Application of Multi-objective Differential Evolution Algorithm in Electric Vehicle Charging and Discharging Coordination Strategy

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ABSTRACT Traditional single-objective strategies for coordinating electric vehicle (EV) charging and discharging are often unable to balance grid stability, user costs, and battery degradation simultaneously, limiting their applicability in intelligent energy management systems associated with modern electromagnetic power infrastructures. This challenge is particularly significant for industrial microgrids, such as those serving manufacturing facilities, where EV fleet integration must preserve the reliable power quality required by sensitive electrical equipment and electromagnetic energy systems. To address these issues, this study proposes an improved Multi-Objective Differential Evolution (MODE) algorithm that explicitly optimizes multiple conflicting objectives in parallel. The conventional differential evolution framework is enhanced through non-dominated sorting and crowding distance mechanisms to improve solution diversity and convergence. A coordinated EV scheduling model incorporating four optimization objectives, including user satisfaction, together with constraints on bus voltage, charging/discharging power, feeder thermal limits, and battery state of charge, is established. A two-dimensional matrix encoding strategy and an external Pareto archive are adopted to enhance optimization stability. Experimental results demonstrate that the proposed MODE approach achieves a grid load standard deviation of 6.95 and a peak-to-valley ratio of 1.63 while maintaining an average battery depth of discharge of 15% and a user satisfaction level of 0.92 for commuting scenarios. These findings verify the effectiveness of MODE for multi-objective coordinated scheduling and provide a practical optimization framework for sustainable EV energy management and industrial microgrids requiring stable electromagnetic power delivery.

INDEX TERMS multi-objective differential evolution, electric vehicle charging and discharging, electromagnetic energy management, industrial microgrid, pareto optimization

I. INTRODUCTION

WITH the rapid development of the new energy vehicle industry, the number of electric vehicles has increased significantly. This trend affects large energy consumers such as factories that integrate EV fleets for logistics and employee transport, thereby increasing the complexity of site-level power management. Their large-scale integration to the power grid has not only brought about profound changes in the load-side structure but also put forward higher requirements for intelligence and coordination of traditional scheduling mechanisms [1,2]. Especially during urban traffic peaks and centralized charging periods, the unbalanced access behavior of electric vehicles may cause severe fluctuations in local loads, grid frequency deviations, and power flow anomalies [3-5]. Therefore, building an intelligent scheduling strategy that considers the safety of power grid operation, user behavior characteristics, and battery performance evolution has become a key path to improving the operating efficiency of electric vehicle clusters and the coordinated response capabilities of the system [6,7]. To achieve this goal, multi-objective optimization algorithms have been widely used in the charging and discharging scheduling of electric vehicles in recent years to consider the interests of multiple parties and dynamic coupling constraints [8,9]. Among many algorithms, DE has become an important tool for optimizing scheduling problems due to its advantages, such as strong convergence, simple structure, and flexible parameter setting. However, traditional DE methods still have problems such as a single objective balancing mechanism, insufficient solution set diversity, and limited constraint modeling capabilities when facing multi-objective scenarios, making it difficult to meet the refined control requirements in complex coordinated scenarios [10,11].

This paper uses a multi-objective differential evolution algorithm that integrates behavioral modeling and system constraints for the intelligent optimization task of "electric vehicle charging and discharging coordination strategy". This method takes minimizing user charging costs, grid load fluctuations, and battery life loss rate and maximizing user satisfaction as coordinated optimization objectives. By adopting non-dominated sorting and crowding distance retention strategies, the distribution balance and evolutionary stability of the solution set on the Pareto frontier are enhanced. At the same time, the optimization model fully considers the user's travel patterns, battery attenuation mechanism, and load dynamic evolution characteristics, making the strategy more feasible and adaptable in practical operation conditions, especially in industrial settings like the sector, where EV charging operations must adapt to unpredictable production schedules and complex power demands. The main contributions of this study are as follows:

(1) An improved MODE algorithm that combines adaptive parameter adjustment with local search is designed. By dynamically adjusting the mutation factor and adopting a simulated annealing mechanism, the algorithm's solution diversity and convergence efficiency are effectively enhanced in multi-objective conflict scenarios.

(2) A satisfaction optimization model driven by user behavior heterogeneity is constructed, which is combined with dynamic weight fusion and classified user demand modeling to achieve a refined balance between user preferences and grid operation constraints.

(3) A dynamic simulation verification framework for large-scale vehicle clusters is designed. Based on 7 days of charging and discharging data of 900 electric vehicles, the comprehensive performance advantages of the algorithm in load leveling, battery health maintenance, and user task assurance are systematically verified.

II. RELATED WORK

In recent years, the problem of electric vehicle charging and discharging scheduling has gradually become a research hotspot [12,13]. Early research mainly focused on simple control methods based on rules or priorities, such as setting fixed time windows for charging, making heuristic judgments based on electricity prices, and other strategies. Such methods are computationally efficient, but they cannot cope with complex system dynamics and multi-constraints [14,15]. Subsequently, a large number of single-objective optimization methods were applied to this field, including linear programming (LP) [16], genetic algorithm (GA) [17], particle swarm optimization (PSO), etc. [18], with the goal of minimizing charging costs, reducing load peaks, or maximizing charging efficiency. These methods have achieved certain results in static scenarios. However, due to the difficulty in considering multiple optimization objectives at the same time and the lack of systematic modeling of the conflicts between objectives, their performance in multi-dimensional balancing decision-making is limited, and they cannot meet the dual requirements of scheduling scheme stability and user experience in actual operation [19,20].

Although the application of multi-objective optimization methods in energy system management continues to deepen, there are still several key issues that need to be addressed. On the one hand, most current scheduling models ignore the long-term impact of battery life loss and health status and fail to effectively incorporate them into the optimization objectives, affecting the sustainability of the solution in the life cycle dimension [21]. On the other hand, individual users are highly heterogeneous in terms of charging and discharging time selection, cost sensitivity, and travel patterns. Existing models mostly use average or static parameter descriptions, lacking dynamic modeling and preference characterization of user response behavior, resulting in low acceptability and feasibility of optimization results in practical applications [22]. Therefore, building a multi-objective optimization framework that can integrate user behavior, battery characteristics, and grid operation constraints has become a key direction for promoting the practicality and refinement of electric vehicle scheduling strategies.

III. MULTI-OBJECTIVE DIFFERENTIAL EVOLUTION ALGORITHM AND PROBLEM MODELING

MODE ALGORITHM PRINCIPLE AND IMPROVEMENT

(1) Basic process of differential evolution algorithm

The differential evolution algorithm is a random search optimization method based on the population evolution mechanism. It is widely used in continuous optimization due to its simple structure, few parameter settings, and strong global search capabilities [23,24]. The algorithm is based on a population composed of real-number coded individuals. It continuously iterates and optimizes the quality of the solution by simulating the "mutation-crossover-selection" process in biological evolution. Figure 1 shows a schematic diagram of its population distribution:

At the initial stage of the algorithm, a set of population individuals is randomly generated within the definition domain of the solution space, each of which represents a feasible solution vector $X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,D}]$, where D is the problem dimension. Subsequently, the algorithm performs a mutation operation on each individual in each generation, that is, randomly selects three different individuals X_{r1}, X_{r2}, and X_{r3} from the population to construct a mutation vector:

$$V_i = X_{r1} + F \cdot (X_{r2} - X_{r3}) \tag{1}$$

A crossover operation is then performed to generate a trial vector $U_i = [u_{i,1}, u_{i,2}, \ldots, u_{i,D}]$, typically using a binary crossover strategy. It is determined for each dimension $j \in \{1, 2, \ldots, D\}$ according to the following rules:

$$u_{i,j} = \begin{cases} v_{i,j}, & \text{if } \mathrm{rand}_j(0,1) \leq CR \text{ or } j = j_{rand}, \\ x_{i,j}, & \text{otherwise.} \end{cases} \tag{2}$$

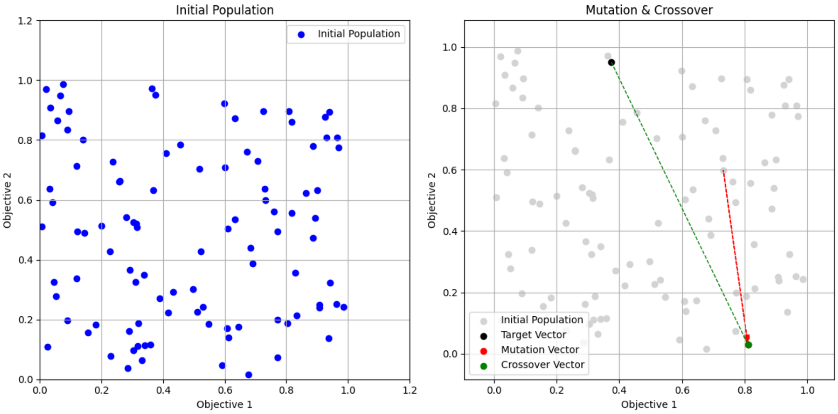

FIGURE 1. Schematic diagram of population distribution in differential evolution algorithm

Among them, $CR \in [0, 1]$ is the crossover probability. rand_j represents a random number in the interval [0,1]. j_{rand} is a random dimension index that guarantees that at least one dimension is from the mutation vector. Finally, the selection phase is entered. By comparing the fitness function of the test individual and the current individual, the one with higher fitness is retained to enter the next generation population. The formal expression is:

$$X_i^{(z+1)} = \begin{cases} U_i, & \text{if } f(U_i) \leq f(X_i), \\ X_i, & \text{otherwise.} \end{cases} \tag{3}$$

Among them, $f(\cdot)$ represents the fitness function, and z is the current generation. Through the above process, the DE algorithm continuously updates the group solution structure and gradually approaches the optimal solution region of the problem.

This paper further refines the improvement strategy by introducing the following mechanisms:

(1) an adaptive parameter adjustment mechanism based on population diversity to dynamically update the mutation factor and crossover probability to enhance the balance between global search and local convergence;

(2) Simulated annealing (SA) is integrated as a local search module to perturb the neighborhood of elite individuals, and accept new solutions combined with Metropolis criterion to improve the ability of the algorithm to jump out of the local optimum;

(3) The adaptive adjustment of parameters is realized through diversity index and dynamic parameters to ensure that the algorithm maintains efficient convergence and diversity in multi-objective conflict scenarios. These improvements significantly improve the optimization performance of MODE under complex constraints, and make it superior to the traditional MOEA method in terms of convergence speed, solution set distribution and engineering applicability.

(2) Multi-objective extension mechanism

To enhance the uniformity of the solution set in the objective space, MODE uses crowding distance as an auxiliary evaluation index within each non-dominated level. For individuals $\{x_1, x_2, \ldots, x_n\}$ in a non-dominated level, each objective function f_k $(k = 1, 2, \ldots, m)$ is first sorted in ascending order. The normalized function value of the individual on the objective dimension after sorting is f_k^i. Then, the crowding distance component of individual x_i on the k-th objective can be expressed as:

$$d_k^i = \frac{f_k^{i+1} - f_k^{i-1}}{f_k^{max} - f_k^{min}} \tag{4}$$

Among them, f_k^{i+1} and f_k^{i-1} represent the target values of the two individuals adjacent to x_i in the sorting. f_k^{max} and f_k^{min} represent the maximum and minimum values of the objective function at the current level.

Finally, the overall crowding distance of individual x_i is:

$$CD(x_i) = \sum_{k=1}^{m} d_k^i \tag{5}$$

The crowding distance of the border individuals is defined as positive infinity to ensure that they are preferentially retained in the selection. Finally, when constructing the next-generation population, MODE preferentially retains individuals with lower non-dominated levels and larger crowding distances, thereby achieving global coverage of the optimal solution area and preventing the solution set from degenerating into a local area due to centralized convergence.

(3) MODE parameter setting

In this study, for the problem of coordinated scheduling of electric vehicle charging and discharging, the parameter configuration of the MODE algorithm not only ensures the optimization effect but also considers the

effective use of computing resources. The main parameters include population size, mutation factor, crossover probability, maximum number of iterations, and external archive size. The selection of these parameters is experimentally verified to ensure that a good scheduling strategy can be obtained in a short computing time. Table 1 lists the specific parameter settings of this study:

TABLE 1. MODE parameter settings

Parameter	Set Value	Illustration
Population Size	120	Ensuring the breadth of the algorithm's exploration in the solution space while avoiding excessive consumption of computing resources
Mutation Factor	0.6	Maintaining global search capability and solution stability
Crossover Probability (CR)	0.8	Enhancing the genetic diversity of populations and promoting information exchange
Maximum Number of Iterations	500	Guaranteeing to converge to a better solution within a reasonable computing time
External Archive Size	60	It is used to record elite solutions (non-dominated solutions), and its maximum capacity is set to 60. When the archive is full, the individuals in the most crowded area will be removed based on the crowding distance mechanism to maintain the distribution and diversity of the solution set.

In order to ensure that the external Pareto archives can effectively maintain the diversity and distribution breadth of the solution set under the fixed capacity, this study uses a file maintenance mechanism based on crowding distance. Specifically, the external archive is designed to store all the non-dominated solutions found during the evolution of the algorithm. When the newly discovered non-dominated solution needs to be added to the file, and the file has reached its maximum capacity (set to 60 in this study), the system will start a deletion program: first, calculate the crowding distance of each solution in the file, which quantifies the density of a solution and its adjacent solutions in the target space. Then, select and remove the solution with the smallest crowding distance in the current file. If there are multiple solutions with the same minimum crowding distance, one of them is randomly selected for removal. This mechanism ensures that in the case of limited file capacity, the solution located in the sparse region of the target space can be retained first, so as to effectively maintain the distribution range and diversity of the final Pareto front, and avoid excessive concentration of the solution set in some specific regions.

(4) Algorithm convergence analysis and improvement

To improve the global convergence and optimization stability of the MODE algorithm in the coordinated scheduling of electric vehicle charging and discharging, this study integrates several improvement strategies while maintaining the advantages of its basic evolutionary structure to enhance its performance in a multi-objective complex constraint environment. The evolution process of the MODE algorithm can be modeled

as a random iterative system that satisfies the Markov property. With appropriate parameter settings and population diversity control, the Pareto optimal solution set can be approached with a high probability. Its built-in non-dominated sorting and crowding distance evaluation mechanism ensures the diversity and distribution balance of the optimization results. On this basis, this study uses indicators such as Spacing and Spread to quantitatively analyze the evolutionary behavior of the Pareto frontier [25,26], which respectively reflect the consistency and distribution breadth of the solution set spacing. They are defined as follows:

$$Spacing = \frac{1}{N-1}\sum_{i=1}^{N}|d_i-\bar{d}|, \quad d_i=\min_{j\neq i}\|f_i-f_j\| \tag{6}$$

$$Spread = \frac{d_f+d_l+\sum_{i=1}^{N-1}|d_i-\bar{d}|}{d_f+d_l+(N-1)\bar{d}} \tag{7}$$

Among them, f_i represents the objective function value vector of the i-th solution. $\bar{d}$ is the mean of the distances of all adjacent solutions. d_f and d_l represent the distances between the most marginal solution and the Pareto frontier, respectively.

To overcome the problems of traditional MODE algorithm falling into local optimality and search ability attenuation in the late stage of evolution, this study constructs an adaptive parameter adjustment mechanism based on population diversity. The mutation factor F and crossover probability CR are no longer statically set but are updated in real time according to the population structure during the evolution process. In the specific implementation, the individual diversity measurement indicators are defined as follows:

$$D_z = \frac{1}{N}\sum_{i=1}^{N}\|x_i^z-\bar{x}^z\|_2 \tag{8}$$

Among them, x_i^z represents the solution vector of the i-th individual in the z-th generation, and $\bar{x}^z$ is the center position of the current population. Based on this diversity index, the dynamic adjustment of the mutation factor is as follows:

$$F_{z+1} = F_z + \alpha\cdot\frac{D_z-D_{z-1}}{D_{z-1}} \tag{9}$$

This strategy dynamically adjusts the search intensity according to the trend of diversity changes: when diversity decreases ($D_z < D_{z-1}$), the mutation intensity is increased to enhance the population perturbation ability; when diversity remains at a high level, the perturbation amplitude is controlled to stabilize the evolution direction. Similarly, the crossover probability CR is fine-tuned based on the law of diversity index changes, thereby achieving a more efficient dynamic balance between global search and local convergence. In addition, to further improve the quality of the solution set boundary, this study adopts a local search mechanism based on the MODE main algorithm, using simulated annealing (SA) as a supplementary optimization module [27]. In the non-dominated solution set after each generation of evolution, some elite individuals with low crowding degree are selected to perform neighborhood perturbations. The perturbation vector is defined as follows:

$$x_i' = x_i + \sigma \cdot N(0,1) \tag{10}$$

Among them, σ represents the perturbation amplitude, and $N(0,1)$ is the standard normal distribution. The acceptance criterion of the new solution is based on the Metropolis criterion:

$$P_{accept} = \begin{cases} 1, & \text{if } f(x_i') < f(x_i), \\ \exp(-\Delta f/H), & \text{otherwise.} \end{cases} \tag{11}$$

Among them, Δf is the fitness difference before and after the perturbation, and H is the current temperature, which decreases from generation to generation according to the exponential decay law. This mechanism enables elite individuals to have the ability to escape local extreme values and, at the same time, balance exploration and convergence by controlling the acceptance probability, further expanding the Pareto frontier.

MATHEMATICAL MODELING OF COORDINATED CHARGING AND DISCHARGING STRATEGY

This study aims at a typical daily scheduling cycle involving multiple electric vehicles and constructs a multi-objective coordinated charging and discharging optimization model, considering core indicators such as system operating costs, grid load stability, battery health status, and user time preferences. The model is designed based on a rolling optimization mechanism, with a 15-minute granularity for the discretization of the scheduling cycle, a daily time step of T, and a set of all electric vehicles of N. The state and behavior of each electric vehicle in the scheduling cycle are explicitly modeled by decision variables.

(1) Design of optimization objective function

To achieve multi-objective coordinated scheduling, this study designs an optimization model with four subobjectives, which correspond to the economy, grid friendliness, battery health, and user satisfaction during the operation of the electric vehicle charging and discharging system. There are potential conflicts between the objectives, so MODE is used to optimize the multi-objective functions in parallel to form a Pareto frontier solution set.

In terms of economy, the objective is to minimize the total charging cost. This cost is affected by the user's access period, expected off-grid time, and preset SOC level. Different user settings can affect the system's schedulable time, thereby affecting the system's flexibility in optimizing charging behavior during low-price periods. The user schedulability factor γ_i is used to represent the scheduling flexibility of the i-th electric vehicle, which is defined as follows:

$$\gamma_i = \frac{T_i^{out} - T_i^{in}}{T} \tag{12}$$

The larger the value, the longer the user's service time window in the scheduling cycle, and the higher the flexibility and economic potential of charging scheduling. Based on this, the cost objective function is defined as:

$$f_1 = \sum_{i \in N} \sum_{t=1}^{T} \left(\frac{p_t P_{i,t}^{ch} \Delta t}{\gamma_i + \epsilon} \right) \tag{13}$$

Among them, ϵ is a small positive number to prevent the denominator from being zero, and p_t is the time period electricity price. To mitigate the grid load fluctuations caused by the large-scale access of electric vehicles, the total load standard deviation is set as the objective, which is defined as follows:

$$f_2 = \frac{1}{T} \sum_{t=1}^{T} (L_t - \bar{L})^2 \tag{14}$$

Among them, the total load L_t of the system at time t includes the baseline load L_t^{base} and the net load of electric vehicle charging and discharging, which is specifically:

$$L_t = L_t^{base} + \sum_{i \in N} (P_{i,t}^{ch} - P_{i,t}^{dis}) \tag{15}$$

In terms of extending battery life, the SOC change and DoD of the battery at different time steps are considered, and the average life loss per unit time is taken as the objective function, which is specifically expressed as:

$$f_3 = \sum_{i \in N} \sum_{t=2}^{T} \alpha \cdot |SOC_{i,t} - SOC_{i,t-1}| + \beta \cdot DoD_{i,t} \tag{16}$$

Among them, α and β are empirical weight coefficients, and $DoD_{i,t}$ is the difference between the maximum charge and the minimum charge. The specific expression is:

$$DoD_{i,t} = SOC_{i,t}^{max} - SOC_{i,t}^{min} \tag{17}$$

$DoD_{i,t}$ is used to quantify the fluctuation of SOC within time t, thereby indirectly reflecting the impact on battery life.

Finally, considering the user experience, the charging satisfaction objective function is adopted. The square of the deviation between the user's expected SOC level and the actual SOC at the set off-grid time T_i^{out} is used as an indicator, which is expressed as:

$$f_4 = \sum_{i \in N} (SOC_i^{target} - SOC_{i,T_i^{out}})^2 \tag{18}$$

Among them, SOC_i^{target} is the expected power set by the user, and $SOC_{i,T_i^{out}}$ is the actual SOC value achieved. In summary, the coordinated charging and discharging scheduling problem is transformed into a

nonlinear multi-objective optimization problem with four sub-objectives, namely minimizing f_1, f_2, and f_3 and maximizing f_4. To facilitate a unified solution, in the actual optimization process, this study converts the maximization problem into a minimization form through symbol transformation and uses the MODE algorithm to perform non-dominated sorting and population evolution to obtain the Pareto solution set and assist in formulating the optimal scheduling strategy with multiple objectives.

To represent user experience, a charging satisfaction objective function is introduced. This function uses the square deviation between the user's expected SOC level and the actual SOC value at the set-off time as the quantitative index $f_4 = \sum_{i \in N}(SOC_i^{target} - SOC_{i,T_i^{out}})^2$, where SOC_i^{target} represents the expected power set by the user, and $SOC_{i,T_i^{out}}$ is the SOC value actually reached by T_i^{out} at the time of off grid set by the user. This formulation converts user satisfaction into a minimization objective for the optimization algorithm by punishing the negative deviation of the actual charging amount from the user expectation. The smaller the deviation is, the more the actual charging results meet user expectations and the higher the user satisfaction is.

(2) Multi-objective balanced relationship modeling

To coordinate the conflicting objectives in multi-objective scheduling, this study constructs the objective function value matrix $F = [f_1, f_2, f_3, f_4]$ based on the non-dominated solution set and quantifies the relationship between the objectives through the Pearson correlation coefficient matrix, as shown in Figure 2:

The correlation between objective functions f_i and f_j is defined as:

$$\rho_{ij} = \frac{\mathrm{cov}(f_i, f_j)}{\sigma_{f_i}\sigma_{f_j}} \tag{19}$$

Among them, $\mathrm{cov}(f_i, f_j)$ represents the covariance between the two objective functions, and σ_{f_i} and σ_{f_j} are the standard deviations of the corresponding objective functions. In the non-dominated solution set, with the change of the user scheduling elasticity factor γ_i, it is found that the correlation between the economic objective (f_1) and the user satisfaction objective (f_4) shows obvious nonlinear fluctuations: when the user

schedulability is low, the two objectives are highly positively correlated, and it is difficult for the system to consider both low cost and user preference; in the high schedulability scenario, the objective conflict is weakened, and some solutions can achieve "double optimization". Therefore, user behavior characteristics become an important variable affecting the objective conflict structure and need to be reflected in the weight configuration stage.

In terms of multi-scenario adaptive weight generation, a fuzzy clustering model is constructed to classify the characteristics of the operating environment. The system state vector $x_t = [L_t, t_p, |N_t|, \cdots]$ of each scheduling cycle is input into the clustering model, and its membership vector $\mu_t = [\mu_1, \mu_2, \ldots, \mu_K]$ to each type of center is calculated to obtain the initial estimate of the objective weight. The weight vector $w_t' = [w_1', w_2', w_3', w_4']$ is normalized to the final scheduling weight through the Softmax function:

$$w_i = \frac{e^{\beta w_i'}}{\sum_{j=1}^{4} e^{\beta w_j'}}, \quad i = 1, 2, 3, 4 \tag{20}$$

To improve the user controllability of the system, the system embeds an interactive module to allow users to set personalized objective weight tendency $w^{user} = [w_1^{user}, w_2^{user}, w_3^{user}, w_4^{user}]$, and weighted synthesize the system calculated value and the user input value through the fusion coefficient $\lambda \in [0, 1]$. The final weight vector used for multi-objective scheduling is expressed as:

$$w^{final} = \lambda \cdot w_t + (1 - \lambda) \cdot w^{user} \tag{21}$$

The fusion coefficient can be dynamically adjusted according to the user authorization level or the urgency of the scheduling scenario, balancing the model's adaptive optimization capability and the user demand expression capability.

(3) Constraint modeling

The design of the scheduling model needs to fully consider the physical constraints, behavioral boundaries, and grid access capabilities of the electric vehicle group in actual operation so as to ensure that the proposed optimization strategy has engineering feasibility and operational stability. First, based on the physical properties of the battery, the charging and discharging power of electric vehicles at any scheduling time should be limited by the rated capacity of their equipment, and the SOC should always be maintained within the safe operating range. Therefore, the charging power $P_{i,t}^{ch}$, discharging power $P_{i,t}^{dis}$, and state of charge $SOC_{i,t}$ of the i-th electric vehicle at time t must satisfy the following inequalities:

$$0 \le P_{i,t}^{ch} \le P_i^{ch,max}, \quad 0 \le P_{i,t}^{dis} \le P_i^{dis,max} \tag{22}$$

$$SOC_i^{min} \le SOC_{i,t} \le SOC_i^{max} \tag{23}$$

In addition, the evolution of the battery state of charge must comply with the principle of energy conservation. In each time step, the SOC at the current moment depends on the state at the previous moment and is updated in combination with the current charging and discharging behavior while considering the charging efficiency η_{ch}, the discharging efficiency η_{dis}, and the battery capacity C_i. The expression is as follows:

$$SOC_{i,t} = SOC_{i,t-1} + \left(\frac{\eta_{ch} P_{i,t}^{ch}}{C_i} - \frac{P_{i,t}^{dis}}{\eta_{dis} C_i} \right) \cdot \Delta t \tag{24}$$

To ensure the practical operability of the scheduling behavior, the user-side behavioral constraints on vehicle use must also be considered, that is, the charging and discharging behavior of each electric vehicle is only performed

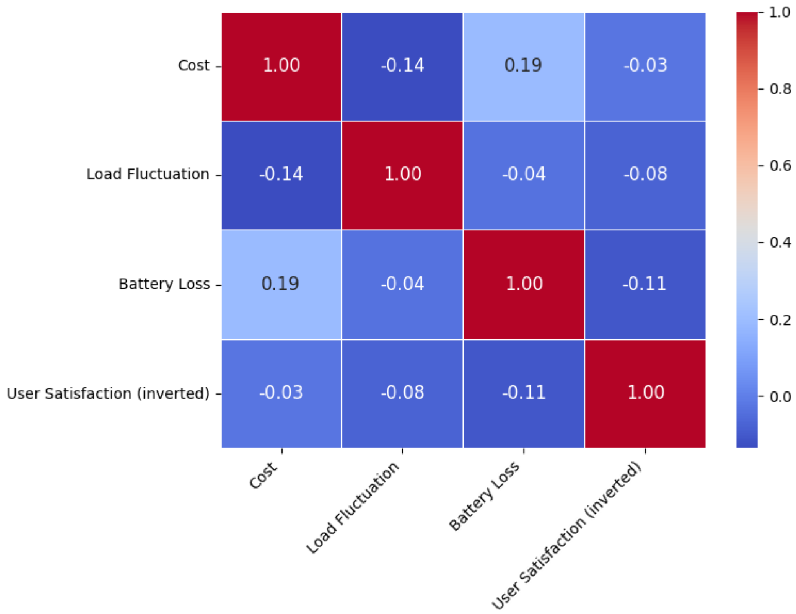

FIGURE 2. Objective function correlation heat map

within the time window allowed by the user. When the scheduling time t does not belong to the vehicle access period $[T_i^{in}, T_i^{out}]$, its charging and discharging power should be forced to zero, and the constraint expression is:

$$P_{i,t}^{ch} = P_{i,t}^{dis} = 0, \quad \forall t \notin [T_i^{in}, T_i^{out}] \tag{25}$$

Finally, from the perspective of safe operation of the power grid, the power regulation capacity of the electric vehicle group should not exceed the upper limit of access to the distribution system. Assuming that the

maximum adjustable load allowed on the grid side is P_{grid}^{max}, then, at any time, the net load power of all electric vehicles must meet:

$$\left| \sum_{i \in N} \left(P_{i,t}^{ch} - P_{i,t}^{dis} \right) \right| \leq P_{grid}^{max}, \quad \forall t \in [1, T] \tag{26}$$

In order to determine a final implementation of the eclectic scheduling strategy from the many non-dominated solutions in Pareto frontier, this study uses a decision method based on the fusion of ideal point and weight. Firstly, based on the fuzzy clustering model and user interaction module, the final target weight vector for the current running scenario is generated. Then, the weighted Euclidean distance from each solution to the ideal point in the Pareto solution set is calculated. The ideal point is composed of the optimal value of each objective function in the current solution set. The final compromise solution is the solution with the minimum weighted distance, and its mathematical expression is as follows:

$$s^* = \arg\min_{s \in P} \sqrt{\sum_{k=1}^{4} w_k^{final} \cdot \left(\frac{f_k(s) - f_k^{min}}{f_k^{max} - f_k^{min}} \right)^2} \tag{27}$$

In formula 27, P represents the Pareto solution set, and f_k^{min} and f_k^{max} are the minimum and maximum values of the kth target in solution set P, respectively, for normalization processing. This method comprehensively considers the adaptive optimization results of the system and the personalized preferences of users, and ensures that the selected scheme achieves the best balance acceptable in engineering among multiple conflicting objectives.

CODING METHOD AND FITNESS FUNCTION DESIGN

A coding scheme and fitness evaluation mechanism for electric vehicle scheduling decisions are designed in the implementation of the MODE algorithm to adapt to the characteristics of the multi-objective coordinated charging and discharging scheduling model in this study.

(1) Individual coding structure design

In this study, the individual coding method uses a two-dimensional real number matrix structure to express the scheduling strategy, and the matrix dimension is set to $|N| \times T$. Each element $x_{i,t}$ in the matrix corresponds to the charging and discharging power value of the i-th electric vehicle at the t-th time step. To accurately characterize the energy interaction state of different vehicles in different time periods, the coding rules are defined as follows: when $x_{i,t} > 0$, it means that the vehicle is charging in the corresponding

time period, and the charging power is $x_{i,t}$; when $x_{i,t} < 0$, it means that the vehicle performs a discharge operation in this time period, and the corresponding discharge power is $|x_{i,t}|$; when $x_{i,t} = 0$, it is regarded as not participating in any energy exchange behavior at this time step. Figure 3 shows an example of this two-dimensional matrix:

In the population initialization stage, the individuals are constrained according to the access time window $[T_i^{in}, T_i^{out}]$ of each vehicle, and the scheduling value in the non-access period is forced to be set to 0 to

ensure the feasibility of the scheduling solution. In the decoding process of each generation of population, a boundary truncation mechanism is also adopted to correct the power value of the individual to meet the charging and discharging power limit and SOC constraint conditions of electric vehicle equipment. This correction mechanism performs restrictive callbacks on elements that exceed the upper or lower limit to avoid distortion of subsequent objective function evaluation due to out-of-range operations, thereby improving the convergence stability of the optimization process and the engineering feasibility of the scheduling solution.

The individual coding scheme designed in this study uses a two-dimensional real matrix structure to express the whole scheduling strategy. The matrix has two clear dimensions: the first dimension is the vehicle dimension, whose size is equal to the total number of electric vehicles participating in the scheduling; The second dimension is the time dimension, whose size is equal to the total number of time steps divided in a complete scheduling cycle. Therefore, each element in the matrix uniquely corresponds to the energy interaction decision of a specific electric vehicle in a specific time step.

Specifically, the value of each element in the matrix directly encodes the charge and discharge power command. When this element is positive, it indicates that the corresponding vehicle is scheduled to charge in the corresponding time period, and its value is the charging power value. When the element is negative, it indicates discharge operation, and its absolute value represents the discharge power value. If the element value is zero, it indicates that the vehicle does not participate in any charging and discharging activities during this time period and is idle.

This coding method integrates scheduling decisions for all vehicles across all time steps into a unified data structure, which not only completely describes the overall picture of the whole scheduling strategy, but also facilitates the unified genetic operation of evolutionary algorithm. When initializing the population, the matrix will be constrained strictly according to the actual schedulable time window of each vehicle to ensure that the value of the matrix element corresponding to the vehicle in the non-access period is forced to zero, so as to ensure the feasibility of the generated scheduling scheme.

(2) Fitness function and objective evaluation method

In terms of fitness function construction and individual objective evaluation, this study evaluates the performance of each individual solution one by one based on the scheduling simulation model. After each individual completes decoding and generates the corresponding scheduling matrix, its performance indicators f_1–f_4 under four key objective dimensions are calculated in turn, corresponding to system economy, load balance, battery health loss control, and user satisfaction. These objective values are dynamically simulated and calculated through an embedded simulation model to ensure that the evaluation results have engineering operability and time series consistency.

In the non-dominated sorting stage of the optimization algorithm, the fast non-dominated sorting method is used to divide the current population into Pareto levels. By constructing a dominance relationship graph, multiple level frontiers are delineated to ensure the efficiency of identifying multi-objective optimal solutions.

Within the same non-dominated level, the crowding distance is used as an evaluation indicator of the sparsity of the solution set to measure the local distribution density of individuals in the objective space. Within the multi-objective optimization framework, this study retains an optional weighted normalization evaluation mechanism to support objective-oriented search in specific situations. Its calculation form is:

$$F = \sum_{k=1}^{4} w_k \cdot \frac{f_k - f_k^{min}}{f_k^{max} - f_k^{min}} \tag{28}$$

Among them, w_k represents the weight coefficient of each sub-objective function, and f_k^{min} and f_k^{max} are the minimum and maximum values of the objective in the current population, respectively. This mechanism is only activated when it is necessary to guide the search direction and does not affect the original multi-objective sorting logic and the extraction of the Pareto optimal solution set.

To deal with individuals that violate constraints, a penalty function mechanism is embedded in the fitness evaluation, mainly targeting two types of core constraints: the first is the dynamic boundary limit of the vehicle state SOC, which requires that the vehicle power be kept within an acceptable range at any time; the second is the safety boundary limit of the power grid load, which ensures that the group scheduling power does not cause local power grid overload. For individuals that violate constraints, corresponding penalty items are assigned according to their violation degree, and their objective function values are adjusted to avoid noncompliant solutions from dominating the evolution process, thereby improving the engineering feasibility and system safety of the scheduling scheme.

IV. EXPERIMENTAL DESIGN AND RESULT ANALYSIS

EXPERIMENTAL SETUP

(1) Experimental dataset construction

The experimental dataset is constructed based on the traffic behavior and power grid operation characteristics of typical urban areas. The user travel data refers to the California Household Travel Survey and TUM CREATE

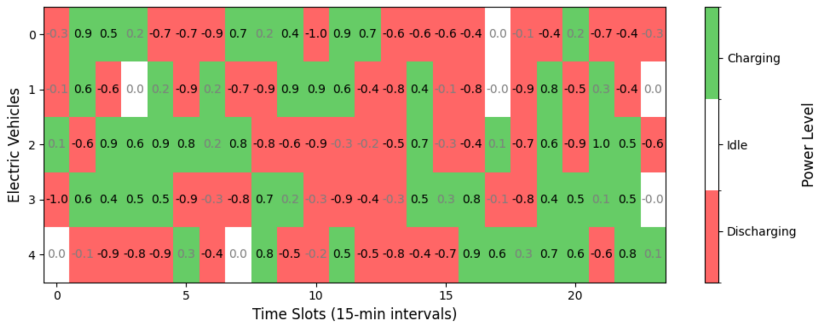

FIGURE 3. Two-dimensional matrix coding examples

electric vehicle travel trajectory data and is localized and adjusted in combination with the travel survey report of first-tier cities in China to generate behavior characteristic data for three types of electric vehicle users: commuting, shared, and commercial. For each type of user, 300 sample vehicles are generated, totaling 900 electric vehicles, forming 1,450 valid charging and discharging task records. The vehicle access

time is modeled using a Poisson process. The expected charging capacity follows a normal distribution (with a mean of 15 kWh and a standard deviation set to 35 kWh), and the stay time is between 0.5 and 6 hours. The distribution network structure adopts the standard IEEE-33 node system, supplemented with common parameter constraints in actual operation, such as transformer capacity and cable current limit. The electricity price information is modeled based on the time-of-use electricity price standard of a provincial power grid company from 2023 to 2024, and a daytime floating electricity price curve is constructed. The simulation period is 7 consecutive days, covering 5 working days and 2 weekend scenarios, with a time granularity of 15 minutes and a total of 672 scheduling time slices. The final constructed dataset contains multiple dimensions, such as vehicle parameters, grid node information, and electricity price time series data, with an overall structure of more than 400,000 records.

(2) Experimental environment and comparison algorithms

The experiment is carried out in a Python environment, mainly relying on the DEAP library to realize the modeling and solution of a multi-objective evolutionary algorithm. The hardware platform is an Intel Core i7 processor and 32 GB memory, which can meet the requirements of computing performance and memory resources in the multi-objective scheduling simulation process, ensuring stable convergence of the algorithm. To comprehensively evaluate the scheduling performance and solution quality of MODE, it is used as the core algorithm of the experimental group, and three representative multi-objective optimization methods are set as the control groups, namely:

Control group 1 uses NSGA-II, which is a classic multi-objective evolutionary framework and has been widely used in energy scheduling and resource optimization scenarios;

Control group 2 uses SPEA2, which uses an external elite archive mechanism and a fitness allocation strategy based on distance density, which helps to improve the distribution balance of the solution set;

Control group 3 uses multi-objective particle swarm optimization (MOPSO), which shows good adaptability in dealing with objective coupling and local extreme value jumps through the speed-position co-evolution and leader selection mechanism between particles.

All algorithms uniformly set the population size, maximum number of iterations, and key control parameters in the experiment to ensure the consistency of the operating environment and the fairness of the result evaluation.

(3) Evaluation indicators

To comprehensively evaluate the optimization performance and operating characteristics of each scheduling algorithm in the management of electric vehicle charging and discharging, this paper constructs a comprehensive evaluation system covering six dimensions. In terms of grid friendliness, the three indicators of the standard deviation of the load curve, the peak-to-valley ratio, and the load rate are used to quantitatively measure the performance of the scheduling strategy in peak cut, improving the stability of grid operation and resource utilization efficiency. In the dimension of battery health, the average DoD and the SOC fluctuation range are selected as evaluation indicators to reflect the potential impact of each scheduling scheme on battery life and operational stability. In the evaluation of the quality of multi-objective solutions, the distribution characteristics of the Pareto frontier solution and the Hypervolume value are combined to analyze the overall performance of the optimization algorithm from the two aspects of the diversity and convergence of the solution set.

EXPERIMENTAL PROCESS AND RESULT ANALYSIS

(1) Load smoothness and grid adaptability

To evaluate the ability of each optimization algorithm in load peak cut and grid resource coordination, based on the constructed city-level electric vehicle charging and discharging simulation environment, the dynamic scheduling process of 900 vehicles in 7 days is simulated, with a sampling interval of 15 minutes. The four types of scheduling algorithms generate scheduling schemes, respectively. The charging power of all vehicles in each time slice is recorded, and the total load curve of the power grid is summarized. Figure 4 shows the total load change trend of each algorithm on a representative day:

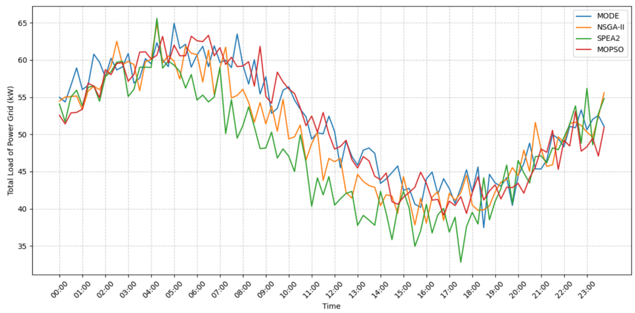

FIGURE 4. Comparison of total grid load curves of various algorithms

Figure 4 shows the impact of four different algorithms on the total load of the power grid on a certain day using the charging and discharging scheduling of electric vehicles. In the figure, the load curves generated by each algorithm are similar in overall trend and show a certain degree of volatility. Based on this load curve, an analysis script is written to extract the load data within a daily 24-hour cycle, calculate the three indicators of standard deviation, peak-to-valley ratio, and load rate, and measure the impact of the strategy on the smooth operation of the power grid and resource utilization. Data processing and visualization are implemented using the NumPy, Pandas, and Matplotlib libraries in Python. Table 2 lists the results:

TABLE 2. Summary of peak-to-valley ratio, standard deviation, and load rate of each algorithm

Algorithm	Standard Deviation of load	Peak-to-Valley Ratio	Load Rate
MODE	6.95	1.63	0.83
NSGA-II	7.63	1.89	0.76
SPEA2	7.07	1.67	0.81
MOPSO	7.17	1.71	0.80
Uncoordinated Charging	18.42	2.71	0.58
Cost-Only	9.85	2.05	0.69

The data in Table 2 shows that the improved MODE algorithm in this paper shows relative advantages in all three key indicators. Its peak-to-valley ratio and standard deviation are the lowest among the four algorithms, indicating that its scheduling strategy has a stronger ability to suppress load fluctuations while effectively carrying out peak cutting. This improvement can be attributed to MODE's explicit modeling of load stability in multi-objective optimization, which makes it more inclined to smooth the time series distribution of charging power when generating scheduling schemes. In terms of load rate, MODE achieves the highest value, indicating that it can make better use of the adjustable resources of the power grid and improve the overall efficiency of power utilization. In contrast, although SPEA2 maintains a strong search capability in some scenarios, its control over the balance between objective functions is slightly insufficient, resulting in a certain offset between load stability and resource utilization in the scheduling results. MOPSO is slightly better than NSGA-II in all aspects but slightly inferior to MODE. Overall, MODE shows better comprehensive performance in balancing multi-objective scheduling needs and improving load curve stability and grid adaptability.

(2) Quality of multi-objective optimization solutions

To compare the performance of each algorithm in the multi-objective optimization task, the DEAP framework is used to uniformly set the population size to 100 and the number of iterations to 300. The optimization

objectives include grid load stability, battery health, and service responsiveness. The non-dominated solution set is recorded in each iteration, and the stabilized Pareto frontier is finally extracted as the performance representative. Figure 5 shows the distribution of Pareto solution sets obtained by the four algorithms:

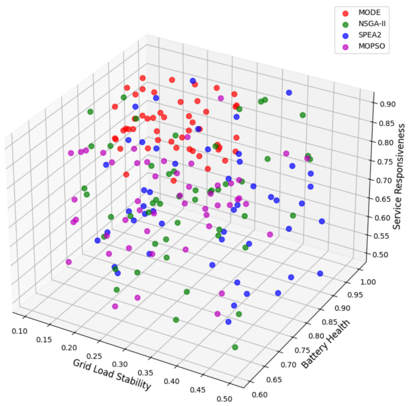

FIGURE 5. Distribution of Pareto frontier solutions of each algorithm

Figure 5 shows the distribution of Pareto frontier solutions of four different algorithms in the electric vehicle charging and discharging scheduling problem. In the figure, the Pareto frontier generated by the MODE algorithm shows a relatively balanced and wide distribution among the three objectives.

The solution set of the MODE algorithm performs well in terms of grid load stability, and its solution set values on this objective are generally low, indicating that it can effectively reduce grid load fluctuations and improve grid operation stability. At the same time, in terms of battery health, the solution set of the MODE algorithm is widely distributed, and there are more solutions in the high health area, indicating that it can better protect battery health and extend battery life during the optimization process. In terms of service responsiveness, the solution set of the MODE algorithm also covers a relatively high area, indicating that it can better meet the charging needs of users and improve user satisfaction. In contrast, the solution set of the NSGA-II algorithm performs slightly weaker in terms of grid load stability.

On this basis, PyGMO and SciPy toolkits are further used to calculate the Hypervolume index of each iteration and draw its change curve with the iteration process to analyze the convergence speed and global optimization ability of the algorithm. Figure 6 shows the results:

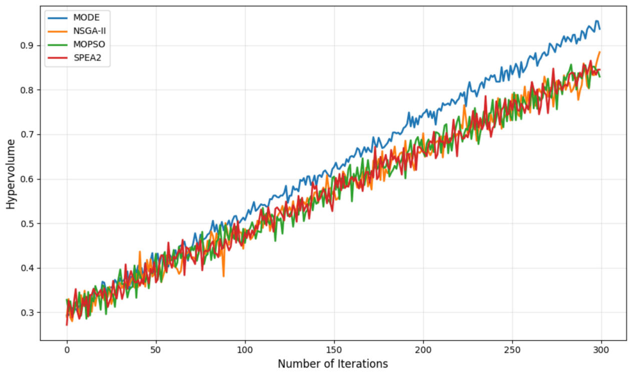

FIGURE 6. Hypervolume change curves of each algorithm

In Figure 6, as the number of iterations increases, the Hypervolume of each algorithm shows an increasing trend. However, the comparison indicates that the improved MODE algorithm implemented in this study demonstrates a relatively fast and stable growth trend during the iteration process. This shows that the MODE algorithm can quickly find a high-quality solution set during the optimization process, and as the iterations proceed, the quality of its solution set continues to improve and eventually reaches a high level. This rapid and stable growth trend reflects the efficiency and global search capability of the MODE algorithm in multi-objective optimization.

In contrast, although other algorithms also show the same growth trend, their growth rate is significantly lower than that of the improved MODE. This shows that the MODE algorithm can better balance the conflicts between multiple objectives and generate high-quality Pareto frontier solutions, providing an effective solution for EV charging and discharging scheduling.

(3) Battery health impact

In the battery health impact analysis, this study focuses on evaluating the battery performance of electric vehicles under different algorithms. For each vehicle, the SOC change trajectory was recorded in real time during the simulation process, and the discharge depth of each task was calculated. In the experimental cycle, this study extracted the SOC trajectory of all vehicles. Figure 7 shows the SOC fluctuation distribution of each strategy:

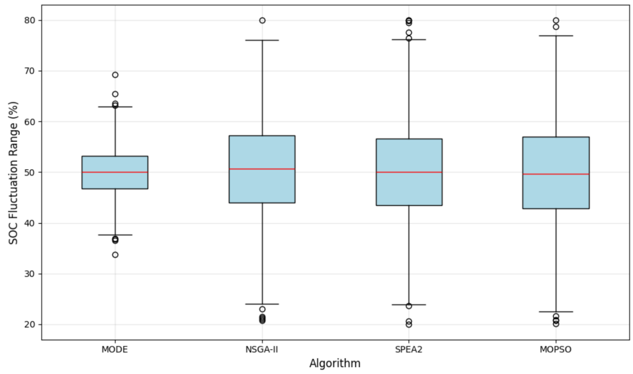

FIGURE 7. SOC fluctuation box plot of each algorithm

Figure 7 shows the SOC fluctuations of different algorithms in the charging and discharging scheduling of electric vehicles. The SOC fluctuation range of the MODE algorithm is the smallest, and the median is relatively stable, indicating that it can effectively control the SOC fluctuations during the scheduling process and reduce the number of deep discharges of the battery. In contrast, the SOC fluctuation range of NSGA-II and SPEA2 algorithms is larger, and the fluctuation of the MOPSO algorithm is the most drastic. This shows that the MODE algorithm performs best in battery health protection and can better maintain the battery state of charge and extend battery life. This result demonstrates the effectiveness of the MODE algorithm in preserving battery health during multi-objective optimization.

On this basis, this study calculates the average DoD and SOC standard deviation corresponding to each strategy through aggregation analysis. Table 3 lists the results:

TABLE 3. Average DoD and SOC standard deviation records

Algorithm	Average DoD (%)	SOC Standard Deviation (%)
MODE	15	5.2
NSGA-II	24	9.8
SPEA2	22	8.3
MOPSO	28	10.5

By analyzing the average DoD and SOC standard deviation data of different algorithms in Table 3, it can be found that the improved MODE algorithm implemented in this study shows significant advantages in battery health protection, and its average DoD and SOC standard deviation are significantly lower than those of other comparison algorithms. This excellent performance is mainly due to the unique multi-objective optimization mechanism and dynamic parameter adjustment strategy of the MODE algorithm. Compared with traditional algorithms, MODE ensures the distribution quality of the Pareto solution set through non-dominated sorting and crowding distance calculation and combines adaptive mutation factors and crossover probability adjustment to effectively balance multiple conflicting objectives such as charging cost, grid load, and battery health. In particular, its integrated simulated annealing mechanism enables the algorithm to jump out of the local optimum and avoid suboptimal solutions that may cause deep discharge of the battery. In contrast, due to the inadequacy of objective conflict handling, the average DoD of NSGA-II and MOPSO algorithms reaches 24% and 28%, respectively, and the SOC standard deviation is also significantly higher, indicating that these algorithms tend to sacrifice battery health to meet other objective requirements during the optimization process. Although the performance of the SPEA2 algorithm is better than that of NSGA-II and MOPSO, its SOC standard deviation of 8.3% is still significantly higher than that of MODE, reflecting that the algorithm still does not fully consider the battery health factor in the solution set selection process. These differences highlight the special design value of the MODE algorithm for battery health protection in the optimization of charging and discharging strategies. Through refined objective weight allocation and dynamic adjustment mechanism, it achieves the objective of maximizing battery life while ensuring grid performance. This finding provides

important technical support for the long-term sustainable development of electric vehicles participating in grid scheduling and also points out the direction for future research, that is, it is necessary to further integrate more precise battery aging models into optimization algorithms to improve the accuracy of health prediction.

(4) User satisfaction performance

In the evaluation of user satisfaction performance, this study uses two methods to evaluate. The first is power satisfaction, which is defined as the ratio of the actual charging amount to the required charging amount; the second is the time window satisfaction rate, which indicates whether the task is completed within the specified time period. A dual satisfaction threshold is set (power satisfaction $\geq$ 90% and completed within the time window), and the proportion of tasks that meet the conditions is used as a comprehensive satisfaction indicator. Furthermore, three types of typical users (commuting, shared, and commercial) are set based on the behavioral model, and the comprehensive satisfaction rates of each type of user under different algorithms are counted. Figure 8 presents the results:

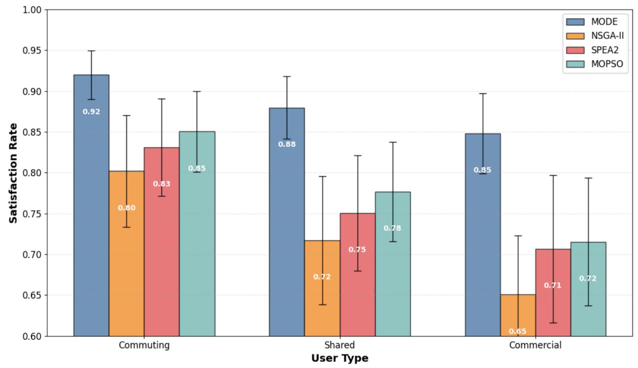

FIGURE 8. Comprehensive satisfaction of different users with different algorithms

Figure 8 shows the user satisfaction performance of the proposed algorithm and the comparison algorithms in the electric vehicle charging and discharging scheduling problem. The improved MODE algorithm implemented in this study achieves the highest comprehensive satisfaction among three different types of users, which are 0.92, 0.88, and 0.85, respectively. In contrast, the satisfaction of MOPSO is second only to that of the algorithm in this study. NSGA-II has the lowest comprehensive satisfaction, which is 0.80, 0.72, and 0.65, respectively, indicating that the algorithm can meet users' charging needs to a certain extent, but there may be room for improvement in the precise matching of time windows and the optimization of power satisfaction.

V. CONCLUSION AND PROSPECT

This paper investigates the intelligent scheduling of electric vehicle fleets under multi-objective optimization. A multi-objective model considering grid friendliness, battery health, and user responsiveness is constructed. An improved differential evolution algorithm is proposed to enhance the optimization ability and solution quality of the scheduling strategy, which is essential for managing the aggregated charging demands of industrial EV fleets, ensuring grid stability for critical operations like production. By building a simulation platform, under the setting of 900 electric vehicles and a 7-day operation cycle, the algorithm in this paper is systematically compared with various mainstream algorithms from the dimensions of load smoothness, grid adaptability, solution set convergence, battery health impact, and user task completion rate. Experimental results show that the proposed method performs well in terms of Pareto solution set distribution balance and Hypervolume indicators, showing good global optimization capabilities and multi-objective balance characteristics. At the power grid level, it effectively reduces load fluctuations and improves the system load rate. On the terminal side, the optimization results significantly suppress SOC fluctuations and DoD, which is beneficial for delaying battery degradation. At the user level, the dual satisfaction index is significantly better than the comparison strategy, reflecting stronger scheduling adaptability and task assurance capabilities.

The model constructed in this paper has good scalability and practical adaptability. Within the framework of multi-objective coordinated optimization, it integrates multi-level objectives for battery protection and user response, considering the overall system and individual operation quality. The algorithm achieves a balance between solution set diversity and convergence speed. It can stably output high-quality and non-dominated solution sets and has strong engineering application potentials. However, the research still has certain limitations. The current model does not apply a dynamic feedback mechanism for user behavior, and satisfaction is mainly driven by static thresholds, lacking modeling of user response behavior. The simulation environment also does not cover complex factors such as traffic perturbations and real-time path changes. In the future, more interactive adaptive strategy research can be carried out in combination with the Internet of Vehicles and real-time scheduling mechanisms. In addition, simplified indicators can be used in the battery degradation assessment. Subsequently, multi-cycle and multi-environment health status modeling and predictive control mechanisms can be adopted to enhance the model's adaptability to actual working conditions, which is crucial for industrial users like factories that need highly reliable EV fleet operation, adapting to variable production schedules and minimizing maintenance downtime.

AUTHOR CONTRIBUTIONS

Xiaowen Mao designed, collected and analyzed the data, and drafted the manuscript. Xiaowen Mao conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaowen Mao participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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