 are random numbers uniformly distributed in $[0, 1]$; $pbest_i$ is the historical optimal solution of the i -th particle; and $gbest$ is the global optimal solution of the whole population.

3.3. Hyperparameter Tuning Method

The optimization performance of PSO is highly dependent on hyperparameter settings. In this paper, the control variable method combined with grid search is employed to complete the hyperparameter tuning, with the convergence accuracy of the composite objective function, the number of iterations to convergence, and the single-solution computation time taken as evaluation metrics. A stepwise screening is performed on five types of parameters: population size, maximum number of iterations, inertia weight, learning factors, and crossover/mutation probabilities.

The candidate ranges for each parameter cover the full spectrum of low, medium, and high values commonly used in evolutionary algorithms, as presented in Table 1.

Table 1. Selection range for each parameter value.

Parameter	Symbol	Candidate Values
Population size	N_p	{20, 40, 60, 80, 100}
Maximum number of iterations	G_{max}	{50, 100, 150, 200}
Inertia weight	ω	{0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0}
Learning factors	(c_1, c_2)	{(1.2, 1.2), (1.5, 1.5), (1.8, 2.2), (2.0, 2.0)}
Crossover probability	P_{cr}	{0.2, 0.3, 0.4, 0.5, 0.6}
Mutation probability	P_{mu}	{0.01, 0.02, 0.03, 0.04, 0.05, 0.08}

The principle of parameter screening is as follows: an excessively high crossover probability may disrupt high-quality solutions, while a too low crossover probability fails to improve population diversity; an excessively high mutation probability degenerates the algorithm into random search, whereas a too low mutation probability makes it difficult to escape local optima. The final parameter combination is selected to balance convergence speed and optimization accuracy, and the specific calibrated values are provided in accordance with the numerical example scenario of this study.

4. Case Study Analysis

4.1. Parameter Settings

The arrival time $t_{arr,m}$, departure time $t_{dep,m}$, and daily driving $R_{d,m}$ range of the m -th EV are all obtained via Monte Carlo sampling based on their respective probability density functions. Considering the randomness of EV travel, the Ss of each EV is assumed to follow a uniform distribution within [0.1, 0.5], and all EVs use the same battery type. Charging station and distribution network data are adopted from Ref. [23], with detailed parameters listed in Table 2.

Table 2. Parameter settings for the EV dynamic pricing coordinated scheduling optimization model.

Category	Parameter	Value/Range
Grid Parameters	Base load peak	970.3 kW
	Transformer capacity $P_{trans, \uparrow \downarrow ax}$	1250 kVA
	Electricity purchase price $c_g(t)$	Off-peak: 0.365 CNY/kWh, Peak: 0.869 CNY/kWh
	Transformer rated active power	1125 kW
	Maximum allowable transformer load rate	90%
Charging Infrastructure	Number of bidirectional charging piles	50 (Scenarios 1–3), 100 (Scenario 4)
EV Parameters	Number of vehicles N	50 (Scenarios 1–3), 100 (Scenario 4)
	Battery capacity E_{max}	33 kWh
	Maximum charge/discharge power P_{cmax}/P_{dmax}	3 kW
	SOC range $[SOC_{min}, SOC_{max}]$	[0.2, 0.9]
	Charging efficiency η_c	0.92
Optimization Parameters	Initial maximum D_{max}	0.4
	Cycle degradation coefficient α	0.8
	Temperature penalty coefficient γ	0.012 K ⁻¹
	Weighting coefficients λ, μ	$\lambda = 0.8, \mu = 0.2$
Dynamic Price Range	Charging price $c_c(t)$	[0.4, 2.0] CNY/kWh
	Discharging price $c_d(t)$	[0.42, 2.24] CNY/kWh

4.2. Scenario Design

This section constructs a typical coupled charging station–distribution network case study to validate the proposed orderly charging and discharging optimization model for electric vehicles (EVs). The simulation horizon is set to 24 h with a time resolution of 1 h.

EV travel states and initial state of charge (SOC) are generated using a Monte Carlo method, while the baseline load profile is obtained from the literature and normalized for analysis.

To systematically evaluate the operational characteristics of different scheduling strategies, four comparative scenarios are designed. Scenario 1 represents an uncontrolled charging and discharging mode, in which EVs follow a plug-and-play operation. Scenario 2 adopts a conventional time-of-use (TOU) pricing-based scheduling strategy. Scenario 3 applies the proposed coordinated optimization strategy integrating dynamic pricing and discharge restraint. Scenario 4 further extends Scenario 3 by increasing the EV fleet size to 100 vehicles, aiming to assess the scalability and robustness of the proposed model.

Subsequent analyses comprehensively compare these scenarios from multiple perspectives, including grid load regulation performance, EV charging and discharging behavior, battery lifetime protection, economic performance, and carbon emission reduction benefits.

4.3. Load Regulation and Peak–Valley Shaving Performance

To clearly illustrate the differences in grid load dynamics under various scheduling strategies, this section compares the baseline load (BLS) with the load time series corresponding to the uncontrolled charging scenario (S1), the time-of-use pricing scenario (S2), and the coordinated dynamic pricing and discharge restraint scenario (S3). Figure 2, entitled “Comparison of system total load profiles and peak–valley shaving effects under different scheduling strategies”, is employed to analyze the load fluctuations as well as the peak and valley characteristics across different scenarios.

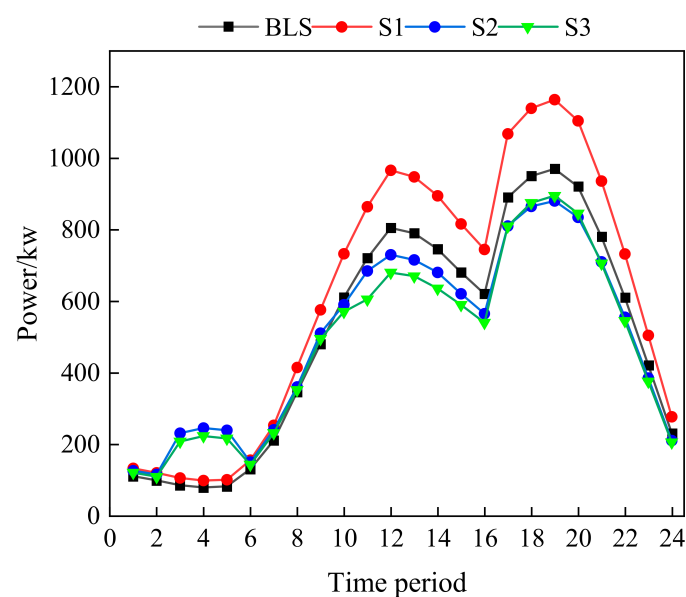


Figure 2. Baseline load and scenario-based load profiles.

As shown in Figure 2, the system total load profiles exhibit significant differences under various scheduling strategies. In the uncontrolled charging scenario (Scenario 1), EVs tend to charge intensively during off-peak periods, which substantially elevates the load valley and creates a new local peak between 2:00 and 4:00. The conventional time-of-use pricing strategy (Scenario 2) partially alleviates this issue; however, its peak-shaving capability remains limited during high-load periods, particularly at 12:00 and between 17:00 and 20:00.

Under the proposed coordinated dynamic pricing and discharge restraint strategy (Scenario 3), EVs actively discharge during system peak hours and charge in an orderly manner during low-load periods, thereby achieving more precise peak–valley regulation. For instance, at 12:00, the system load is reduced from the baseline value of 805.3 kW to

680.1 kW, corresponding to a reduction of 15.6%. During the period from 17:00 to 20:00, the overall system load is decreased by 7.7–13.4%. In terms of aggregated performance indicators, the peak–valley difference in Scenario 3 is reduced to 664.8 kW, representing reductions of 11.8% and 9.8% compared with Scenarios 1 and 2, respectively, while the load variance is decreased by 31.1%. These results demonstrate that the proposed strategy can effectively suppress load fluctuations at the system level and significantly enhance grid operational stability.

4.4. Charging and Discharging Behavior Mechanism Driven by Dynamic Pricing

To reveal the internal mechanism driving the charging and discharging behavior of EVs under the proposed strategy, this subsection analyzes the interaction between dynamic pricing signals, discharge restraint, and aggregated EV power response.

Figure 3 illustrates the temporal variations in dynamic charging and discharging prices, maximum allowable depth of discharge, and aggregated EV charging and discharging power in Scenario 3. It can be observed that EV discharging behavior exhibits a pronounced response to the price differential between charging and discharging electricity. When the price difference exceeds 1.0 CNY/kWh (e.g., at 12:00, where the price gap reaches 1.04 CNY/kWh), the aggregated EV discharging power increases rapidly to 120 kW. By contrast, during periods when the price difference falls below 5%, EVs hardly participate in discharging.

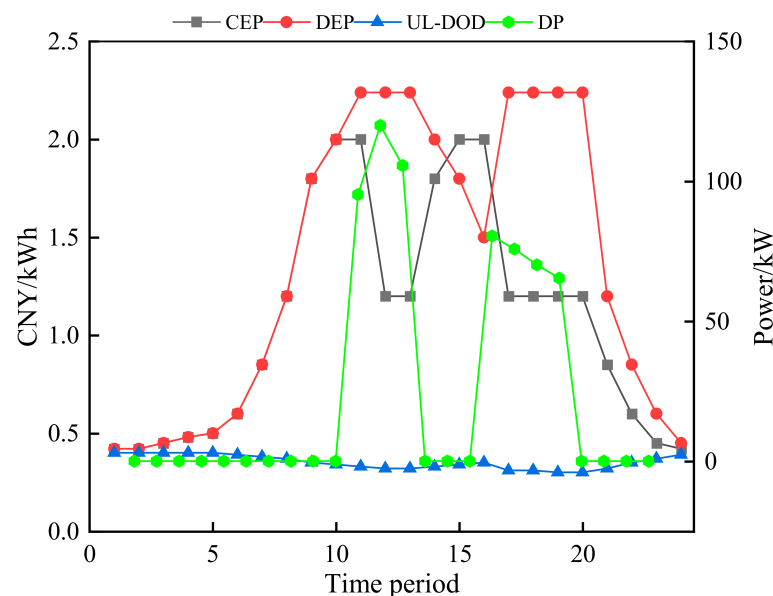


Figure 3. Aggregated EV charging and discharging behavior response under dynamic pricing and discharge restraint constraints (Scenario 3), where CEP is Charging Electricity Price (CNY/kWh), DEP is Discharging Electricity Price (CNY/kWh), UL-DOD is Upper Limit of Depth of Discharge, and DP is Total Discharging Power of EV fleet (kW).

Meanwhile, the discharge restraint mechanism effectively constrains the discharging power of EVs. During consecutive high price-difference periods from 17:00 to 20:00, although the discharging price remains at a relatively high level, the aggregated discharging power gradually decreases from 118 kW to 86 kW, accompanied by a dynamic contraction of the maximum depth of discharge from 0.38 to 0.33. These results indicate that the dynamic pricing mechanism primarily determines whether EVs participate in discharging, whereas the discharge restraint mechanism further regulates the discharging intensity. The coordination of these two mechanisms jointly shapes a rational and controllable EV charging and discharging behavior.

4.5. Scalability and Economic Performance Analysis

To investigate the economic benefits and scalability of the proposed strategy, this subsection analyzes system performance under different EV penetration levels from both operational and economic perspectives.

Figure 4 shows that increasing EVs from 50 to 100 (Scenario 4) preserves peak-shaving without load rebound or concentrated charging/discharging. Charging occurs mainly in low-load periods, while discharging covers peak hours, demonstrating that the proposed dynamic pricing and discharge restraint strategy ensures stable, scalable scheduling under high EV penetration.

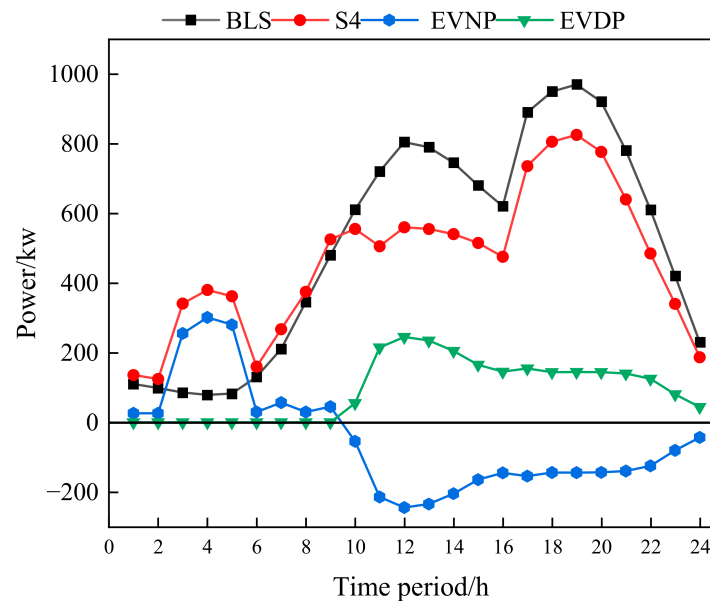


Figure 4. Comparison of key performance indicators in Scenario 4 (100 EVs), where BLS is baseline load (kW), S4 denotes Scenario 4 (the scheduling scenario with 100 EVs), and EVNP is Electric Vehicle Net Power (kW). Positive values indicate charging power drawn from the grid (increasing system load), while negative values indicate discharging power injected into the grid (reducing system load). EDVP is Aggregated Electric Vehicle Discharging Power (kW), presenting the total discharging output of the EV fleet with all positive values.

Figure 5 compares charging station revenues under different scheduling strategies. With 50 EVs, Scenario 3 increases the charging station revenue to 1073.7 CNY through the dynamic pricing mechanism, representing a 6.2% improvement over Scenario 2 (1010.7 CNY) and a substantial 48.8% increase compared with the uncontrolled charging scenario (Scenario 1, 721.5 CNY). Importantly, this revenue growth is not due to a simple increase in discharging volume; rather, it results from the coordinated and concentrated response of EV discharging behavior during periods of high electricity prices and peak system value. By strategically aligning discharging with these high-value periods, the mechanism effectively maximizes economic return per unit of discharged energy. These findings highlight that dynamic pricing, coupled with targeted discharging strategies, can simultaneously optimize EV operation and improve the financial performance of charging infrastructure, providing a strong incentive for large-scale adoption.

Furthermore, Table 3 compares the key operational and economic indicators as the EV fleet size increases from 50 to 100 vehicles. The results show that the total system revenue increases from 1073.7 CNY to 2168.6 CNY, corresponding to an increment of approximately 101.9%, which is highly consistent with the growth rate of the total discharged energy (99.0%). This indicates that the revenue enhancement exhibits an approximately linear relationship with the scale expansion.

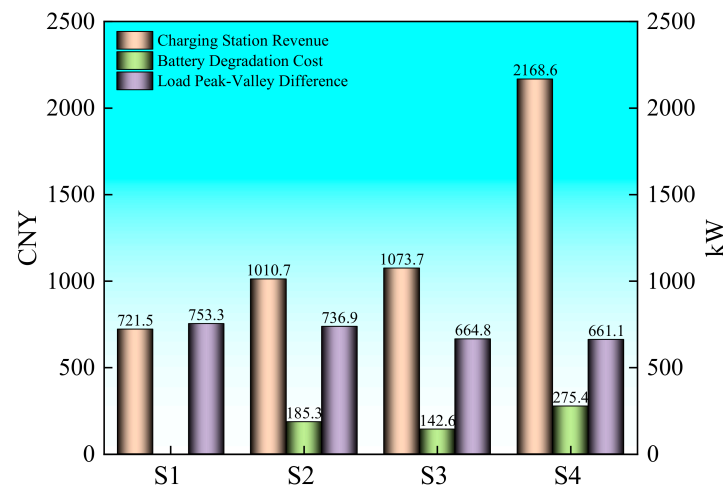


Figure 5. Comparative analysis of key performance indicators under different scheduling strategies.

Table 3. Comparison of key performance indicators between Scenario 3 and Scenario 4.

Indicator	Scenario 3	Scenario 4	Rate
Charging station revenue (CNY)	1073.7	2168.6	+101.9%
Peak–valley load difference (kW)	664.8	661.1	−0.6%
Battery degradation cost (CNY)	142.6	275.4	+93.1%
Average depth of discharge	0.32	0.31	−3.1%
Total discharged energy (kWh)	1250.8	2488.5	+99.0%

Meanwhile, the peak–valley load difference slightly decreases by 0.6%, and the average depth of discharge remains stable within the range of 0.31–0.32. Although the total battery degradation cost rises alongside the growing total discharged energy, the nearly unchanged average depth of discharge reveals that battery wear intensity per vehicle does not increase with fleet expansion. It means that the scale expansion does not trigger excessive discharging intensity or aggravated battery utilization. Overall, the proposed strategy achieves substantial economic gains while effectively maintaining system operational constraints and battery lifetime protection objectives, thereby demonstrating strong potential for large-scale practical application.

4.6. Impact of Discharge Restraint on Battery Lifetime Protection

As shown in the above figures and tables, the depth-of-discharge (DoD) distribution and battery aging of EVs are significantly influenced by the applied scheduling strategy. Under the conventional time-of-use pricing scenario, deep discharging events occur frequently, with an average DoD of 0.36, which can accelerate battery degradation. In contrast, the introduction of the discharge restraint mechanism effectively limits the average DoD to below 0.32, reduces the frequency of high-depth discharging events (DoD > 0.4) by 28.6%, and lowers battery degradation costs by 23.1%. When the EV fleet size is further increased to 100 vehicles, the average DoD decreases slightly to 0.31, while the overall battery degradation cost remains nearly unchanged, demonstrating that the mechanism scales well with fleet size. These results indicate that the proposed strategy not only mitigates deep discharging and protects battery lifespan but also maintains reliable peak-shaving performance, highlighting its practical value for large-scale EV integration.

As shown in Figure 6, after 1000 cycles, the battery capacity under the conventional discharge strategy decreases to approximately 70%, whereas under the controlled discharge condition, it remains around 80%. At the 500-cycle mark, the capacity retention is 85% for conventional discharge (15% degradation) and 90% for controlled discharge (10% degradation). These results indicate that the controlled discharge strategy can effectively

mitigate capacity fade throughout the battery's cycling life. Specifically, at 1000 cycles, the capacity retention is improved by about 10 percentage points, demonstrating the strategy's effectiveness in prolonging battery lifespan.

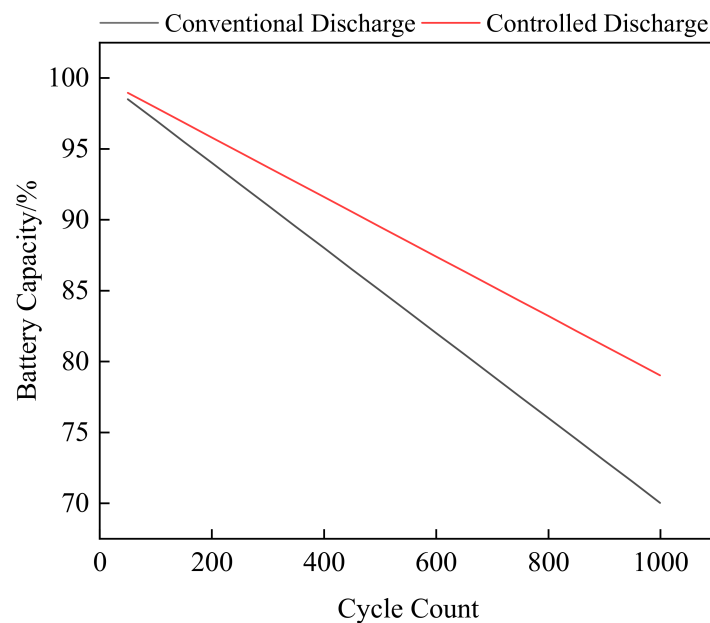


Figure 6. Impact of discharge curtailment mechanism on EV battery degradation.

4.7. Carbon Reduction and System-Wide Benefits

The load shifting refers to the temporal transfer of power consumption or injection without changing the total electric energy demand. As a neutral scheduling behavior, it does not directly produce carbon reduction benefits by itself. The peak shaving is a targeted form of load shifting that focuses on cutting down the peak value of system load. Its direct effect is to reduce the peak–valley difference and improve system operation stability, and it has carbon reduction potential only under specific grid structure and power supply structure. The actual carbon emission reduction: It refers to the net reduction of carbon dioxide emissions on the power supply side. It can be realized only when load is transferred from periods with high marginal carbon intensity to periods with low marginal carbon intensity, or when peak shaving reduces the operation of high-emission, low-efficiency peaking units.

In this study, the proposed ordered charge–discharge strategy achieves actual carbon emission reduction based on the peak-shaving effect, rather than merely completing temporal load shifting. The reduction in load peak-to-valley differences contributes to carbon emission mitigation through two complementary pathways: (1) smoothing load fluctuations reduces the start-stop frequency of coal-fired peaking units, thereby minimizing their operation under low-efficiency conditions; and (2) increasing the accommodation capacity for renewable energy. Based on the China Regional Grid Baseline Emission Factors (2023), the marginal emission factor of the North China power grid is 0.948 tCO₂/MWh [24]. The factor serves as a standard conversion coefficient for further translating the renewable energy accommodation capacity into carbon emission reduction equivalents, thereby enabling the assessment of the additional carbon contribution arising from the improvement in renewable energy integration facilitated by ordered charging and discharging.

Peak-shaving fuel savings (50-EV Scenario 3):

$$\Delta E = \frac{\Delta P_{\text{peak-valley}} \times T_{\text{peak}} \times 365}{\eta \times q_{\text{tce}}} = \frac{(753.3 - 664.8) \times 5 \times 365}{0.38 \times 8141} = 52.2 \text{ tce/year} \quad (19)$$

where $T_{peak} = 5$ h refers to the daily average peak period, $q_{tce} = 8141$ kWh/tce is the calorific value equivalent of 1 ton of standard coal, and $\eta = 0.38$ is the average efficiency of coal-fired power units.

The carbon emission reduction:

$$\Delta C = \Delta E \times 2.516 = 52.2 \times 2.516 = 131.4 \text{ tCO}_2/\text{year} \quad (20)$$

where the emission factor of standard coal is adopted as 2.516 tCO₂/t standard coal.

The new energy accommodation capacity:

$$\begin{aligned} \Delta W_{clean} &= \Delta P_{peak-valley} \times T_{peak} \times \xi = \\ 88.5 \times 5 \times 1.28 &= 565.2 \text{ kWh/day} \end{aligned} \quad (21)$$

where $\xi = 1.28$ denotes the fluctuation coefficient of new energy, clarifying the quantitative relationship between load peak–valley reduction and new energy accommodation space improvement.

Table 4 presents a comparison of key grid-peaking and low-carbon performance indicators across the four different scenarios.

Table 4. Comparison of Key Grid-Peaking and Low-Carbon Performance Indicators under Different Scenarios.

Scenario	Peak-to-Valley (kW)	Reduction (%)	Fuel Saved (tce)	CO ₂ (t)	RE (kWh/day)
S1	753.3	-	-	-	-
S2	736.9	2.2%	9.7	24.4	105.6
S3	664.8	11.8%	52.2	131.4	565.2
S4	661.1	12.2%	54.4	136.9	586.3

By reducing the system load peak–valley difference, the proposed strategy significantly reduces the peak regulation demand of the grid, thereby generating substantial carbon reduction benefits at the system level. Under the 50-EV condition (Scenario 3), the peak–valley load difference is reduced by 11.8%, corresponding to an annual coal saving of 52.2 tce and an associated carbon reduction of 131.4 tCO₂. Meanwhile, the smoothed load profile frees approximately 565.2 kWh/day of renewable energy accommodation capacity, further amplifying the clean energy substitution effect.

When the number of EVs is expanded to 100 (Scenario 4), annual carbon reduction increases to 136.9 tCO₂, indicating that the proposed strategy maintains robust carbon mitigation potential under scaled-up conditions. Overall, coordinated EV charging and discharging not only provides operational and economic benefits but also serves as a critical flexible resource to support low-carbon power system operation.

4.8. Hyperparameter Tuning Process of the Optimization Algorithm

The optimization performance of PSO is highly dependent on hyperparameter settings. In this paper, the control variable method combined with grid search is adopted to complete the full set of hyperparameter tuning based on the 50-EV benchmark scenario (Scenario 3). The evaluation indicators include the convergence accuracy of the composite objective function, convergence iteration number, and single solution time. The specific tuning process is as follows:

4.8.1. Tuning of Basic Scale Parameters

When $N_p < 60$, the population is prone to lose optimal solutions with insufficient diversity; when $N_p > 60$, the computational time increases significantly while the optimization accuracy barely improves.

When $G_{max} < 100$, the algorithm fails to converge completely; when $G_{max} > 150$, the objective function value remains basically stable with no further accuracy improvement.

According to the comprehensive trade-off between accuracy and efficiency, the population size $N_p = 60$ and the maximum iteration number $G_{max} = 100$ are determined.

4.8.2. Tuning of Inertia Weight

Grid test results show that when $\omega = 0.7$, the composite objective function achieves the optimal convergence speed and solution accuracy.

4.8.3. Tuning of Learning Factors

Tests show that the combination ($c_1 = 1.8$, $c_2 = 2.2$) can take into account the constraint feasibility of individual EVs and the global revenue optimization of the fleet.

4.8.4. Tuning of Crossover and Mutation Probabilities

After tests, the crossover probability $P_{cr} = 0.4$ and the mutation probability $P_{mu} = 0.03$ are selected.

4.8.5. Summary of Tuned Hyperparameters

Table 5 details the tuned hyperparameter settings for the improved PSO algorithm.

Table 5. Tuned hyperparameters of the improved PSO algorithm.

Hyperparameter	N_p	G_{max}	ω	c_1	c_2	P_{cr}	P_{mu}
Tuned Value	60	150	0.7	1.8	2.2	0.4	0.03

4.8.6. Sensitivity to Algorithm Selection

Three typical optimization algorithms, namely standard PSO, improved PSO and genetic algorithm (GA), are selected for comparative solution under the same constraint conditions and calculation environment. The key performance indicators are compared in the Table 6.

Table 6. Performance comparison of different optimization algorithms.

Algorithm	Charging Station Revenue (CNY)	Peak–Valley Difference (kW)	Battery Degradation Cost (CNY)	Convergence Iterations	Calculation Time (s)
Standard PSO	1007.2	692.5	168.3	112	8.7
Improved PSO	1073.7	664.8	142.6	98	10.2
GA	982.5	708.1	176.9	146	18.5

The results show that:

(1) There are certain differences in the solution results of different algorithms. Compared with standard PSO and GA, the improved PSO increases the charging station revenue by 6.6% and 9.3%, reduces the peak–valley difference by 4.0% and 6.1%, and cuts the battery degradation cost by 15.3% and 19.4%, respectively, verifying the performance advantage of the improved PSO.

(2) From the perspective of convergence efficiency, the improved PSO has the fastest convergence speed and the shortest effective convergence iterations; GA has the slowest convergence and the longest calculation time, which is not suitable for large-scale fleet scheduling.

(3) Although the quantitative values of indicators vary with algorithms, the core conclusion that “the proposed coordinated strategy can improve revenue, reduce peak–valley difference and suppress battery degradation” remains consistent under all three algorithms, indicating that the research conclusion is robust to algorithm selection.

4.8.7. Sensitivity to Hyperparameter Values

Two key hyperparameters (inertia weight ω and population size N_p) are selected to analyze their impacts on core indicators, and the results are shown in the Table 7.

Table 7. Sensitivity analysis of key hyperparameters of the improved PSO algorithm.

Hyperparameter	Value Range	Variation Range of Revenue	Variation Range of Peak–Valley Difference	Variation Range of Degradation Cost
Inertia weight ω	0.5–0.9	$\pm 3.8\%$	$\pm 2.7\%$	$\pm 4.2\%$
Population size N_p	40–80	$\pm 2.1\%$	$\pm 1.5\%$	$\pm 2.5\%$

The results show that:

(1) The core indicators have moderate sensitivity to the inertia weight. When ω fluctuates within the reasonable range of 0.5–0.9, the fluctuation amplitude of all indicators is less than 5%, and the optimal value appears near 0.7, which is consistent with the tuning result.

(2) The core indicators have low sensitivity to the population size. When N_p varies from 40 to 80, the fluctuation of each indicator is less than 3%, indicating that the algorithm has good robustness to the population scale setting.

(3) Overall, the tuned hyperparameters in this paper are located in the robust optimal interval. Within the reasonable parameter range, the core conclusions of the study are stable and reliable, and will not be subverted due to small adjustments of hyperparameters.

5. Conclusions and Outlook

This study tackles challenges from large-scale uncoordinated EV charging and discharging, which increase grid peak-to-valley differences and accelerate battery degradation. A single-level weighted multi-objective coordinated strategy integrating dynamic discharge curtailment and three-dimensional coupling of electricity price, grid status, and battery state is proposed. By adaptively linking discharge limits with a net revenue threshold, the approach simultaneously protects battery life, balances grid load, and optimizes economic outcomes, achieving enhanced operational revenue, prolonged battery lifespan, and improved grid stability.

Despite the progress made in optimizing interactions among charging stations, the grid, and batteries, two main limitations remain. First, the model primarily focuses on charging station operators’ revenue and grid stability, without quantifying the elasticity of EV users’ participation in discharging, which may lead to actual response rates lower than theoretical predictions. Second, the discharge depth constraints do not account for individual cell heterogeneity, resulting in high-cycle batteries degrading at rates approximately 18% above the mean.

Future research will incorporate user behavior game-theoretic models to establish multi-agent benefit allocation mechanisms. Simultaneously, an online state-of-health (SOH) identification module will be integrated to enable cluster-based differentiated discharge

control, further enhancing system fairness and the precision of battery lifespan protection. In addition, future work will further improve the carbon emission quantification method. Hourly time-varying marginal emission factors and time-varying renewable energy penetration will be incorporated to construct a refined dynamic carbon accounting model, so as to support the design of low-carbon-oriented vehicle-grid scheduling strategies.

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Abbreviations

The following symbols and abbreviations are used in this manuscript:

Name	Explanation
BLS	Baseline load
CC BY	Creative Commons Attribution
CEP	Charging Electricity Price
DEP	Discharging Electricity Price
Dmax	Maximum allowable depth of discharge
DoD	Depth of discharge
DP	Total Discharging Power of EV fleet
EDVP	Aggregated Electric Vehicle Discharging Power
EOL	End-of-life
EVRP	Electric Vehicle Routing Problem
EV	Electric vehicle
EVNP	Electric Vehicle Net Power
gbest	Global best particle position
Lcal	Calendar aging capacity fade
LiFePO ₄	Lithium Iron Phosphate
NSGA-II	Nondominated Sorting Genetic Algorithm II
pbest	Personal best particle position
Pcr	Crossover probability
Pmu	Mutation probability
PSO	Particle swarm optimization
RE	Renewable energy
S1/S2/S3/S4	Scenario 1/Scenario 2/Scenario 3/Scenario 4

SOC	State of charge
SOH	State of health
tce	ton of standard coal equivalent
TOU	Time-of-use
UL-DOD	Upper Limit of Depth of Discharge
V2G	Vehicle-to-grid

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