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Satisfaction aware orderly charging strategy for electric vehicles using particle swarm optimization

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Abstract: To mitigate grid load fluctuations caused by large-scale electric vehicle (EV) charging while preserving user experience, this paper proposes a satisfaction-aware orderly charging coordination framework. First, based on Kano theory, a comprehensive fitness evaluation model is developed to characterize diverse user charging demands, integrating the grid load peak-to-valley difference, total charging cost, and user satisfaction into a unified scheduling objective. To efficiently solve this complex high-dimensional problem, an improved particle swarm optimization (PSO) approach is employed. By incorporating adaptive inertia weights, asynchronous learning factors, and Lévy flight perturbation, the proposed algorithm enhances global search capability and alleviates premature convergence. Simulation results based on the IEEE 33-node distribution system demonstrate the effectiveness of the proposed strategy. Compared with disorderly charging, the proposed method significantly reduces the grid peak-to-valley difference and total charging cost. Meanwhile, the comprehensive user satisfaction is improved and consistently outperforms the conventional PSO method. These results indicate that the proposed strategy effectively balances grid operation and user benefits.

Key words: dynamic electricity price, EV, IPSO, orderly charging, user satisfaction

1. Introduction

By the end of 2023, global EV sales had surpassed 13 million units, with market share exceeding 20% for the first time. China maintained its leading position in this market. By 2030, EV charging demand is projected to account for 6% to 7% of total societal electricity consumption [1], and peak charging loads could reach 11% to 12% of grid capacity [2]. The large-scale integration of EVs into the grid will increase network and line losses while reducing

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the operational stability of the power system [3], and it will also heighten the complexity of charging scheduling [4].

EV charging management currently faces many challenges. On the one hand, users' charging behaviour exhibits randomness and temporal concentration; on the other hand, traditional strategies fall short in balancing load management with economic efficiency [5]. Current research on orderly charging for EVs focuses on two areas: load forecasting and regulation strategies [6], as well as addressing the broader technological barriers and grid infrastructure challenges associated with large-scale adoption [7].

Current EV orderly charging strategies predominantly rely on time-of-use (TOU) pricing to facilitate load shifting. To enhance demand response, recent studies have increasingly incorporated user satisfaction into scheduling frameworks. Reference [8] uses traditional TOU pricing as a baseline, the study divides the day into multiple time slots, and implements differentiated pricing, combined with algorithmic optimization to guide orderly charging of electric vehicles. Reference [9] develops a bi-level deep reinforcement learning strategy for electric vehicle management, which effectively achieves peak shaving and regulates distribution network voltage violations while explicitly incorporating user charging willingness. Moreover, integrating TOU pricing with charging station configurations [10] and user choice behavior modeling [11] significantly reduces idle connection times. Reference [12] balances financial returns and user satisfaction, highlighting the role of user experience in improving scheduling effectiveness. To solve these complex scheduling models, heuristic optimization algorithms have been widely adopted. Regarding optimization, advanced algorithms like rotation-matrix-based PSO [13] and hybrid gravitational search-based PSO [14] significantly enhance EV scheduling. Recent studies further indicate that intelligent hybrid optimization methods can effectively handle multi-objective and constrained optimization problems in complex domains such as IoT networks [15], project investment systems [16] and robust parameter optimization for nonlinear physical control systems [17]. Although existing studies have made significant progress in EV charging optimization, several limitations still remain. Most current methods mainly focus on single objectives such as load smoothing, charging cost reduction, or algorithm improvement, while the orderly consideration of user satisfaction, dynamic pricing, and charging scheduling is still insufficient. In addition, traditional TOU pricing lacks adaptability to real-time load fluctuations, and conventional PSO algorithms are prone to premature convergence in high-dimensional constrained optimization problems.

To address these limitations, this paper proposes a satisfaction-aware orderly charging coordination framework. The main contributions are summarized as follows:

1) A Kano theory-based hierarchical satisfaction model is established. Moving beyond conventional cost metrics, it uniquely integrates basic, expected, and surprise needs to accurately quantify user charging psychology.
2) A dynamic real-time pricing mechanism based on an exponential smoothing load model is designed. This mechanism accurately captures the load deviation between actual and baseline demands, providing a robust economic signal to guide EVs in shifting their charging periods to valley hours without causing secondary load peaks.

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3) An improved particle swarm optimization (IPSO) algorithm is proposed. By integrating adaptive inertia weights, asynchronous learning factors, and a Lévy flight mechanism, it effectively overcomes premature convergence and enhances global search capability.

2. EV Charging load modelling

To accurately characterize EV charging behavior and establish a realistic scheduling foundation, it is first necessary to model the charging load characteristics and user charging demands.

2.1. Charging start time

User driving behavior significantly influences EV charging patterns, and the charging start time of different types of EVs approximately follows a normal distribution [18].

$$f_s(x) = \begin{cases} \frac{1}{\sigma_{\mathrm{out}}\sqrt{2\pi}} \exp\left(-\frac{(x-\mu_{\mathrm{out}})^2}{2\sigma_{\mathrm{out}}^2}\right), & \mu_{\mathrm{out}} - 12 < x \le 24 \\ \frac{1}{\sigma_{\mathrm{out}}\sqrt{2\pi}} \exp\left(-\frac{(x+24-\mu_{\mathrm{out}})^2}{2\sigma_{\mathrm{out}}^2}\right), & 0 \le x \le \mu_{\mathrm{out}} - 12 \end{cases}, \tag{1}$$

where x is the charging start time; μ_{out} and σ_{out} are the expected value and standard deviation, the specific parameter settings for different vehicle types are shown in Table 1.

2.2. Daily mileage

The daily mileage of private EVs follows a lognormal distribution. $f_D(d)$ is the probability density of daily mileage.

$$f_D(d) = \frac{1}{d \cdot \sigma_D \sqrt{2\pi}} \exp\left(-\frac{(\ln d - \mu_D)^2}{2\sigma_D^2}\right), \tag{2}$$

where d is the daily mileage; μ_D and σ_D are the expected value and standard deviation, the specific parameter settings for different vehicle types are shown in Table 1.

2.3. Charging duration and methods

The charging time for EVs depends on the battery capacity and initial charge level.

$$T_c = \frac{(1-\mathrm{SOC}_i^{\mathrm{start}}) \cdot C_a}{\eta \cdot P_i}, \tag{3}$$

where $\mathrm{SOC}_i^{\mathrm{start}}$is the state of charge (SOC) at the start of charging; T_c is the charging time; C_a is the battery capacity; η is the charging efficiency, η = 0.9; P_i is the charging power.

Table 1. Travel and charging characteristics of different types of EVs

type	**Charging start time**	**Daily mileage**

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Private EVs	$N(17.47,3.41^2)$	$N(3.1,1.1^2)$
Taxi	$N(21.5,1.3^2)$	$N(7,1.1^2)$
Bus	$N(14,1.3^2)$ $N(23,1.3^2)$	$N(144.4,0.35^2)$

Based on charging power levels and usage scenarios, EV charging methods are typically categorized into fast charging and slow charging. Fast charging features high power output and short charging times, mainly serving taxis, buses, and other time-sensitive transportation needs. Its load is concentrated and highly volatile. In contrast, slow charging operates at lower power levels with flexible charging windows, mainly targeting private passenger vehicles. Its load is dispersed and adjustable, providing a solid basis for regulating orderly EV charging.

2.4. User satisfaction modelling

As illustrated in Fig. 1Fig. 1, different user needs exhibit distinct satisfaction characteristics under the Kano model framework [19]. This study integrates the hierarchical characteristics of the Kano model to construct a satisfaction objective function that balances “basic needs, expected needs, and surprise needs,” which are mathematically formulated in the following equations.

1. Basic needs

First, EVs must satisfy basic travel requirements upon departure, which is modelled as a minimum energy constraint. This ensures sufficient power for the next day's driving. If the actual charge fails to meet this baseline, energy supply cannot support basic travel needs, making the charging scheduling practically invalid.

$$\mathrm{SOC}_i^{\mathrm{act}} \geq \mathrm{SOC}_i^{\mathrm{req}}, \tag{4}$$

where $\mathrm{SOC}_i^{\mathrm{act}}$ is the actual charge amount; $\mathrm{SOC}_i^{\mathrm{req}}$ is the minimum electricity required to complete the next day's basic mileage.

2. Expected and surprise needs

Expected requirements reflect users' linear sensitivity to two critical aspects of the charging experience: time expectations and cost expectations. Unlike the rigid baseline nature of basic needs, expectation-based needs emphasise overall service quality. Furthermore, surprise needs in the Kano model are implicitly incorporated into this satisfaction framework; they are reflected through the significant improvement of user satisfaction when the actual charging performance greatly exceeds the expected time and cost baselines.

Time expectations primarily manifest in whether the charging system can complete the charging task before the user's anticipated departure time. When the actual completion time exceeds this expected cutoff, user satisfaction exhibits a proportional and significant decline.

$$S_t = \exp[-\gamma_1(T_i - T_i^e)], \tag{5}$$

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where γ_1 is the time-sensitive coefficient; T_i is the actual charging duration; T_i^e is the expected charging duration.

Cost expectations reflect users' sensitivity to whether the charging costs are reasonable. When actual costs deviate from the benchmark value, user satisfaction changes accordingly.

$$S_c = \exp[-\gamma_2(C_i - C_i^e)], \tag{6}$$

where γ_2 is the cost-sensitive coefficient; C_i is the actual charging cost; C_i^e is the expected charging cost.

After obtaining satisfaction scores for time expectations and cost expectations, a composite user satisfaction metric is constructed through weighting to reflect the overall user experience level between charging time and charging costs, as expressed in Eq. (7).

$$S_i = \alpha S_t + (1-\alpha)S_c, \tag{7}$$

where α is the weighting coefficient, $\alpha = 0.5$.

To ensure overall service quality, the system's average satisfaction level must not fall below a specified threshold:

$$\frac{1}{N}\sum_{i=1}^{N} S_i \geq S_{\min}, \tag{8}$$

where N is the number of EVs, $S_{\min}$ is the minimum satisfaction threshold, $S_{\min} = 0.5$.

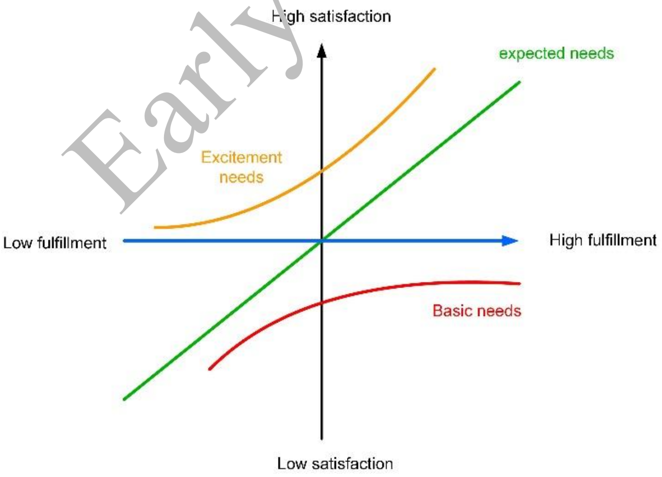

Fig. 1. Kano model diagram

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3. Calculation of disordered charging based on MCS

Based on the established EV charging behavior and satisfaction models, the charging load characteristics under disorderly charging conditions are further analyzed using the Monte Carlo simulation method.

3.1. Calculation of charging load

To obtain the aggregated charging load of EVs in a given region over a single day, this paper employs the Monte Carlo method to simulate disordered charging behavior [20].The day is divided into 24 discrete time intervals, each lasting 1 hour. The specific calculation process is as follows:

1. Initialize parameters: assume a region has *N* EVs, with a simulation time of 24 hours.
2. For each EV *i*, its initial charging time, daily travel distance, and initial SOC are randomly generated according to the probabilistic distribution parameters listed in Table 1.
3. Calculate the charging duration using Eq. (3) , then aggregate the load from all EVs. The aggregation formula is as follows:

$$P_t = \sum_{i=1}^{N} P_i(t), \tag{9}$$

where P_t is the total load at time *t*; $P_i(t)$ is the charging power of the *i*-th EV at time *t*.

3.2. Case simulation

This paper compares application scenarios for 300, 400, and 500 EVs (90% private EVs, 8% taxis and 2% buses) under disorderly charging conditions. To analyze the impact of varying charging power on grid load, it is assumed that private EVs use slow charging mode (P_i = 7 kW), while other EVs employ fast charging mode (P_i = 30 kW), with a charging efficiency set at 0.9.

Based on the Monte Carlo simulation method, the charging loads of individual EVs are aggregated according to Eq. (9) to obtain the aggregated charging load curves under different EV scales, as shown in Fig. 2 disorderly charging leads to concentrated EV charging demand during evening hours, and the charging peak power increases significantly with the number of EVs. These results highlight the necessity of orderly charging scheduling.

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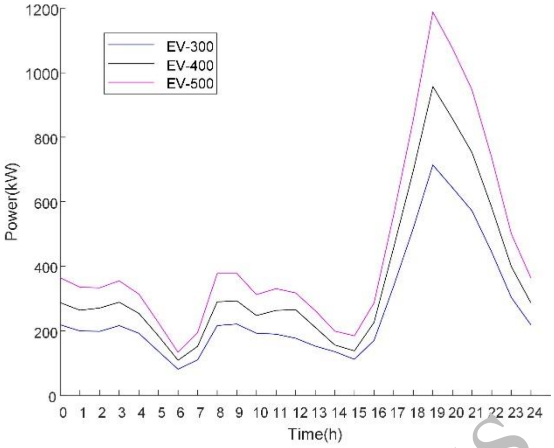

Fig. 2. Schematic diagram of disordered charging

3.3. Dynamic real-time pricing

Time-of-use (TOU) pricing is a mechanism that differentiates electricity rates based on consumption periods. Pricing is typically structured according to peak, off-peak, and low-demand periods of system load to guide users toward rational electricity consumption and alleviate peak load pressure [21].The TOU pricing structure is shown in Table 2.

Table 2. TOU pricing segmentation

Time	Time category	Price
0:00–8:00	Valley hours	0.35
8:00–10:00	Peak hours	0.93
10:00–17:00	Regular hours	0.73
17:00–21:00	Peak hours	0.93
21:00–0:00	Regular hours	0.73

To more accurately reflect electricity price fluctuations across varying load levels within the power system, this study employs a dynamic real-time pricing mechanism where rates adjust linearly based on the deviation between actual load and the baseline load.

To mitigate the impact of instantaneous load fluctuations on pricing, an exponential smoothing load model is introduced, and the related parameters are given by Eq. (10).

$$\overset{\sim}{L_t} = \lambda L_t + (1-\lambda)\overset{\sim}{L_{t-1}}, \tag{10}$$

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$$\Delta L = \frac{\tilde{L}_t - \bar{L}}{\bar{L}}, \tag{11}$$

where $\tilde{L}_t$ is the smoothed load at time *t*; λ is the load smoothing coefficient, λ = 0.5; L_t is the total load at time *t*; ΔL is the load deviation quantity. $\bar{L}$ is the load mean.

Based on the load deviation, the dynamic real-time price is obtained as shown in Eq. (12).

$$C(t) = C_s(t) \times (1 + \delta \times \Delta L), \tag{12}$$

where $C(t)$ is the dynamic real-time price; $C_s(t)$ is the TOU price; δ is the dynamic coefficient, δ is set to 0.5 to balance pricing responsiveness and operational stability.

The dynamic pricing curve generated by Eq. (12) is shown in Fig. 3. During peak system load periods, the dynamic price adaptively increases; conversely, it decreases accordingly during off-peak periods, thereby guiding EV users to perform load shifting.

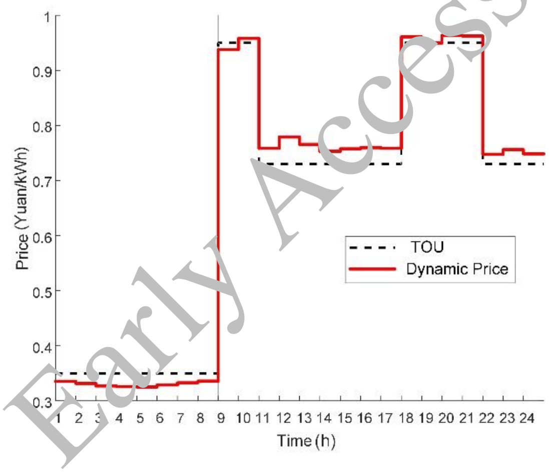

Fig. 3. Comparison of TOU and dynamic real-time prices

4. Ordered charging strategy

The above analysis indicates that disorderly charging can significantly increase grid load fluctuations, while dynamic pricing provides an effective economic signal for load regulation. Therefore, an orderly charging scheduling strategy is further developed to coordinate EV charging behavior and improve both grid performance and user satisfaction.

4.1. Objective function

The magnitude of peak load directly impacts the safe operation of distribution networks. Excessively high peak loads may cause grid overloads. Therefore, the peak-to-valley difference is incorporated as one of the optimization objectives.

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$$F_1 = \max(P_t) - \min(P_t), \tag{13}$$

$$P_t = P_0 + \sum_{i=1}^{N} P_i(t), \tag{14}$$

where P_0 is the base load.

Under the dynamic real-time pricing mechanism, users tend to charge their vehicles during off-peak or low-cost periods. This charging behavior not only helps shift electricity demand but also reduces user costs. Therefore, this paper also incorporates charging costs into the objective function.

$$F_2 = \min C_t = \sum_{i=1}^{N}\sum_{t=1}^{24} P_i(t) \cdot C(t), \tag{15}$$

where F_2 is the total charging cost of N EVs over 24 hours; $C(t)$ is the dynamic real-time price at time t.

To ensure the active participation of EV users in the orderly charging scheduling, the comprehensive satisfaction evaluated via the Kano model must be maximized.

$$\max S = \frac{1}{N}\sum_{i=1}^{N} S_i, \tag{16}$$

where S is system's average comprehensive satisfaction.

To provide a clear mathematical definition for the IPSO algorithm, the overall optimization problem for satisfaction-aware orderly charging is summarized as follows. The primary objective is to minimize the comprehensive fitness function F. The decision variable matrix P_{ch} represents the EV charging power allocation over the 24-hour scheduling horizon, while the proposed IPSO algorithm is employed to search for the optimal charging scheduling solution under the defined operational constraints:

$$\min F(P_{ch}) = \omega_1 F_1^* + \omega_2 F_2^* + (1 - \omega_1 - \omega_2)(1 - S^*), \tag{17}$$

where F_1^* and F_2^* are the normalized values of the grid peak-to-valley difference, total charging costs; $(1 - S^*)$ is introduced to convert the maximization of satisfaction into a minimization problem, ensuring unified optimization direction; ω_1 and ω_2 are the weighting coefficients and are both set to 1/3, resulting in equal weights for the three optimization objectives.

4.2. Constraints

The proposed optimization is subject to a comprehensive set of system constraints. In addition to the user satisfaction constraints established through the Kano model, operational constraints, such as battery state of charge (SOC), charging duration, and grid load limits, must be strictly enforced to ensure the overall safety and stability of the power distribution network. These constraints are summarized as follows:

1. To prevent overcharging or deep discharging of EV batteries and effectively extend battery life, the SOC should be:

$$\mathrm{SOC}_{\min} \le \mathrm{SOC}_i^{\mathrm{end}} \le \mathrm{SOC}_{\max}, \tag{18}$$

where $\mathrm{SOC}_{\max}$ and $\mathrm{SOC}_{\min}$ are the maximum and minimum charge states.

2. Charging time constraints

$$0 \le T_c \le \frac{(1-\mathrm{SOC}_i^{\mathrm{start}}) \cdot C_a}{\eta \cdot P_i}. \tag{19}$$

3. Dynamic pricing bounds constraint

$$C_{\min} \le C(t) \le C_{\max}, \tag{20}$$

where $C_{\min}$and $C_{\max}$ are the lower and upper limits of the dynamic price, respectively.

4. Node voltage security constraint

$$U_{\min} \le U_j(t) \le U_{\max}, \tag{21}$$

where $U_j(t)$ is the actual voltage amplitude of node j at time t. $U_{\min}$ and $U_{\max}$ are the minimum and maximum permissible voltage limits, respectively.

Based on the above objective functions and operational constraints, the orderly EV charging scheduling problem is formulated as a constrained weighted optimization problem. The objective is to determine the optimal EV charging power allocation during the scheduling horizon by minimizing the comprehensive objective function, which integrates the grid peak-to-valley difference, charging cost, and user satisfaction through a linear weighting method. The proposed IPSO algorithm is employed to solve the formulated optimization problem.

5. Improved particle swarm optimization framework

To solve the established scheduling model effectively, an improved PSO algorithm is developed. By integrating adaptive control parameters and Lévy flight mechanisms, the algorithm's search efficiency is significantly enhanced. Furthermore, to provide a more holistic assessment beyond simple grid performance, a multi-criteria evaluation model is constructed. This model transforms the sub-objectives of grid load fluctuation (F_1), charging cost (F_2), and user satisfaction (S) into a composite fitness function, enabling a balanced trade-off among the interests of different stakeholders.

5.1. Particle swarm optimization design

The PSO algorithm is a type of intelligent heuristic search algorithm [22]. In PSO, the velocity and position of particle *i* at the *k*-th iteration are updated as follows:

$$\boldsymbol{v}_i^{k+1} = \omega \boldsymbol{v}_i^k + c_1 r_1 \left(\boldsymbol{P}_i^b - \boldsymbol{x}_i^k\right) + c_2 r_2 \left(\boldsymbol{G}_b - \boldsymbol{x}_i^k\right), \tag{22}$$

$$\boldsymbol{x}_i^{k+1} = \boldsymbol{x}_i^k + \boldsymbol{v}_i^{k+1}, \tag{23}$$

where ω is the inertia weight; c_1 and c_2 are learning factors; r_1 and r_2 are random numbers between 0 and 1; $\boldsymbol{P}_i^b$ and $\mathbf{G}_b$ are the personal best and global best.

5.2. Improved PSO framework

To efficiently solve the charging coordination problem, this section proposes the IPSO algorithm. Each particle represents a candidate scheduling solution over the 24-hour horizon, with its position vector corresponding to the charging power allocation. The algorithm iteratively identifies the global best position ($\boldsymbol{G}_b$) by minimizing the comprehensive fitness function F. This mechanism ensures a unified optimization direction that inherently balances load smoothing, cost reduction, and user satisfaction.

To better balance global exploration and local exploitation across different iteration stages, this study introduces a nonlinear decreasing inertia weight strategy.

$$\omega(k) = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \cdot \left(\frac{k}{k_{\max}}\right)^2, \tag{24}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum values of the inertia weight; k is the current iteration number; $k_{\omega_{\max}}$ is the maximum iteration number.

To improve the algorithm's convergence speed and its local exploitation capability, an asynchronous adjustment strategy is employed for the learning factors [23].

$$\begin{cases} c_1(k) = c_{\max} - (c_{\max} - c_{\min}) \cdot \frac{k}{k_{\max}} \\ c_2(k) = c_{\min} + (c_{\max} - c_{\min}) \cdot \frac{k}{k_{\max}} \end{cases}, \tag{25}$$

where $c_{\max}$ and $c_{\min}$ are the maximum and minimum values of the learning factors.

To ensure the feasibility of the charging scheduling solution, a constraint handling mechanism is integrated into the optimization. Since each particle position represents the charging power allocation scheme, the particle update process must satisfy the SOC constraints and charging power limits ($0 \leq P_i \leq P_{\max}$, where $P_{\max}$ is 7 kW for slow charging and 30 kW for fast charging). Post-update charging powers are clipped within their allowable limits, and the charging demand constraint is enforced by adjusting the power allocation accordingly. Through this repair strategy, all particles remain within the feasible solution space during iterations.

5.3. Adaptive levy flight and greedy strategy

Lévy flight is a stochastic process with a heavy-tailed step-length distribution, which facilitates a natural trade-off between local exploitation and global exploration [24].The Lévy flight is expressed as follows in Eqs. (26) and (27):

$$L(s) = \frac{\mu}{|\nu|^{1/\beta_L}}, \tag{26}$$

$$\begin{cases} \sigma_\mu = \left[\frac{\Gamma(1+\beta_L)\sin(\pi\beta_L/2)}{\Gamma[(1+\beta_L)/2]\beta_L \cdot 2^{(\beta_L-1)/2}}\right]^{1/\beta_L} \\ \sigma_\nu = 1 \end{cases}, \tag{27}$$

where $\mu \sim N\left(0, \sigma_\mu^2\right)$; $\nu \sim N\left(0, \sigma_\nu^2\right)$.

According to [25], the system remains stable only when the stability index $\beta_L \in (0, 2)$, this article selects $\beta_L = 1.5$.

To address the issues of fixed step sizes and a lack of effective guidance associated with traditional stochastic perturbations in high-dimensional constrained spaces, this study proposes an adaptive Levy flight strategy based on satisfaction feedback. The particle position updates are as follows:

$$\boldsymbol{x}_i^{\text{new}} = \boldsymbol{x}_i^k + \left(1 - S_i^k\right) L(s) \cdot \left(\boldsymbol{x}_i^k - \boldsymbol{G}_b\right), \tag{28}$$

where S_i^k is the comprehensive satisfaction of the i-th particle at iteration k.

To ensure iterative superiority while maintaining physical feasibility, the position update criterion is defined as follows:

$$\boldsymbol{x}_i^{k+1} = \begin{cases} \boldsymbol{x}_i^{\text{new}} F(\boldsymbol{x}_i^{\text{new}}) \leq F\left(\boldsymbol{x}_i^k\right) \\ \boldsymbol{x}_i^k \text{Otherwise} \end{cases}, \tag{29}$$

where $F(\boldsymbol{x}_i^{\text{new}})$is the objective function value of the updated solution.

6. Case analysis

6.1. Parameter settings

This study adopts the IEEE 33-node distribution system for simulation analysis, as shown in Fig. 4. Node 1 serves as the slack node, while the remaining nodes are modelled as PQ nodes. The system base capacity is 10 MVA with a rated voltage of 12.66 kV. A total of 500 EVs, including 450 private cars, 40 taxis, and 10 buses, are integrated into residential nodes 7, 14, and 19 as charging loads. According to relevant national standards, the permissible voltage deviation range for distribution networks of 10 kV and below is ±7%. During the optimization process, the node voltage security constraint is strictly enforced, ensuring that the voltage deviations of all nodes are maintained within the safe range.

To ensure the fairness and reproducibility of the comparative analysis, the specific algorithmic parameters are explicitly defined in Table 3. All algorithms are independently executed 30 times, and the optimal results are adopted for the following case studies.

Table 3. algorithmic parameters setting

Parameter	**Value**	**Parameter**	**Value**
N_p	100	$k_{\max}$	300
ω	0.8	c_1, c_2	2.0
$\omega_{\max}$	0.9	$\omega_{\min}$	0.4

$c_{\max}$	2.5	$c_{\min}$	0.5

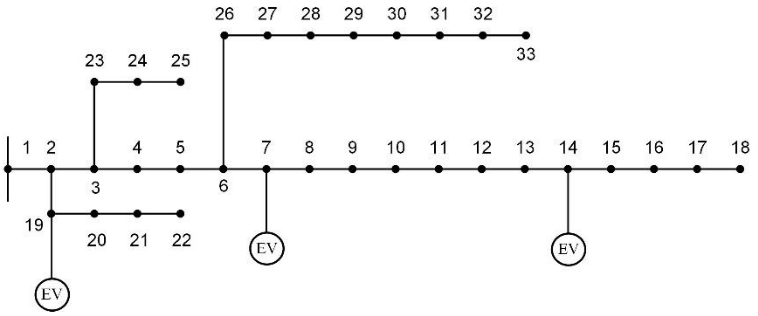
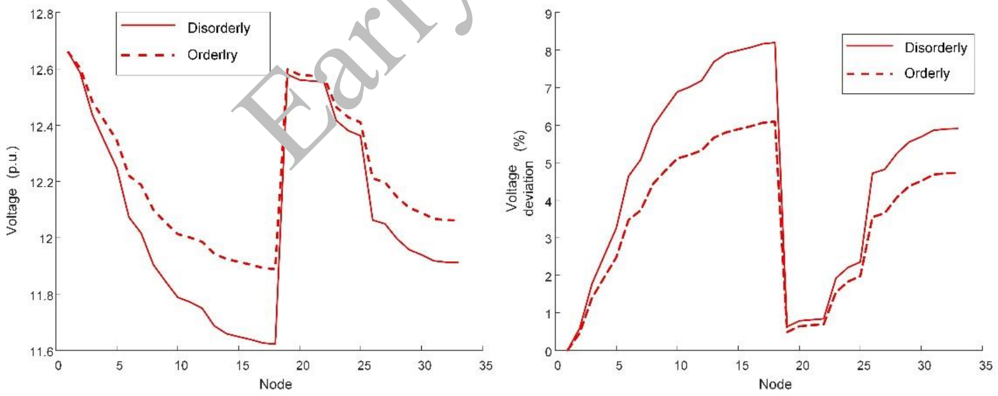


Fig. 4. IEEE-33 node network diagram

6.2. Simulation and analysis

EV loads are connected to distribution network nodes 7, 14, and 19, with connection ratios of 0.5, 0.25, and 0.25, respectively. The analysis focuses on the charging loads at node 33 during the peak charging period at 20:00, when EV charging power is highest.

As shown in Fig. 5, under the disorderly charging strategy, the integration of a large number of EV loads causes the voltage magnitude at system nodes to decrease significantly, and the voltage deviation rate at terminal nodes shows a marked upward trend.



(a) (b)

Fig. 5. Comparison of node voltage quality under different scheduling strategies

In the disorderly charging scenario, the voltage deviations at some terminal nodes exceed the standard limits, threatening the safe and stable operation of the power grid. In contrast, after adopting the orderly charging dispatch strategy proposed in this paper, the voltage magnitudes at all nodes are effectively improved, and the maximum voltage deviation rate is successfully controlled within the safe limits, thereby significantly enhancing the power quality of the distribution network.

Figure 6 and Table 4 show the total load curves and performance indicators under different scheduling strategies. Under disorderly charging, EV charging demand heavily overlaps with the base load. This overlap leads to a substantial peak-to-valley difference of 2 103.54 kW, which poses a potential threat to grid safety and stability. By implementing the orderly charging strategy, the charging load is effectively shifted from peak hours to valley periods, thereby reducing the overall peak load. Compared to disorderly charging, the peak-to-valley load differences under the traditional PSO and the proposed IPSO decreased by 1 036.84 kW and 1 191.09 kW, respectively. In addition, regarding charging costs and satisfaction, the PSO algorithm reduces the total cost to 7 169.47 and increases satisfaction to 0.71. In contrast, the IPSO algorithm demonstrates superior optimization capabilities, further reducing costs to 6 465.22 while maintaining a high satisfaction level of 0.78, thereby validating the effectiveness of the IPSO algorithm in complex optimization problem with multiple indicators.

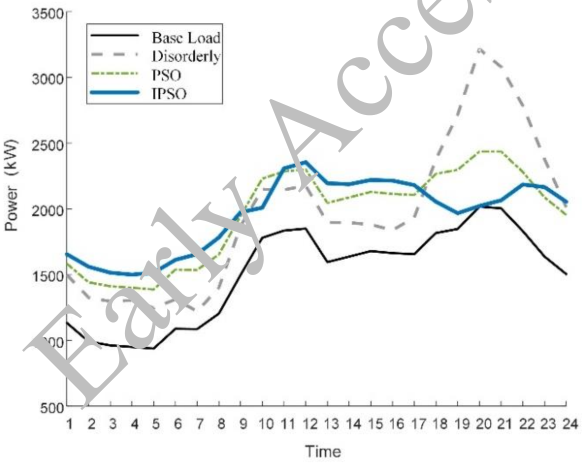


Fig. 6. Total load curves under different scheduling strategies

Table 4. Performance indicators of different scheduling strategies

	Peak-to-valley difference (kW)	**Charging costs(Yuan)**	**Satisfaction**
Disorderly charging	2 103.54	8 512.97	0.63
PSO	1 066.70	7 169.47	0.71
IPSO	912.45	6 465.22	0.78

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To further validate the performance of algorithmic parameters during optimization, the convergence characteristics of IPSO and PSO are compared in Fig. 7. While both curves decline rapidly in the initial stages, as iterations proceed, the conventional PSO gradually stagnates, while IPSO converges to a significantly lower fitness value. This result verifies that asynchronous learning factors and non-linear weights effectively enhance search capability. Furthermore, the Lévy flight perturbation enhances exploration and helps the algorithm avoid premature convergence, thereby improving optimization accuracy.

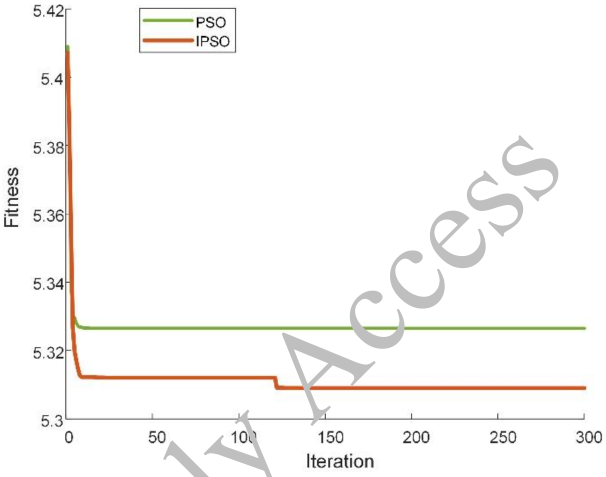

Fig. 7. Algorithm convergence comparison

7. Conclusions

To address the challenges of grid load fluctuations caused by large-scale EV integration, this paper proposes a satisfaction-aware orderly charging scheduling framework. First, a dynamic real-time pricing mechanism based on an exponential smoothing load model is designed to provide robust economic signals for load shifting. Second, a hierarchical user satisfaction model based on Kano theory is established to comprehensively quantify users' basic, expected, and surprise needs. Furthermore, an Improved Particle Swarm Optimization (IPSO) algorithm is developed by incorporating adaptive inertia weights, asynchronous learning factors, and Lévy flight. Simulation results on the IEEE 33-node system demonstrate that, compared with disorderly charging and the conventional PSO algorithm, the proposed strategy significantly reduces the grid peak-to-valley difference and charging costs while maintaining high user satisfaction. The IPSO algorithm effectively overcomes premature convergence and exhibits superior global search capability under strict operational constraints. Future research will further explore the impact of external electricity market price uncertainties and heterogeneous user behaviors to enhance the robustness of the charging coordination strategies.

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