# Research on Intelligent Operation and Maintenance Decision-Making of Electric Vehicle Charging and Discharging Equipment based on Full Life Cycle Management

**Songling Pang[1], Ruien Zhang[2], Kaidi Fan[3], Lulu Zhang[4]**

*[1] Electric Power Research Institute of Hainan Power Grid Co., Ltd.*
*Joint Laboratory of Smart Grid and Island Microgrid，Haikou 570100, China*
*Address:Electric Power Research Institute, Hainan Power Grid Co., Ltd., No. 23, Hairuihou Road, Longhua District, Haikou City, Hainan Province*
*Post Code:570100*
*[2]Electric Power Research Institute of Hainan Power Grid Co., Ltd.*
*Joint Laboratory of Smart Grid and Island Microgrid，Haikou 570100, China；*
*Address:Electric Power Research Institute, Hainan Power Grid Co., Ltd., No. 23, Hairuihou Road, Longhua District, Haikou City, Hainan Province*
*Post Code:570100*
*Fund: Science and Technology Project of China Southern Power Grid Co., Ltd.（073000KK52220001）*
*[3]Electric Power Research Institute of Hainan Power Grid Co., Ltd.*
*Joint Laboratory of Smart Grid and Island Microgrid，Haikou 570100, China；*
*[4]Organization: Hainan Power Grid Co., Ltd.，*

**Abstract:**

The electric vehicle (EV) charging and discharging process involves a large number of energy devices, and the full life-cycle cost of these devices can significantly impact the energy usage strategy of electric vehicles. To address this, the article proposes an optimization mathematical model for electric vehicle charging and discharging that considers the system's electricity cost, equipment operation and maintenance costs, and depreciation costs of the devices. Based on the consideration of the equipment's full life-cycle costs, an optimization scheduling model for daily operating costs is established with the goal of minimizing the operating costs of electric vehicle charging and discharging equipment. An adaptive genetic algorithm is used to schedule the charging plan for electric vehicles throughout the day. The results of case studies show that the proposed optimization strategy reduces the full life-cycle costs, improves energy utilization efficiency, and optimizes the energy consumption structure. Since the full life-cycle costs of the equipment are taken into account, this strategy has better practical application value in engineering.

**Keywords:** Intelligent Charging and Discharging; Adaptive Genetic Algorithm; Economic Dispatch; Total Life-Cycle Cost

## 1. Introduction

As issues such as energy security and the climate crisis become increasingly prominent, the transformation of the energy structure and changes in energy consumption have become urgent. Electric vehicles (EVs), as a focal point for economic development industries, are also key areas within regional energy systems. The structure of electric vehicles is complex, with diverse energy supply methods, and there is multi-energy flow coupling at various production stages. However, electric vehicles have long faced problems such as an irrational energy structure and low energy efficiency, which indicates there is significant room for optimization in their charging and discharging processes [1-2]. Therefore, improving the energy efficiency of electric vehicles and achieving a transformation and reform of their energy structure is a breakthrough for coordinated development between the economy, energy, and the environment. In this context, the optimization of the charging and discharging of electric vehicles, which incorporate various distributed energy sources, has become a research hotspot. The goal of such systems is to optimize the energy structure and improve energy utilization efficiency. By coordinating and optimizing the use of various energy sources, taking into account their respective advantages, disadvantages, and complementary characteristics, these systems aim to efficiently utilize different types of energy. This approach fundamentally adjusts the energy consumption structure and promotes the sustainable development of energy, economy, and environment. It represents an important direction for the future development of China's electric vehicle energy systems [3-4].

The main components of electric vehicle charging and discharging equipment include the following:(1) Charging Pile. A charging pile is a facility that provides electricity for electric vehicles, typically installed in public or private locations for the purpose of charging [5]. Charging piles come in different types, which can be categorized based on charging speed and interface standards as follows: Slow Charging Pile (generally for AC charging), Fast Charging Pile (typically for DC charging) and Ultra-fast Charging Pile (high-power DC charging) [6]. (2) Battery Management System (BMS). The Battery Management System is the "brain" of the electric vehicle battery, responsible for real-time monitoring and managing the health of the battery, the charging and discharging process, temperature, state of charge (SOC), etc. It ensures battery safety and optimizes charging strategies [7]. (3) Inverter. During the charging process, electric vehicles typically use DC batteries for energy storage, while the power grid usually supplies AC electricity. The inverter is used to convert AC power into DC power to charge the battery. (4) Charging Controller. The charging controller is responsible for monitoring and regulating the charging process, ensuring that the charging follows safety standards, and adjusting the charging power and current based on the battery's state [8]. (5) Metering Device. The metering device is used to measure the electrical energy consumed during the charging process for billing or settlement purposes. These devices work together to manage the charging and discharging of electric vehicles, ensuring that the charging process is efficient and safe [9].

V2G (Vehicle-to-Grid) technology is an emerging grid technology that enables electric vehicles (EVs) not only to consume electricity but also to discharge energy back to the grid when idle, facilitating bidirectional energy flow between the grid and the EVs. Smart V2G helps to maintain the battery's lifespan. The power battery is the main component of an electric vehicle, and its lifespan and performance determine the overall performance of the vehicle. It is not necessarily true that less usage time and fewer charging cycles always lead to a longer battery life. If an electric vehicle remains idle for an extended period and does not undergo optimal charge-discharge cycles, its battery life may be compromised. Proper implementation of V2G can not only reduce damage to the battery but also bring benefits to the vehicle owner [10]. A study by the University of Warwick in the UK indicates that battery degradation is a more complex process than previously thought, depending on factors such as battery lifespan, capacity throughput, temperature, charge state, current, and discharge depth. V2G is an effective technology that can optimize the battery's state, minimize degradation, and extend the battery life by discharging excess energy from idle electric vehicles to the grid. However, excessive use of V2G can damage the battery’s lifespan. Optimizing the scheduling of electric vehicles essentially involves planning the charging and discharging power of each EV that enters the grid at every moment in time, which is an optimization problem. Therefore, optimization algorithms can be used to find the optimal charging and discharging power for EVs. In reference [11], particle swarm optimization is used to find the optimal solution for a time-of-use electricity pricing optimization model. In reference [12], an adaptive genetic algorithm is applied to optimize the intelligent charging model for electric vehicles. In reference [13], to address the issue of real-time and orderly charging and discharging control for large-scale electric vehicles, an electric vehicle cluster optimization scheduling model is established, and the gray wolf algorithm is used to solve the optimal scheduling strategy for each electric vehicle. Chen et al. [14] considered various aspects such as the construction of charging and swapping facilities, operation of charging stations, battery swapping stations, monitoring, and intelligent scheduling operations. They modeled the cost-benefit structure of charging and swapping stations and proposed a cost-benefit analysis method based on the lifecycle theory. However, the economic comparison of the two modes was not conducted under the same electricity supply scale, which limits the ability to fully reflect the economic advantages and disadvantages of the two modes. Yin et al. [15] considered the operation and maintenance costs, depreciation costs, startup and shutdown costs over the full lifecycle of the equipment and established an economic scheduling model for a multi-energy microgrid in a factory, aiming to minimize the overall operating costs of the factory. The mixed-integer linear programming method was used to solve the model. The results show that the proposed economic scheduling strategy can increase the utilization rate of local renewable energy, minimize energy losses during conversion and storage, and enhance the economic benefits of the factory.

As shown above, current research on the optimization of electric vehicle charging and discharging schedules mainly focuses on the cost of primary energy, without considering the full lifecycle costs of energy equipment involved in the charging and discharging process. In actual EV charging and discharging, considering the full lifecycle cost of the equipment can have a significant impact on the optimization results. Therefore, in this paper, based on the current situation of EV charging and discharging, we incorporate the daily electricity cost, operation and maintenance costs, and depreciation costs over the full lifecycle of the equipment. The objective is to minimize the overall operational costs of EV charging and discharging. We establish a factory-level EV charging and discharging scheduling model that takes the full lifecycle costs of the equipment into account, and solve it using an adaptive genetic algorithm. The results of the case study show that the proposed economic scheduling strategy can improve energy utilization, minimize energy losses during conversion and storage. Additionally, by considering the full lifecycle costs of the equipment, the model is closer to actual conditions, making it more practical and providing a more accurate energy usage strategy for the economic optimal operation of EV charging and discharging.

## 2. Electric Vehicle Charging and Discharging Optimization Mathematical Model

The Electric Vehicle (EV) Charging and Discharging Optimization Mathematical Model is designed to address various issues related to the integration of electric vehicles into the power grid, including load management, energy distribution, cost minimization, and system stability. The goal of such a model is to optimize the charging and discharging schedules of EVs, considering factors such as grid load, electricity price, battery capacity, and user constraints, while ensuring the stability and efficiency of the power system.

The model typically aims to minimize the total energy cost and optimize the charging/discharging process for a fleet of EVs under various operational constraints. It takes into account the timing of EV charging, battery state-of-charge (SOC), charging/discharging power limits, grid load, electricity pricing, and other factors.

### 2.1 Optimization Objective

The economic optimization scheduling strategy for the factory developed in this paper aims to minimize the daily operating cost $C_{all}$, which takes into account the total life-cycle cost of the equipment. This includes the system's electricity cost $C_A$, the equipment's operation and maintenance cost $C_B$, and the equipment's depreciation cost $C_C$.

$$\min C_{all} = C_A + C_B + C_C \tag{1}$$

where $C_{all}$ is the daily operating cost considering the equipment's total life-cycle cost, $C_A$ is the system's electricity purchase cost, $C_B$ is the equipment's operation and maintenance cost, and $C_C$ is the equipment's depreciation cost.

(1) Electricity cost $C_A$

Based on the charging schedule of electric vehicles throughout the day, the day is divided into $T$ time periods. The decision variable is whether the $i$-th electric vehicle charges at time $t$, with the objective of minimizing the standard deviation of the total load.

$$C_A = \min \sqrt{\frac{1}{T} \cdot \sum_{i=1}^{T} \left[ \sum_{i=1}^{N} \left( x_t^i \times P_{\mathrm{EV}i} \right) \times \eta + P_{\mathrm{load}t} - P_{\mathrm{avg}} \right]^2} \tag{2}$$

where $N$ is the total number of electric vehicles. $T$ is the total calculation duration. $x_t^i$ is a binary decision variable indicating whether the i-th electric vehicle charges at time t (1 if charging, 0 if not). $P\mathrm{EV}i$ represents the rated charging power of the i-th electric vehicle, in kW. η is the charging efficiency. $P\mathrm{load}t$ is the total conventional load in the network at time t, in kW. $P$ represents the average value of the daily load curve, and the specific formula for calculating $P_{\mathrm{avg}}$ is as follows:

$$P_{\mathrm{avg}} = \frac{1}{T} \cdot \sum_{t=1}^{T} \left[ \sum_{i=1}^{N} \left( x_t^i \times P_{\mathrm{EV}i} \right) \times \eta + P_{\mathrm{load}\,t} \right] \tag{3}$$

(2) Operation and maintenance cost $C_B$:

$$C_{\mathrm{OM}} = \sum_i \sum_t \xi_i^{\mathrm{om}} P_{\mathrm{out},i}^t T \tag{4}$$

where $\xi_i^{\mathrm{om}}$ is the operation and maintenance cost per unit power output of device. $P_{\mathrm{out},i}^t$ is the output power of device during time period t.

(3) Equipment depreciation cost $C_C$.

Assuming that the energy equipment maintains a relatively constant output energy throughout its entire life cycle, the depreciation cost $c_{\mathrm{bw}}$ for the cumulative output of 1 kW·h of energy by the equipment is:

$$c_{\mathrm{bw}} = \frac{C_{\mathrm{bat\,,\,rep}}}{Q_{\mathrm{lifetime}}} \tag{5}$$

$$C_{\mathrm{bw}} = \sum_i \sum_t c_{\mathrm{bw}} P_{\mathrm{out}\,,i}^t T \tag{6}$$

where $C_{\mathrm{bat\,,\,rep}}$ is the replacement cost of the energy equipment, and $Q_{\mathrm{lifetime}}$ is the total output energy of a single unit of energy equipment over its entire lifespan.

2.2 Constraint Conditions

(1) Total Power Balance Constraint

$$P_{\mathrm{buy}}^t = P_{\mathrm{AC-load}}^t + P_{\mathrm{AC-DC}}^t \tag{7}$$

where $P_{AC-\mathrm{load}}^t$ represents the AC load. $P_{AC-\mathrm{DC}}^t$ represents the power of the converter.

(2) AC-DC Converter Constraint

$$P_{\mathrm{AC-DC}}^t = \begin{cases} \eta_{\mathrm{AD}} P_{\mathrm{DC}}^t, \text{ if } P_{\mathrm{DC}}^t > 0 \\ 0, \text{ if } P_{\mathrm{DC}}^t = 0 \\ \eta_{\frac{\mathrm{D}}{\mathrm{A}}} P_{\mathrm{DC}}^t, \text{ if } P_{\mathrm{DC}}^t < 0 \end{cases} \tag{8}$$

where $P_{\mathrm{DC}}^t$ Represents the total load of the DC bus. $\eta_{\mathrm{A/D}}$ and $\eta_{\mathrm{D/A}}$ represent the conversion efficiencies for AC-to-DC and DC-to-AC conversions, respectively.

(3) DC Bus Total Load Constraint

$$P_{\mathrm{DC}}^t + P_{\mathrm{PV}}^t + P_{\mathrm{B,r},i}^t = P_{\mathrm{DC\text{-}load}}^t + P_{\mathrm{B,\,s},i}^t \tag{9}$$

where $P_{\mathrm{PV}}^t$ represents the photovoltaic power generation. $P_{\mathrm{DC\text{-}load}}^t$ represents the DC load.

The electric vehicle charging and discharging optimization model is a powerful tool for balancing grid loads, minimizing electricity costs, and ensuring a smooth integration of electric vehicles into the power grid. This model incorporates a variety of constraints, such as power limits, battery state-of-charge, and grid capacity, while seeking to optimize charging and discharging behavior for economic and operational efficiency.

2.3 Optimization solution

Genetic Algorithm (GA) is a randomized search method inspired by the evolutionary principles observed in biology. Through a series of operations such as selection, crossover, and mutation, GA evolves individuals, with the one exhibiting the highest fitness being output as the optimal solution. However, simple genetic algorithms use fixed crossover and mutation probabilities, ignoring the adaptive characteristics of the population's evolutionary process. This can affect the global search capability and lead to premature convergence to a local optimum.

Adaptive Genetic Algorithm (AGA) addresses this issue by dynamically adjusting the crossover and mutation probabilities, maintaining genetic diversity within the population, and preventing premature convergence to local optima. Through comparisons between AGA and GA in solving certain optimization problems, it has been found that AGA can converge to the global optimum more quickly. Therefore, in this study, an adaptive genetic algorithm is used to investigate intelligent charging strategies for electric vehicles.

Considering the constraint conditions, the optimal charging strategy is obtained using an Adaptive Genetic Algorithm. The process involves steps such as population initialization, selection, crossover, and mutation. Before the computation begins, the environment parameters for the AGA need to be set, including the maximum number of iterations, population size, and the parameters for crossover and mutation probabilities.

The optimization process flow is shown in Fig. 1. The key steps in the optimization process are:

1.Reading Input Data (1) Load Information: This includes the power demand at different times of the day, either for the entire grid or specific parts (e.g., residential or commercial areas). The load profile is typically time-varying, depending on factors like time of day, weather, and seasonal patterns. (2) Energy Equipment Information: This consists of details about the EVs (number of vehicles, battery capacity, charging power limits, etc.), as well as the power generation capacity of the grid (renewable, conventional power sources) and the characteristics of any energy storage systems (batteries, distributed generation like solar panels, etc.). (3) Electricity Price Data: This is often time-of-use (TOU) pricing information, which fluctuates throughout the day. The electricity price at different times will affect when it is most cost-effective to charge or discharge the EVs. Typically, prices are lower during off-peak hours (late night) and higher during peak hours (afternoon).

2. Establishing the Objective Function: The objective function represents the goal of the optimization, which can vary depending on the focus of the problem.

3. Defining the Constraints: Constraints ensure that the solution is feasible and respects the technical, operational, and economic limitations of the system.

4. Using the Adaptive Genetic Algorithm (AGA):

The Adaptive Genetic Algorithm (AGA) is a search heuristic used to find optimal solutions for complex optimization problems. AGA works by simulating the process of natural evolution, where the best solutions (individuals) are selected and combined to produce new solutions over multiple generations. Steps in the Adaptive Genetic Algorithm: Initialization: The algorithm starts by randomly generating an initial population of possible solutions (chromosomes). Each chromosome represents a potential charging schedule, where genes correspond to the charging/discharging power for each EV at each time step. Fitness Evaluation: The fitness of each individual (solution) is evaluated based on the objective function (e.g., minimizing cost or balancing grid load). Solutions that incur lower costs or are closer to the desired grid load balance will have higher fitness. Selection: The algorithm selects the best individuals based on their fitness to reproduce. This can be done using techniques like roulette wheel selection or tournament selection. Crossover (Recombination): Selected individuals are combined through crossover operations to produce offspring. Crossover swaps parts of the solutions to create new candidates. Mutation: The offspring may undergo mutation, where small random changes are introduced to explore new regions of the solution space and avoid getting stuck in local optima. Adaptation: The genetic algorithm can adapt by adjusting its parameters (like mutation rate, crossover rate, or selection pressure) based on the progress of the algorithm, improving the search process over time. Termination: The algorithm terminates after a certain number of generations or when a stopping criterion is met (e.g., no improvement in the objective function over a set number of generations). The adaptive aspect of the algorithm allows it to modify its search strategy as the optimization progresses, thus improving efficiency and increasing the likelihood of finding a good solution.

(5) Output the Daily Operating Costs:

After the adaptive genetic algorithm finds the optimal charging strategy, the results are used to calculate the daily operating costs.

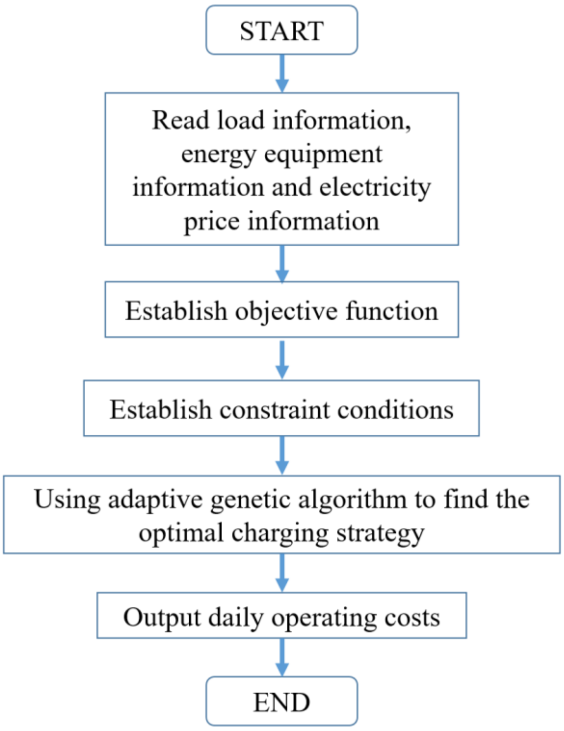
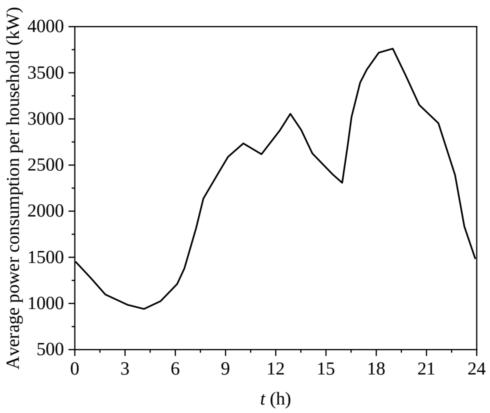



Fig. 1 The optimization process flow.

**3. Case study analysis**

The study investigates the impact of charging loads on the distribution network under two charging strategies: uncontrolled charging and smart charging, based on a case study. The typical daily load curve of the system is shown in Fig. 2.




To simplify the analysis, it is assumed that the rated battery capacity of each electric vehicle is 60 kWh. The conventional charging mode is adopted, with a rated charging power of P = 4 Kw. The charging efficiency is 95 and the user's desired charging energy follows a uniform distribution between 80 and 100 kWh.

The specific parameters for the adaptive genetic algorithm are set as follows: the genetic algorithm is set to run for 80 iterations. The total number of individuals in the population is 200. The maximum crossover probability is set to 0.9, while the minimum crossover probability is set to 0.4. For mutation, the maximum probability is 0.1, and the minimum mutation probability is 0.01.

The intelligent optimized charging strategy discussed in this article is compared with the unordered charging strategy, with the results shown in Table 1. In the unordered charging strategy, users connect to the grid and begin charging immediately after their last trip. This charging behavior typically occurs during the evening hours, causing the charging load of electric vehicles (EVs) to overlap with the peak load of the grid, resulting in a phenomenon known as the "peak-peak" effect. This phenomenon not only intensifies the load pressure on the power system but also increases the system's peak-to-valley difference (i.e., the difference between peak and off-peak loads). Due to the concentrated charging demand from electric vehicles at a specific time, the grid load curve experiences a sharp rise during the evening, which, in severe cases, may exceed the grid's capacity. In this situation, the utilization efficiency of electrical resources significantly decreases, and the stability and power quality of the grid are at greater risk. Particularly during periods of high load, the grid may need to activate additional backup generators or take other emergency measures to cope with the surge in load, which not only increases operational costs but may also cause grid instability or overload risks.

In contrast, the intelligent charging strategy adjusts the timing of electric vehicle charging, shifting most of the charging load to the off-peak period of the original load. Intelligent charging systems generally rely on real-time grid load data and electricity price information to ensure that electric vehicles charge during periods of low electricity demand, thus avoiding placing excessive pressure on the power system during peak load periods. Through this approach, intelligent charging effectively reduces the peak load on the grid, helping to improve overall load balancing, and plays a role in "peak shaving and valley filling." Compared to unordered charging, the intelligent charging strategy significantly reduces the peak-to-valley difference, making the grid's load curve smoother and reducing dramatic fluctuations in system load. This stability in load helps to decrease the frequency of power plant startups and shutdowns, reducing energy waste and equipment wear during power generation, thereby improving the efficiency and economics of the system.

Moreover, intelligent charging provides grid operators with greater flexibility, enabling more precise prediction and dispatch of electrical resources, thereby avoiding electricity shortages or waste during peak periods. In the long term, intelligent charging not only contributes to the safety and stability of grid operations but also provides reliable infrastructure for the widespread adoption of electric vehicles, promoting the efficient use of green energy and sustainable development. Therefore, compared to unordered charging, the intelligent charging strategy makes a greater contribution to the stability, economy, and environmental goals of the power grid system.

| Load Value (kW) | Peak Load | Valley Load | Peak-Valley Difference Rate (%) | Total Load Standard Deviation |
|---|---|---|---|---|
| Original Load | 3731 | 941 | 73.1 | 631.4 |
| Unordered Charging | 4329 | 1132 | 71.3 | 981.5 |
| Smart Charging | 3782 | 1891 | 51.3 | 359 |

## 4. Conclusion

This paper proposes an economic dispatch strategy for electric vehicle charging and discharging equipment, considering the full lifecycle cost of the equipment. The strategy incorporates electricity consumption costs, operation and maintenance costs, and depreciation costs throughout the equipment's lifecycle, with the goal of minimizing the overall operational costs of the electric vehicle. An optimization model is established, and an adaptive genetic algorithm is used for solving it. After optimization, the electric vehicle charging and discharging model improves the efficiency of local energy utilization. With the incentive of time-of-use electricity pricing, smart charging leverages the demand-side flexibility of the equipment, enhancing its participation in system operations and energy markets. This optimizes the energy consumption structure of the equipment, effectively reduces operational costs, and has significant potential for practical implementation in engineering.

**REFERENCES:**

[1] Shi T, Zhao F, Zhou H, et al. Research on intelligent energy management method of multifunctional fusion electric vehicle charging station based on machine learning[J]. Electric Power Systems Research, 2024, 229: 110037.

[2] Das R, Wang Y, Busawon K, et al. Real-time multi-objective optimisation for electric vehicle charging management[J]. Journal of Cleaner Production, 2021, 292: 126066.

[3] El Hadraoui H, Ouahabi N, El Bazi N, et al. Toward an Intelligent diagnosis and prognostic health management system for autonomous electric vehicle powertrains: A novel distributed intelligent digital twin-based architecture[J]. IEEE Access, 2024.

[4] Wu Y, Zhang J, Ravey A, et al. Real-time energy management of photovoltaic-assisted electric vehicle charging station by markov decision process[J]. Journal of Power Sources, 2020, 476: 228504.

[5] Lipu M S H, Hannan M A, Karim T F, et al. Intelligent algorithms and control strategies for battery management system in electric vehicles: Progress, challenges and future outlook[J]. Journal of Cleaner Production, 2021, 292: 126044.

[6] Xu L, Wu F, Chen R, et al. Data-driven-aided strategies in battery lifecycle management: prediction, monitoring, and optimization[J]. Energy Storage Materials, 2023, 59: 102785.

[7] Anandavel S, Li W, Garg A, et al. Application of digital twins to the product lifecycle management of battery packs of electric vehicles[J]. IET Collaborative Intelligent Manufacturing, 2021, 3(4): 356-366.

[8] Guo S, Zhao H. Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective[J]. Applied Energy, 2015, 158: 390-402.

[9] Loganathan M K, Mishra B, Tan C M, et al. Multi-Criteria decision making (MCDM) for the selection of Li-Ion batteries used in electric vehicles (EVs)[J]. Materials Today: Proceedings, 2021, 41: 1073-1077.

[10] Chen Q. Research on implementation strategy of ubiquitous power internet of things[J]. Power Generation Technology, 2019, 40(2): 99-106．

[11] Yang C，Zhao Q，Qi B，et al．Charge and discharge scheduling strategy of electric vehicle based on interest and travel intention of users[J]．Electrical Measurement & Instrumentation, 2018, 55(8):106-112．

[12] Zhang C，Xu X H，Sun H S，et al．Smart charging strategy of large-scale electric vehicles based on adaptive genetic algorithm[J]．Power System Protection and Control，2014，42(14):19-24．

[13] Pan Z, Zhang X, Yu T, et al. Hierarchical real-time optimized dispatching for large-scale clusters of electric vehicles[J]. Autom. Electr. Power Syst, 2017, 41(16): 96-104.

[14] Chen Guangkai, Qu Dapeng, Hu Xiaojing, et al. Cost benefit evaluation of electric vehicle charging/swapping station based on life cycle analysis[J]. Electric Power Construction, 2016, 37(1): 30-37.

[15] Yin Wei，Tong Qinyi，Xu Yang, et al. An Economic Dispatch Strategy of Plant Multi-Energy Microgrid Considering Life Cycle Cost of Equipment [J]. Electric Power Construction, 2017, 38(12): 97-103.