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(Research Article)

Electric vehicle charging and discharging scheduling strategy under dynamic traffic network considering battery health

Zhou Zhou * and Yifan Lv

School of Electric Power Engineering, Nanjing Institute of Technology, Nanjing, Jiangsu, China.

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Abstract

In order to enhance user engagement in power grid scheduling, this paper proposes a battery health assessment method based on electric vehicle charging curves, combined with a traffic network model to dynamically determine EVs' state-of-charge distribution. First, by analyzing EV charging curves, an algorithm is introduced that accurately evaluates battery health, relying on characteristic changes observed during the charging and discharging processes. Second, a dynamic traffic network model is designed to monitor and predict the state-of-charge distribution at various charging stations in real time, thereby enabling more rational allocation of power resources and improving energy efficiency. Finally, the Kepler optimization algorithm is employed to solve the charging strategy, aiming to balance battery health and grid load. Simulation results show that the proposed method effectively predicts EV battery health status while optimizing the state-of-charge distribution among charging stations, thus reducing grid load fluctuations and enhancing both the stability and operational efficiency of the power grid.

Keywords: Charge-discharge optimization; Battery degradation; Dynamic Traffic network; KOA

1. Introduction

As environmental concerns intensify, global demand for green electricity continues to rise, and large-scale renewable energy installations represented by wind and photovoltaic power are expanding rapidly worldwide [1,2]. The inherent uncertainty and low inertia of renewable energy pose significant challenges for grid frequency stability and renewable power integration, creating an urgent need for large-scale, high-quality regulation resources[3]. Against this backdrop, electric vehicles—often idle for extended periods—can, through cluster-based management, provide large-capacity, fast-response regulation capabilities for the grid, thereby attracting extensive attention both domestically and internationally [4-6]. Moreover, under a power market environment, coordinating and optimizing scheduling strategies for electric vehicle aggregators can further enhance cluster revenues and control flexibility [7].

Most existing research focuses on reducing charging costs or smoothing load fluctuations, yet frequently overlooks battery life degradation caused by frequent, deep, or high-level discharges[8]. Rapid capacity decay can lead to user range anxiety, diminishing willingness to participate in grid scheduling and constraining the long-term development of EV cluster management. Consequently, balancing grid regulation demands with EV battery life and mitigating battery deterioration has become a critical issue for achieving large-scale bidirectional EV interaction[9,10]. Although significant progress has been made in orderly EV charging and discharging, certain limitations remain. Reference [11] relies on probabilistic statistics based on extensive historical data, making it difficult to account for real-time vehicle usage, real-time traffic conditions, and evolving charging demands, thus resulting in less accurate forecasts on holidays or other atypical days. Reference [12] establishes a multi-objective scheduling model aimed at EV charging costs and the number of charge-discharge cycles, restricting frequent EV charging and discharging. References [13,14]

* Corresponding author: Zhou Zhou

incorporate battery degradation costs arising from various discharge depths to limit deep discharges, yet their approach considers discharge depth only from a full state of charge and overlooks how different discharge intervals affect battery wear. Therefore, this paper proposes a battery health assessment method based on electric vehicle charging curves, integrates a traffic network model to dynamically determine EV state-of-charge distributions, and employs the Kepler optimization algorithm to solve charging strategies, thereby facilitating more efficient allocation of power resources and optimizing energy utilization.

2. Electric Vehicle Charging Navigation Model

2.1. Road Network Topology

In this section, it is assumed that all roads in the study area are bidirectional and are represented by an undirected graph for the corresponding topology. According to graph theory, the road network topology can be expressed as G = (U, A), where U denotes the set of nodes in the road network topology—namely, the start points and intersections of real roads—and A represents the connections between nodes in the network topology, reflecting the actual road segments. When using an adjacency matrix to represent the road network topology, G = (U, A) corresponds to a K×K matrix D . Let $\boldsymbol{\omega}$ be the link weight function in the road network topology, i.e., the road impedance function. The elements of matrix D are assigned as follows:

$$d_{ij} = d_{ji} = \begin{cases} \boldsymbol{\omega}_{ij} & (i, j) \in A \\ 0 & i = j \\ \boldsymbol{\omega}_{f(ij)} & (i, j) \notin A \end{cases} \quad \ldots\ldots\ldots\ldots(1)$$

$$\boldsymbol{\omega}_{ij} = \frac{1}{T(i, j)} \quad \ldots\ldots\ldots\ldots\ldots(2)$$

where (i, j) refers to the direct-connected road segment between nodes i and j ; $\boldsymbol{\omega}_{ij}$ refers to the weight of the direct-connected segment between nodes i and j ; and $\boldsymbol{\omega}_{f(ij)}$ refers to the weight of the non-direct-connected segment between nodes i and j .

Based on the total delay function of vehicles on each road segment, the transportation network is assigned weighted values, thereby representing the energy consumption of electric vehicles across different time periods and locations. This approach further reflects how real-time traffic conditions affect the SoC distribution at each charging station, constituting a dynamic traffic network model that considers traffic flow variations.

2.2. Road Segment Weight Function

In traditional static traffic networks, road segment weights are typically determined based on the actual road length; however, road length is a static value that cannot reflect the real-time impact of traffic conditions on electric vehicles. To accurately describe the influence of real-time traffic conditions on the SoC distribution at each charging station, this section employs a Logit-based flow delay function to characterize road speed levels, vehicle flow, and intersection delays, which is used to compute the road segment weight elements of matrix D . For the directly connected road segment with nodes i and j as endpoints, the total delay function of vehicles on this road segment is given as follows:

$$T(i, j) = (L(i, j) + I(i, j)) \times 60 \quad \ldots\ldots\ldots\ldots(3)$$

where $T(i, j)$ is the total delay time for the direct road section; $I(i, j)$ is the total delay time for the intersection along the direct road section; and $L(i, j)$ is the total delay time for the road section along the direct road section.

The total delay time for intersections along the direct route is calculated as follows:

$$\begin{cases} L(i,j) = L_0 c_1 \left(\dfrac{1+\exp(c_3 - c_4\lambda_1)}{1+\exp(c_3 - c_4\lambda_1) - c_2} \right) \\ \lambda_L = \dfrac{q_{ij}}{C_{ij}} \end{cases} \quad \text{......................(3)}$$

where L_0 is the free average travel time of a direct link without considering the impact of traffic volume; q_{ij} is the traffic volume of a direct link with nodes i and j as its ends, i.e., the number of vehicles passing through the link per unit time, which is usually obtained from a traffic meter; C_{ij} is the efficiency of the direct link with nodes i and j as its ends; and c_1, c_2, c_3, c_4 are often related to the speed limit of the road and the actual road conditions, which are used to characterize the adaptability of different direct links.

The total delay time of the direct route is calculated as follows:

$$\begin{cases} I(i,j) = I_0 p_1 \left(1 + \dfrac{p_2}{1-\exp(p_3 - p_4\lambda_I)} \right) \\ \lambda_I = \dfrac{q_{ij}}{X_{ij}} \end{cases} \quad \text{............(4)}$$

Where I_0 is the free average travel time at the intersection, which does not take into account the impact of traffic flow; X_{ij} is the intersection throughput efficiency of the direct road sections with nodes i and j as ends; and p_1, p_2, p_3, p_4 is used to characterize the adaptability of different direct road sections, which is often related to the road speed limit and the actual road conditions.

3. Battery Health Estimation Model for Electric Vehicles

If battery degradation is assumed to occur only during the discharge phase, the mathematical expression is formulated based on the battery degradation mechanism and a semi-empirical model as follows:

$$Q_{\mathrm{site}} = c_{\mathrm{ref}} T_{\mathrm{acc}} S_{\mathrm{acc}} D_{\mathrm{acc}} N \quad \text{......................(5)}$$

$$T_{acc} = e^{\frac{-E_a}{R}\left(\frac{1}{T} - \frac{1}{T_{ref}}\right)} \quad \text{......................(6)}$$

where Q_{site} represents the battery capacity degradation rate; N denotes the number of charge-discharge cycles; T_{acc} is the environmental temperature acceleration factor derived from the Arrhenius equation; T represents the ambient thermodynamic temperature; T_{ref} is the standard ambient temperature, set at 293.15 K; S_{acc} is the discharge interval acceleration factor derived from the Tafel equation; and E_a is a constant with a value of 48,724 J/mol.

$$S_{\mathrm{acc}} = \mathrm{e}^{\frac{\alpha F}{R}(SoC_{dis,init} - SoC_{dis,ref})} \quad \text{......................(7)}$$

$$D_{acc} = \left(\frac{DoD}{DoD_{ref}} \right)^{\beta} \quad \text{......................(8)}$$

where $SoC_{dis,init}$ represents the initial state of chargeat the start of the discharge cycle; $SoC_{dis,ref}$ is the standard initial state of charge for the discharge cycle; D_{acc} is the depth-of-discharge acceleration factor derived from the Wohler equation; DoD denotes the depth of discharge; and DoD_{ref} is the standard depth of discharge. α and β are obtained through battery experimental data fitting.

The battery cycle life loss model considering discharge depth and discharge interval was established as follows:

$$N_{life} = N_0 \left(\frac{DoD}{DoD_{ref}}\right)^{-\lambda_1} \cdot e^{-\lambda_2 (SoC_{dis,init} - SoC_{dis,ref})} \text{........................(9)}$$

Where, N_{life} is the total number of discharge cycles experienced by the battery when the capacity decay rate is 20%, that is, the actual battery cycle life; λ_1 and λ_2 are the fitting parameters of experimental data.

By converting the actual number of battery cycles into the standard number of cycles, the equivalent number of discharge cycles corresponding to any discharge interval in this scheduling can be obtained as follows:

$$n_{eq} = \frac{N_0}{N_{life}} = \left(\frac{DoD}{DoD_{ref}}\right)^{\lambda_1} \cdot e^{\lambda_2 (SoC_{dis,init} - Soc_{dis,ref})} \text{........................(10)}$$

Then, the SoH estimation formula is as follows:

$$SoH = \frac{N_0 - \sum n_{\mathrm{eq}}}{N_0} \text{........................(11)}$$

Where, N_0 is the cycle life of the battery under standard test conditions;

4. Electric vehicle charge and discharge scheduling model

4.1. Objective function

Considering the operational stability of the distribution network and the comprehensive benefits of users, the optimization objective of this section is to maximize the benefits of users and minimize the net load fluctuation of the distribution network system.

A scheduling model was established based on the combination of minimum network loss and minimum user cost, and the multi-target was converted into a single target based on the linear weighted sum method for standardized processing as follows:

$$\begin{cases} \min & F = \mu_1 \lambda_1 f_1(X_1) + \mu_2 \lambda_2 f_2(X_2) \\ \text{s.t.} & \mu_1 + \mu_2 = 1 \end{cases} \text{........................(12)}$$

Where, F is the optimization objective; f_1 is the comprehensive network loss function; f_2 is the user cost function; μ_1, μ_2 are the optimization weight coefficient; λ_1, λ_2 are the normalization coefficient; X_1, X_2 are the respective function variable.

The comprehensive network loss function is calculated as follows:

$$f_1(X_1)=\frac{1}{2}\left(\frac{\min P_{fg}}{P_{fg,\max}}+\frac{\min P_{fc}}{P_{fc,\max}}\right) \quad \text{.......................(13)}$$

Where, P_{fg} is the load peak-valley difference and P_{fc} is the load mean square error.

The user cost function is calculated as follows:

$$f_2(X_2)=\min\sum_{i=1}^{N}\sum_{t=1}^{T}(C_f+C_{re}+C_{else}) \quad \text{....................... (14)}$$

Where, N is the total number of electric vehicles waiting to be charged at the target power station, and T is the number of optimization periods for electric vehicles.

$$C_{else}=N_{eq}\cdot C_{loss}+C_0(k)\cdot t_k \quad (15)$$

$$C_{loss}=SoH\cdot\frac{\sum\max\left\{0,SoC_{i,i-1}-SoC_{i,t}\right\}}{100}\cdot C_{bat} \quad \text{.......................(16)}$$

Where, C_{bat} is the investment cost of the battery, $SoC_{i,t}$ is the state of charge of the electric vehicle i at time t.

4.2 Constraint condition

4.1.1. Charge and discharge constraints:

$$\mathrm{SOC}(t,k+1)=\mathrm{SOC}(t,k)+\frac{P_{ch}(t,k)\cdot\Delta t}{E_{bat,k}}\cdot\eta_{\mathrm{ch}}-\frac{P_{dis}(t,k)\cdot\Delta t}{E_{bat,k}\cdot\eta_{\mathrm{dis}}} \quad \text{.......................(17)}$$

Where, $\mathrm{SOC}(t,k)$ is the state of charge of electric vehicle k in the time period t; $P_{ch}(t,k)$ is the charging power of electric vehicle k in time period t, kW; $P_{dis}(t,k)$ is the discharge power of electric vehicle k in time period t, kW; Δt is the unit time, 15min; η_{ch} and η_{dis} are the charging efficiency and discharge efficiency, respectively, and their values are 0.95.

4.1.2. Charge status constraints:

$$\mathrm{SOC}_{\min}\le\mathrm{SOC}(t,k)\le\mathrm{SOC}_{\max} \quad \text{.......................(18)}$$

$$\underline{P}\le P_{i,t}\le\overline{P} \quad \text{.......................(19)}$$

$$SOC_{ex}\le SOC_{fin}\le SOC_{\max} \quad \text{.......................(20)}$$

Where, $P_{i,t}$ is the power of electric vehicle i at time t; $\underline{P}$ stands for rated discharge power; $\overline{P}$ is the rated charging power; SOC_{ex} is the user's expected charging state, and $SOC_{\max}$ is the maximum charging state of the electric vehicle. SOC_{fin} is the final state of charge of the electric vehicle.

5. Algorithm and example analysis

5.1. Improved Kepler optimization algorithm

This paper presents an improved KOA method based on dynamic orbit parameter adjustment. The core idea is to dynamically adjust the orbit radius and gravity intensity of the planet in the optimization process, so that the algorithm has different search capabilities in different optimization stages, so as to balance the global exploration and local development more efficiently.

The specific solution flow of the improved Kepler optimization algorithm is shown as follows:

- Generate random planets and candidate solutions.
- Setting the initial orbit parameters and dynamically adjusting the orbit radius can enhance the global search capability.
- The gravitational action is calculated. The gravitational intensity $\mu(t)$ is dynamically adjusted to keep a small value in the early stage, promote global search, increase in the late stage, and promote local convergence.
- Calculate the fitness value of each planet at its current position and update the orbital parameters. If a planet performs better in its current orbit than its previous optimal orbital position, update the center and radius of the planet's orbit.

According to the distance from the optimal solution, the orbit radius is dynamically adjusted, and the mathematical formula is as follows:

$$R_i(t+1) = R_i(t)\cdot\left(1-\frac{t}{T_{\max}}\right)^{\alpha} + \kappa\cdot\| X_i(t) - X_s(t)\| \text{ ....(21)}$$

Where, α is the parameter that controls the radius contraction rate and $T_{\max}$ is the maximum number of iterations.

In the course of orbital correction, the center of the planet's orbit brings it gradually closer to the current optimal solution, and the mathematical formula is as follows：

$$X_i\ (t+1) = \beta X_i\ (t) + (1-\beta) X_S(t) \text{ ....(22)}$$

Where, β is a smoothing factor that controls the rate of adjustment of the center of the track.

- Convergence judgment: If the convergence condition is met, the optimal solution is output. Otherwise, return to Step 3 to continue the iteration

5.2. Example analysis

In this paper, a residential area is taken as an example, and simulation verification is carried out on the MATLAB R2022b platform to ensure the effectiveness and feasibility of the proposed electric vehicle (EV) charge and discharge scheduling strategy in practical application scenarios. In the simulation environment, the intelligent charging device is set as the key equipment to control the charging and discharging state of the electric vehicle, and the power is supplied by four transformers with a capacity of 1600kVA, a power factor of 0.85 and a operating efficiency of 95% to ensure the high efficiency of the power supply. In terms of EV parameter configuration, the simulation model considers 545 electric vehicles, and the battery capacity of each vehicle is set at 56.75kW·h. In order to simulate the energy consumption under real driving conditions, the power consumption for 100 km is set at 20kW·h. In order to reflect the actual loss during the energy conversion process, the charge and discharge power is set to 7kW and the charge and discharge efficiency is 90%.

In the case of disorderly charge and discharge, the base load of the simulation example is shown in Figure 1, the charging demand of the electric vehicle is shown in Figure 2, and the time-of-use price data of the electric vehicle is shown in Table 1.

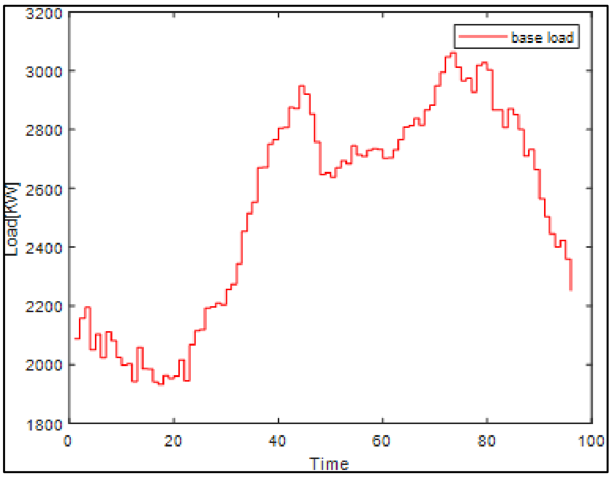

Figure 1 Base load diagram

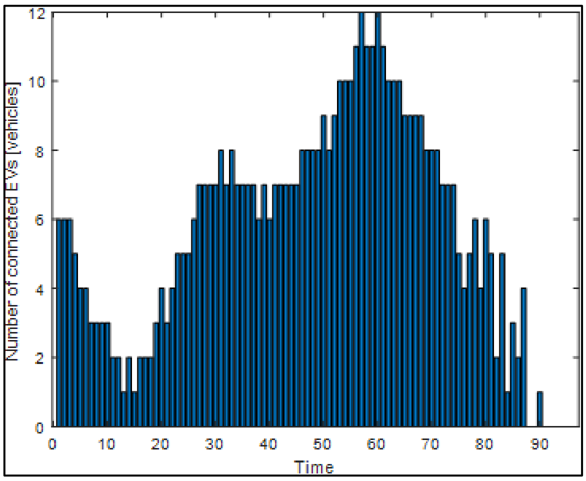

Figure 2 Electric vehicle charging demand diagram

Table 1 TOUT for EV Charging and Discharging

Item	Time period	Price/(Yuan/kWh)
Peak period	11:00-17:00;20:00-22:00	0.64
Parallel period	8:00-11:00 17:00-20:00 22:00-24:00	0.54
Valley stage	0:00-8:00 the next day	0.36

The topology of road weights generated according to the traffic delay function parameter table in Table 2 is shown in Figure 3. These weights reflect characteristics such as road congestion, flow, or traffic efficiency to some extent: a higher value of the edge may correspond to more traffic congestion or higher traffic costs, while a smaller value of the edge usually means better traffic efficiency.

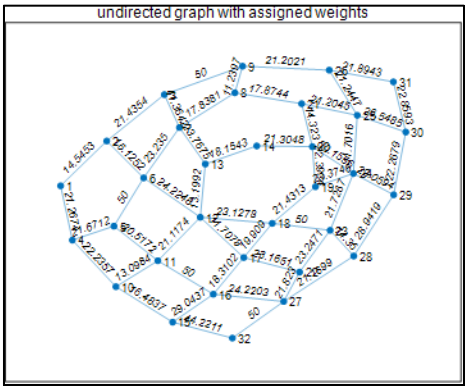

Figure 3 A road topology with weights

Table 2 Parameter values of traffic delay function

Speed limit class	c_1	c_2	c_3	c_4	p_1	p_2	p_3	p_4
fast	0.9526	1	3	3	0.0405	500	3	3
normal	0.9526	1	2	2	0.0405	500	2	2
Low speed	0.9526	1	1.5	1.5	0.0405	500	1.5	1.5

Figure 4 is the charging demand diagram of electric vehicles before optimization, and Figure 5 is the charging demand diagram of electric vehicles after optimization. It can be intuitively seen from the figure that before optimization, the charging demand of electric vehicles has a high peak value in some periods and nodes, and the distribution is obviously concentrated, which is easy to lead to the phenomenon of "sudden increase" of power load in a local period. After scheduling optimization, the overall charging demand tends to be more flat, and the peak value is significantly reduced and more evenly distributed in time and nodes, indicating that the optimization strategy adopted is effective in peak cutting and valley filling and balancing the load of each node. This will not only help reduce the pressure on the distribution network during peak hours, but also better meet the charging needs of the electric vehicle community.

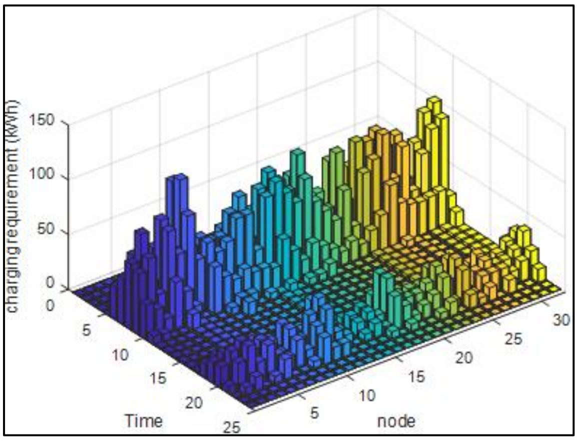

Figure 4 Optimize pre-EV charging requirements

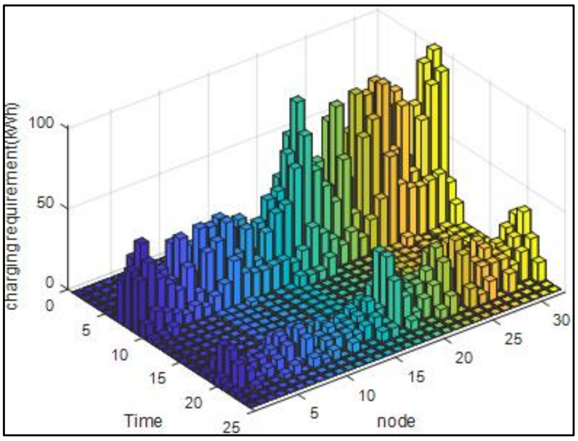

Figure 5 Optimized charging requirements for electric vehicles

Figure 6 is the load curve before and after optimization, and Figure 7 is the charge and discharge capacity diagram of electric vehicles at different periods. As can be seen from Figure 6, after optimization, the peak value of the system load has decreased, the trough has increased, and the overall curve is smoother, indicating that charge and discharge scheduling has achieved remarkable results in peak cutting and valley filling. Figure 7 shows the charging and discharging power of electric vehicles at different time periods: positive values indicate power injection into the grid, and negative values indicate energy absorption from the grid. By reasonably arranging the charging and discharging of electric vehicles in different periods, it can not only meet the energy demand of the vehicle itself, but also effectively smooth the load fluctuation of the grid.

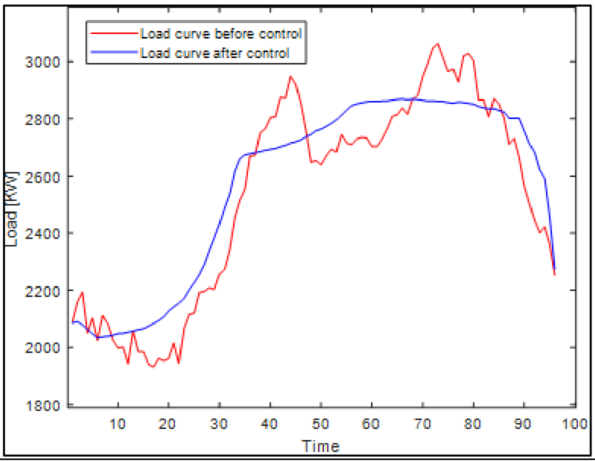

Figure 6 Load curves before and after optimization

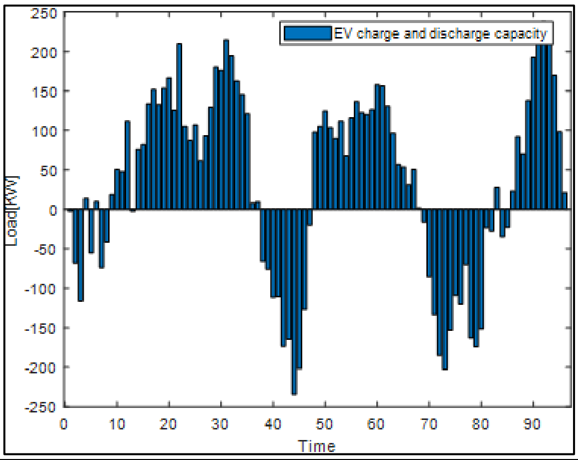

Figure 7 Charge and discharge amount of electric vehicle

Table 3 Comparison of different charging models

Item	Unordered charging	Ordered charging
Standard deviation of load fluctuation	672.3	463.2
Load curve Valley value/kW	1913.9	2078.2
Peak load curve/kW	3024.7	2844.7
Battery Depletion/CNY	391.7	193.5

As can be seen from Table 3, orderly charging significantly reduces the battery loss cost from 391.7 yuan to 193.5 yuan, indicating that the battery attenuation caused by deep and frequent discharge can be effectively alleviated through reasonable arrangement of charging and discharging periods. At the same time, the standard deviation of load fluctuation decreased from 672.3 to 463.2, and the peak load and valley load were optimized accordingly. Orderly scheduling not only reduced the battery maintenance cost of users, but also further smoothed the load fluctuation of the power system.

6. Conclusion

In order to improve users' participation in grid scheduling and balance battery health with grid load, this paper proposed a battery health evaluation method based on EV charging curve, and combined with dynamic traffic network model to monitor and predict the charge distribution of different charging stations in real time. By analyzing the changes of battery characteristics during charging and discharging, the health evaluation algorithm built can reflect the attenuation of battery more accurately, and avoid the anxiety of battery range and the decline of user stickiness caused by excessive discharge or unreasonable scheduling. In addition, with the real-time monitoring and prediction of the traffic network, the distribution of charging demand in each region can be mastered more accurately to better allocate power resources.In terms of charging strategy, this paper uses the Kepler optimization algorithm to solve, and the optimization goal focuses on the balance between battery health and grid load leveling. The simulation results show that the proposed method effectively reduces the peak load fluctuation, improves the scheduling flexibility and stability of the power grid under uncertain environment, and can reasonably predict and evaluate the battery health, thus providing a feasible technical scheme for the implementation of large-scale electric vehicle two-way interaction and power grid optimization scheduling.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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