



Local Self-Made Interactive Strategy for High Proportion of Vehicle-Optical Access Distribution Network for Vehicle-Optical Collaboration

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Abstract

This paper studies the local self-made interactive strategy for electric vehicles and photovoltaics connected, aiming to optimize operating network through the vehicle-light collaboration mechanism. As a distributed synergy between electric vehicles and photovoltaic power generation can provide regulation when the grid load fluctuates, improving the reliability and economy of the distribution network. Experiments show that the photovoltaic power output has a significant impact on the response of distribution network load. When the photovoltaic penetration rate increases from 10% to 25%, the photovoltaic output of the system reaches 8.2 MW at noon, and increases by 137% at lower penetration rates. During the peak load at night, the photovoltaic power output drops sharply, causing the equivalent load of the system to surge by 19.3%. By introducing a dynamic reactive power compensation device, the power factor of the photovoltaic inverter is increased from 0.95 to 0.98, which can effectively smooth the voltage fluctuation of the photovoltaic output to the power grid. Based on the above data analysis, the local self-made interaction strategy of vehicle-light collaboration proposed in this paper can achieve a high proportion in the context of renewable energy access, optimizing the dispatching and interaction of electric vehicles and photovoltaics not only effectively reduces power grid load fluctuations, but also improves the operating efficiency and reliability of the system. Especially under the high proportion of access, a reasonable dispatching strategy can balance to the maximum extent, reduce energy loss, and enhance the anti-interference ability of the power grid.

Keywords: Vehicle-light collaboration, Electric vehicles, Photovoltaic power generation, Distribution network.

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1. Introduction

With the acceleration of global energy transition and the increasing penetration of renewable energy sources, distribution networks face significant challenges in maintaining stability and efficiency. The integration of electric vehicles (EVs) and photovoltaic (PV) systems presents both opportunities and challenges for grid operation. This paper addresses the critical research gap in local self-made interaction strategies for vehicle-light collaborative distribution networks, which remains underexplored in existing literature. The key research problems investigated in this study include: (1) how to effectively coordinate EV charging/discharging with PV generation fluctuations at the local distribution level; (2) how to develop autonomous

interaction strategies that can mitigate grid instability caused by high penetration of intermittent resources; and (3) how to optimize the economic and technical performance of distribution networks through vehicle-light collaboration mechanisms.

With the acceleration of global energy transition, the development of distributed energy and smart grid has become future.^[1] In particularly, solar photovoltaics and Electric Vehicles (EVs), as representatives of green and clean energy, are gradually penetrating daily energy consumption.^[2] With continuous progress of photovoltaic power generation technology, the distribution network is facing unprecedented opportunities and challenges. How to effectively coordinate and manage these distributed resources to ensure the stability and efficient operation of the system has become a hot research topic at present.

In the context of a high proportion of electric vehicles and photovoltaic access, the research on vehicle-light synergy has gradually attracted attention.^[3] Electric vehicles are not only a means of transportation, but also have energy storage functions

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and can be used as a regulating resource for the power grid. At the same time, as a new energy source with high volatility, the output of photovoltaic power generation is affected by factors such as weather and time periods. How to effectively integrate the characteristics of these two resources to form a synergistic effect is the key to improving system. Key to energy efficiency. The strategy of vehicle-light collaboration can alleviate the problem of large volatility in photovoltaic power generation to some extent, and at the same time, provide charging and discharging scheduling methods for electric vehicles.

However, existing research has mostly focused on the macro level of vehicle solar collaboration, with insufficient attention paid to the autonomous interaction strategies between distributed photovoltaics and electric vehicles in the distribution network.^[4] This blank highlights three key issues: how to effectively coordinate the random charging and discharging of electric vehicles and photovoltaic output fluctuations at the local power grid level, avoiding blockage and voltage exceeding limits; How to build a decentralized and self-organizing collaborative strategy, achieve real-time autonomous response between distributed resources, and enhance system resilience; How to coordinate and optimize the technical and economic efficiency of the distribution network under high penetration rate access, ensuring stable, reliable, and economical operation. Solving the above problems is crucial for improving the operational efficiency and economic benefits of the distribution network.^[5] Localized autonomous interaction strategies can not only achieve self-regulation of regional energy, but also reduce the operating pressure of the power grid and enhance anti-interference capabilities.

The purpose of this paper is to discuss the local self-made interactive strategy of a high proportion of vehicle-light connected to the distribution network, study the mechanism and method of vehicle-light collaboration, and propose an optimization strategy based on the local area. By introducing intelligent interactive algorithms and combining the characteristics of electric vehicles and photovoltaic power generation, an efficient and stable local self-made interactive model is established, which provides future application vehicle-light collaboration in distribution networks.

2. Theoretical basis and related research

2.1 Research status of energy management optimization algorithms

Extensive research has been conducted on energy dispatch and management in the power grid. Various optimization methods have been applied to address the challenges in high penetration distribution networks for electric vehicles and photovoltaic systems. Mathematical optimization algorithms, including mixed integer linear programming, dynamic programming, and mixed integer nonlinear programming, have been widely adopted. This article utilizes MILP for optimizing vehicle optical collaborative systems and applies dynamic programming methods. On the other hand, intelligent optimization algorithms such as GA, PSO, SFLA, and ACO

have demonstrated strong performance in handling complex optimization problems with discrete variables and multiple constraints.

Extensive power grid energy dispatching management.^[6,7] Due to the diverse types of equipment connected to the distribution network, their models are not completely unified. When factors such as vehicle-light coordination, a high proportion of electric vehicles, and renewable energy access are considered, the problem models will also be quite different, thus affecting the selection of optimization algorithms. The main algorithms used in this field include mathematical optimization algorithms and intelligent optimization algorithms.

In the power system energy dispatch optimization model, there are usually a variety of constraints, including linear constraints and nonlinear constraints, and these constraints often make integer variables appear in the model.^[8] Aiming to address the optimal scheduling problem of a vehicle-optical cooperative system, various methods are proposed. Some studies employ a mixed-integer linear programming model and utilize a branch-and-bound algorithm based on linear programming to solve it, thereby achieving good results in calculation accuracy. Some studies solve the optimal scheduling problem through dynamic programming methods.^[9] In addition, some studies have proposed an MILP model for energy scheduling in vehicle-optical collaborative systems, highlighting that this model can be solved using existing commercial software. Another type of research proposes a mixed-integer nonlinear programming model for the thermoelectric optimal scheduling problem, which is solved using CPLEX's MIP and CONOPT's NLP solver in the GAMS software.

In addition to various traditional mathematical optimization methods, a series of intelligent optimization algorithms are widely used to solve energy management problems in vehicle-optical collaborative systems. Intelligent optimization algorithms mainly include Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Shuffled Frog Leaping Algorithm (SFLA), and Ant Colony Optimization (ACO).^[10] The advantage of an intelligent optimization algorithm lies in its powerful global optimization ability, which can deal with problems involving discrete variables. It does not require the solved problems to meet the conditions of continuity, derivability, and convexity, and usually does not need derivative information. At the same time, they are robust and simple to implement. These intelligent optimization algorithms have been widely used in the research on energy scheduling for the vehicle-optical cooperative systems.

In the research on optimization scheduling of vehicle light collaborative systems, traditional mathematical programming and intelligent algorithms are mainly used to solve mixed integer programming problems with discrete variables. Traditional methods such as mixed integer linear programming often use branch and bound methods to solve nonlinear problems, while commercial solvers such as CPLEX or

CONOPT can be used. At the same time, intelligent optimization methods such as genetic algorithms and particle swarm optimization are widely used due to their powerful global optimization capabilities, independence from problem gradient information, and ability to directly handle discrete variables.

In this paper, a vehicle-light collaborative dispatching optimizes the economic operation, aiming to dispatch vehicles load photovoltaic power generation.^[11] The model is a nonlinear programming problem with discrete variables, and it is solved using GA. Different optimization approaches have also been adopted in other related studies. In this paper, a scheduling strategy is proposed for the dispatching problem of a high proportion of electric vehicles and photovoltaics connected to the, to minimize the system operating cost, and an it. The model considers the constraints of combining conventional electric vehicles and photovoltaic systems, as well as specific constraint requirements. In addition, some studies have proposed an orderly charging optimization scheduling strategy for electric vehicle battery swap stations in the vehicle-optical collaborative system, aiming and smooth the load curve.

2.2 Research status of power grid energy management connected to electric vehicles

One of the main challenges of smart grid operation is how to effectively combine the emerging high-proportion vehicle-light synergistic system with traditional fuel-based power generation methods.^[12,13] With the rapid growth of electricity demand and the increasing concern for reducing dependence on fossil fuels to, the utilization of vehicle-light collaborative systems has become increasingly important, especially in smart grids.^[14] Although, such as electric vehicles and photovoltaic power generation, have been widely adopted, they are intermittent and have limited predictability. To solve this problem, the storage of electric energy has become an indispensable part of the smart grid and a key link to improving grid performance.

In the face of the global economic crisis, exhaust emissions, and rising oil prices, electric vehicles have gained more and more attention in recent years. Compared to traditional vehicles, electric vehicles are more energy-efficient and environmentally friendly, providing a low-cost transportation solution for urban traffic environments.^[15] In the near future, electric vehicles may provide economical and clean demand response services to the grid by feeding electrical energy back to the grid or regulating charging power, especially in high-proportion vehicle-light collaborative systems.

Electric vehicle charging is random in time and space, and the characteristics of charging load reflect its influence on the vehicle-optical collaborative distribution network, and this influence results in a change affected by the characteristics of charging load. The main factors the charge state, charging and discharging, etc. of electric vehicles.^[16] Some studies have adopted the PHEVs battery model in MATLAB to analyze the

charge and discharge behavior through Monte Carlo simulation, but the charge and discharge constraints are not considered;^[17] Some studies have proposed a two-stage Poisson distribution agglomeration model of electric vehicle charging stations in residential areas, but it does not involve V2G;^[18] Some studies use Monte Carlo method to calculate charging load and classify charging behavior;^[19] Some studies have also established battery replacement station models;^[20] some studies have established a free charging load model based on American data, taking, battery characteristics and driving habits;^[21] Furthermore, some studies have explored the effects loads without considering V2G.

Electric vehicles in the power grid are not only loads, but also power generation units, so higher requirements are put forward for their energy management. Research shows that charging loads vehicle-optical collaborative distribution network will have a profound impact on the planning, power market. Effective scheduling and control methods are crucial for minimizing negative impacts and maximizing the benefits of energy storage. Some studies discuss electric vehicle charging optimization to reduce grid losses, but do not consider V2G; Some studies have analyzed the matching and economy of electricity consumption before and after the addition of electric vehicles to minimize the total cost throughout the year, but have not considered the departure of electric vehicles at night and during working hours; There is also research and establishment of an electric vehicle-photovoltaic wind power collaborative dispatching model to analyze how to smooth grid load fluctuations and absorb excess wind power; Some studies have considered the uncertainty discharging power and renewable energy, and constructed stochastic optimal scheduling models. Existing studies mostly overlook and their response ability to energy management, and fail to allocate power according to the energy state of each electric vehicle. This may lead to battery overcharge or over-discharge, thereby affecting normal use and battery life.

3. Load characteristics and modeling of electric vehicles

As the basis for studying vehicle-optical collaborative distribution network and their participation in energy management, load is of great significance to the planning and operation of the power system.^[22] This chapter firstly analyzes the characteristics of electric vehicle load, and introduces the concept and mode of V2G. Then, on this basis, the electric vehicle is modeled, and the statistical model of driving simulation method based on this statistical model are studied.

3.1 Load characteristics of electric vehicles

The popularity of EVs has brought unprecedented challenges and opportunities to charging demand of has special load characteristics. First of all, the charging load of electric vehicles has a strong time period, and centralized charging usually occurs at night or during specific peak hours. This load mode may lead to fluctuations in power demand in local

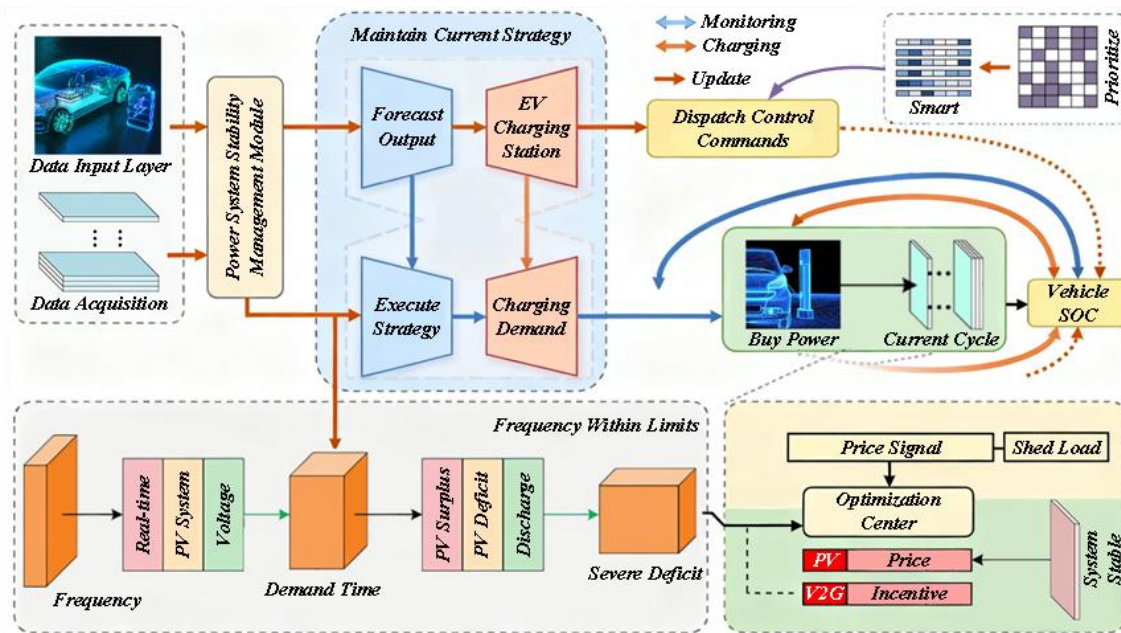


Fig. 1: Flow chart of electric vehicle charging load dispatching and power system stability management.

distribution networks, increasing the burden on the power Grid.^[23] Especially when a high proportion of electric vehicles are connected, the lack of effective dispatching and management strategies may pose a threat to the stability. The flow chart of electric vehicle charging load dispatching and power system stability management is shown in Fig. 1.

The solid lines represent power flows, including grid power supply, EV charging load, and photovoltaic output. The dashed lines represent control signal flows or logical decision processes, such as scheduling commands and stability feedback signals. Secondly, the load of electric vehicles has strong adjustability. Different from the traditional household appliance load, the charging process flexibly scheduled through intelligent charging control.^[24] For example, by setting the charging time window or dynamically adjusting load status of the grid, not only can the charging needs of electric vehicles be balanced, but the pressure on the grid can also be reduced. In addition, with the development of on-board energy storage technology, electric vehicles can not only charge but also discharge during peak load periods of the grid, and participate in load regulation and auxiliary services of the grid as energy storage resources, thereby achieving two-way load regulation. The charging power adjustment formula and the charging demand and grid load balancing formula are shown in Eq. (1) and (2).

$$P_c(t) = P_{c0} \times f(t, \Delta P_{net}, \Delta t) \tag{1}$$

$$P_{net}(t) = \sum P_{c,i}(t) + P_{base}(t) - P_{pv}(t) \tag{2}$$

here, $P_c(t)$ represents the charging power at time t , P_{c0} represents the initial charging power, $P_{net}(t)$ represents the net load of the distribution network at time t , which is calculated as the sum of all electric vehicle charging loads ($\sum P_{c,i}(t)$), plus the base load ($P_{base}(t)$), minus the photovoltaic output

($P_{pv}(t)$). This net load represents the actual power that needs to be supplied by the main grid after accounting for local generation and consumption. Eq. (1) is the dynamic adjustment basis for the charging power of a single electric vehicle. By adjusting the initial power and time period correction coefficient, the charging power can be adapted in real-time with the grid load, which is the basis for subsequent load balancing calculations. Eq. (2) quantifies the net load of the power grid after vehicle photovoltaic integration by superimposing all electric vehicle charging loads, base loads, and photovoltaic outputs, providing a direct calculation basis for the 'load balancing target' for charging scheduling optimization.

The charging needs of electric vehicles are closely related to factors such as driving range and charging station layout. In cities or areas with dense road networks, the charging demand of electric vehicles is dispersed, whereas in fixed locations such as parking lots and charging stations, the demand may be concentrated during peak periods.^[25] This type of load fluctuation presents numerous challenges to the distribution network, especially when a high proportion of electric vehicles are connected to it. Therefore, how to reasonably dispatch the charging load of electric vehicles in local areas has become an important issue in power system optimization, dispatching, and load management. The formula of the relationship between charging station demand and layout is shown in Eq. (3).

$$P_{station}(t) = \sum_{i=1}^n f(L_i, D_i) \tag{3}$$

here, $P_{station}(t)$ represents the total charging demand of the charging station at time t , L_i represents the position of the charging station i , and D_i represents the number or capacity of charging facilities of the charging station i . Eq. (3) combines

the location of charging stations and facility capacity to calculate the centralized charging load within the area, which is used to determine the "charging station cluster charging and discharging priority" in the vehicle light coordination scheduling.

Finally, the load characteristics of electric vehicles are also affected by climate change and, in the hot summer, electric vehicles may increase, increasing by charging load; The change of electricity price may guide users to choose to charge during the period of low electricity price, and the volatility of this behavior further aggravates the uncertainty of load.^[26] Therefore, optimizing the charging dispatching strategy volatility according to the charging behavior characteristics of electric vehicles, combined with climate change and electricity price fluctuations, is an important issue that must be considered when a high proportion of electric vehicles are connected to the distribution network. The objective function formula of charging scheduling optimization is shown in Eq. (4). The real-time photovoltaic output calculated by Eq. (4) ($P_{pv}(t)=G(t) \times A \times \eta_{pv}$) is the core input variable for optimizing charging scheduling. When there is an excess photovoltaic output sum the excess electricity; When the photovoltaic output suddenly decreases (such as $G(t) \approx 0$ at night), the scheduling strategy triggers electric vehicle discharge to compensate for the load gap, ultimately achieving the optimization goal of "smoothing load fluctuations". ($P_{pv}(t)$ is large), the scheduling strategy prioritizes guiding electric vehicles to charge and co

$$P_{solar}(t) = G(t) \cdot A \cdot \eta_{pv} \tag{4}$$

where $G(t)$ represents the light intensity, A represents the effective area of the photovoltaic panel, and η_{pv} represents the conversion efficiency of the photovoltaic panel. Through in-depth analysis of the load characteristics of electric vehicles, it can provide data support and theoretical basis for the charging

of electric vehicles and improves energy efficiency.

intelligent dispatching of distribution network and the design of vehicle-light collaborative strategy. Effective load management can not only ensure that the charging needs of electric vehicles are met, but also minimize the pressure on grid operation and improve the reliability and operating efficiency.

3.2 V2G technology

V2G technology utilizes the energy storage capabilities of a large number of electric vehicles as a buffer for the vehicle-light collaborative distribution network and renewable energy sources. When the power grid load is low, use electric vehicles to charge to avoid the waste of excess power in supply is unstable or peak, electric vehicles serve as energy storage units to feed power to the grid and share the grid pressure.^[27]

As shown in Fig. 2, the charging and discharging power of the electric vehicle population exhibits significant fluctuations at different time periods. In the first half of the chart, the vehicle power reaches its peak, reaching a maximum of nearly 25 kW, while the battery charging state remains at a low level, about 20%. The power control curve effectively regulates power fluctuations during this period, ensuring that the battery is not overcharged and the grid load is reasonably balanced. As time progresses to the latter half, the charging status of the battery gradually increases, the power output tends to stabilize, and the grid power gradually takes over more charging tasks, with a maximum power of around 35 kW. The load curve shows a relatively gentle fluctuation, reflecting the gradual adaptation and stable operation of the power grid load. This process demonstrates that through the strategy of vehicle light coordination, the charging and discharging power regulation of the electric vehicle population can be effectively matched with the demand of the power grid, which not only avoids the overload of the power grid, but also ensures the normal

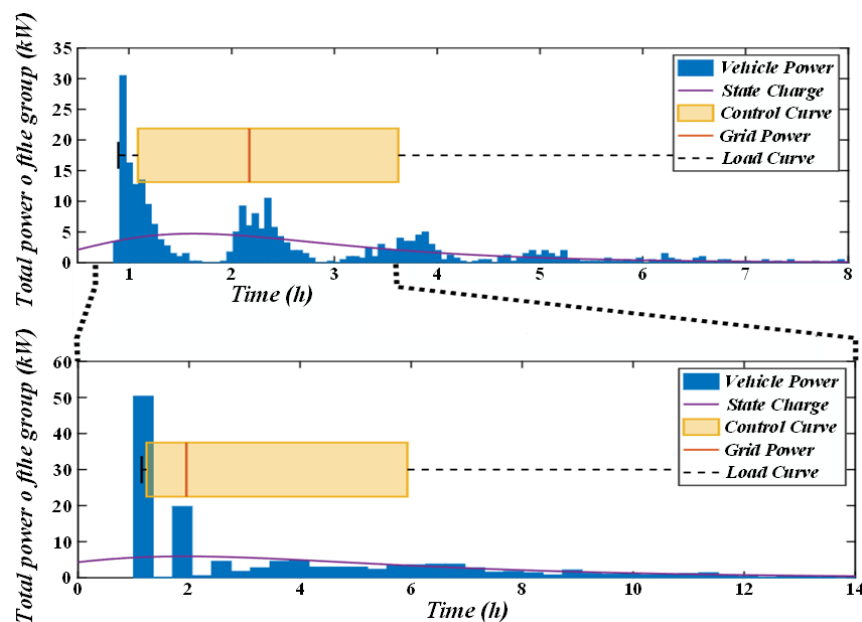


Fig. 2: Schematic diagram for optimizing and regulating the charging and discharging behavior of electric vehicles.

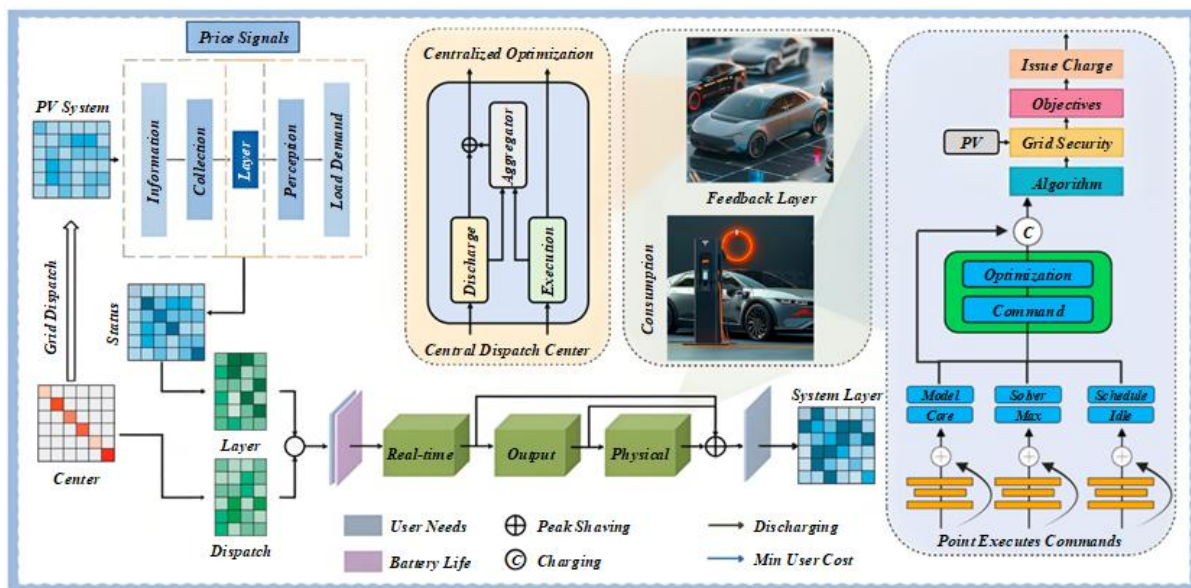


Fig. 3: Flow chart of electric vehicle energy scheduling and management in centralized V2G mode.

Centralized V2G mode refers to gathering multiple electric vehicles in a specific area, connecting them to a vehicle-optical collaborative distribution network as a whole, and performing unified energy dispatching according to the power grid's requirements. This mode also coordinates and controls processes of each electric vehicle through specific management strategies. Because this model uniformly dispatches and centrally manages several electric vehicles, it increases the capacity available for dispatch, achieves overall optimization, and of the power grid. It is usually used in charging stations or large parking lots. The energy management strategy research in this paper is based on the centralized V2G model. Fig. 3 is a flow chart of electric vehicle energy scheduling and management in centralized V2G mode.

The V2G mode based on battery replacement is derived from the energy supply mode of battery replacement and is usually used in electric vehicle battery swap stations. In the battery swap station, a large number of power batteries are stored, some of which are used for the replacement of electric vehicles, and the remaining batteries can be integrated into the vehicle-optical collaborative distribution network in a centralized manner. This method is similar to centralized V2G. It does not require electric vehicles directly, nor does it affect their normal driving. It is easy to operate and has broad application prospects, but it still needs to solve the standardization problem of electric vehicles and batteries.

3.3 Electric vehicle modeling

Given that lithium-ion battery technology is widely used in current electric vehicle power battery systems, this study focuses on exploring the charging and discharging characteristics of lithium-ion batteries. Although there are individual differences in the actual charging curves of different types of batteries, their overall trend shows significant consistency. According to the stability of charging power and

the proportion of third stage charging shown in Fig. 4, it can be observed that the charging power shows a stable characteristic during the main period of the power battery charging process. Among them, CST represents charging stability, TCR represents the proportion of third stage charging, SOC represents the state of charge of the battery, and CCV represents the change in charging current. When the battery's state of charge is between 20% -40%, CST begins to stabilize with a charging power of approximately 6 kW. As SOC increases, the charging power continues to decrease and remains at a lower level within the SOC range of 60% -80%. The TCR during this process is relatively small, accounting for about 15% -20% of the total charging process, indicating that electric vehicle users generally start charging operations when the battery's state of charge is low. Based on the consideration of symmetry in the charging and discharging process, existing research generally adopts the assumption model of constant charging and discharging power. It is worth noting that electric vehicle users usually only perform charging operations when the battery is in a low state of charge. To ensure the normal use needs of the vehicle, the third stage charging process accounts for a relatively small proportion in practical applications.^[28-29]

Due to the limitation of battery capacity and power, electric vehicles are generally suitable for short-distance and small-range driving. According to modeling analysis, private cars follow a normal distribution pattern of morning and evening peak hours when traveling to and from the office area on weekdays, and return to residential charging points with similar characteristics. Due to the lack of significant differences in usage value between electric vehicles and traditional vehicles, their travel characteristics can be analyzed by referring to traditional vehicle data. The formula of the grid loss model is shown in Eq. (5).

$$P_{loss} = \sum_{i=1}^N R_i \cdot I_i^2 \tag{5}$$

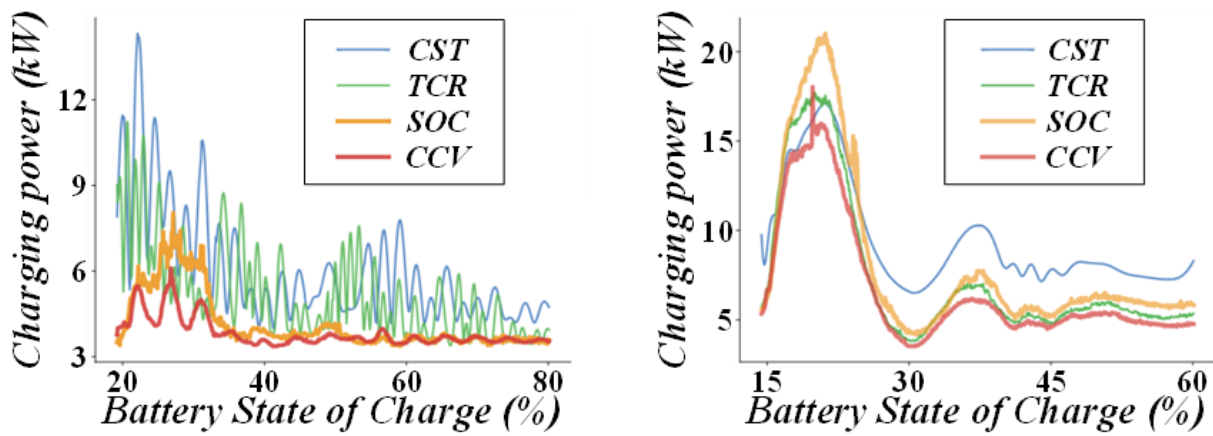


Fig. 4: Stability of Charging Power and Proportion of Third Stage Charging.

Among them, P_{loss} represents the grid loss, R_i represents the resistance of the i segment of the grid, I_i represents the current of the i segment of the grid, and N represents the number of grid segments. Therefore, given the battery power, daily mileage and hourly distribution of the electric vehicle, the power consumed be calculated. When not driving, electric vehicles can participate in the dispatching of the vehicle-optical collaborative distribution network. Because a high proportion of electric vehicles will be suspended most of the time, it is possible to dispatch electric vehicles optimization management of the power grid.^[30] Assuming that there are N electric vehicles in the vehicle-optical cooperative distribution network studied, the relationship between the number N of electric vehicles that can be dispatched at each time of the day and the probability G of stopping is shown in Eq. (6):

$$N_d(t) = N * G(t) \tag{6}$$

Among them, $N_d(t)$ represents the number of dispatchable EVs at time t , and N represents the number of samples. The initial state of charge SOC0 of different electric vehicles is different, but it can be expressed as a function of the state of charge SOC1 after the previous charge and the driving range. The functional relationship is as shown in Eq. (7):

$$SOC_0 = SOC_1 - \frac{L}{S} \tag{7}$$

Among them, L represents the driving mileage after the previous charge; S is the mileage that an electric vehicle can travel on a full charge.

To accurately simulate the travel behavior of electric vehicles, this study established a statistical model consisting of two parts: departure time and daily driving distance based on actual data: departure time follows a log normal distribution, the morning peak parameter corresponds to a travel peak of about 8:30, and the evening peak parameter corresponds to a concentrated return of about 17:45; The daily driving distance follows a Weibull distribution with shape parameter $k=2.3$ and scale parameter $\lambda=40.5$. This model generates typical electricity consumption scenarios through Monte Carlo simulation, providing a basis for analyzing charging demand and V2G scheduling potential.

3.4 Simulation method based on statistical model and calculation model of free charge

The Monte Carlo Method is a statistical method for estimating mathematical functions based on random sampling and random simulation. The basic solution idea is: according to the statistical law of physical phenomenon itself, or artificially construct a suitable probability model depending on random variables, so that the statistics of some random variables are solutions with solving problems. The Monte Carlo method is based on the following two theories:

1. Law of large numbers: In the domain $[a, b]$, the function $f(x)$ randomly extracts N numbers with a uniform probability distribution, and the arithmetic mean of the function converges to the expected value of the function. After enough samples are randomly selected, the Monte Carlo estimate of the vehicle-optical cooperative distribution network will converge to the correct result of this estimate, and the formula of the Monte Carlo estimate is shown in Eq. (8). Where N represents the number of samples, $f(x_i)$ represents the function value, and x_i represents the i sample point.

$$\hat{I}_N = \frac{1}{N} \sum_{i=1}^N f(x_i) \tag{8}$$

2. Central limit theorem: The random variable accumulated by a large number of weak factors obeys a single normal distribution. The error c of Monte Carlo method depends on the standard deviation σ and the number of samples N , and is proportional to the standard deviation and inversely proportional to the square root of the number of samples. The error formula of Monte Carlo method is shown in Eq. (9).

$$Error(N) = c \cdot \frac{\sigma}{\sqrt{N}} \tag{9}$$

where $Error(N)$ represents the estimation Error of the Monte Carlo method, c represents the constant factor, σ represents the standard deviation, and N represents the number of samples. The Monte Carlo estimation error bound formula is shown in Eq. (10).

$$Error(N) \leq \frac{\sigma}{\sqrt{N}} \tag{10}$$

where $Error(N)$ represents the Error of Monte Carlo estimation, σ represents the standard deviation of random variables in the estimation problem, and N represents the number of samples.

The simulation calculation steps of Monte Carlo method include constructing or describing the probability process, sampling from known probability distributions, and establishing various estimators. The specific methods are as follows:

(1) Constructing or describing probabilistic processes

For problems with randomness, it is mainly to correctly describe and simulate the probabilistic process; If the event itself is not a random problem, it is necessary to generate an artificial probability model in advance to simulate the process when simulating this process, and use statistical methods to characterize the digital characteristics of the model, that is, the problem without randomness is simulated as a random process.

(2) Sampling from a known probability distribution

According to the constructed probability distribution model, the random variables obeying the known probability distribution are generated on the computer, and then a sufficient number of random numbers needed for a simulation process is realized. This is the basic means to realize the simulation experiment of Monte Carlo method, and it is also the reason why this method is called random sampling. Obeying a certain probability distribution, which constitutes a simple sample. The random sampling formula of the Monte Carlo method is shown in Eq. (11).

$$S_N = \frac{1}{N} \sum_{i=1}^N f(X_i) \quad (11)$$

Where S_N denotes the expected value or integral value estimated by the Monte Carlo method, N denotes the number of samples randomly sampled, $f(X_i)$ denotes the value of the objective function at the i random variable X_i , and X_i denotes the i random variable generated from a known probability distribution.

(3) Building various estimators

After the probabilistic model is constructed and sampling is completed, the random simulation experiment is completed. Next, it is necessary to determine an unbiased estimated random variable as a solution to solve the problem. By establishing various estimators and using the results of simulation experiments, the solution of the problem is finally obtained.

In the vehicle light collaborative optimization framework proposed in this study, Monte Carlo simulation is used to handle the uncertainty of electric vehicle charging behavior. By setting a probability distribution and implementing random sampling, representative charging demand scenarios and error boundaries are generated as inputs for the optimization model. This method can evaluate multiple random scenarios and support the optimization model to develop robust scheduling strategies under charging constraints, photovoltaic output, and grid safety conditions, effectively improving the stability and operational efficiency of the grid in uncertain environments.

This study uses Monte Carlo simulation to generate random samples of electric vehicle charging behavior, with sampling parameters including starting time, initial SOC, and charging power. Based on 1000 sets of samples covering different penetration scenarios, it reflects the actual charging uncertainty; On this basis, a vehicle light collaborative optimization model is constructed with the goal of minimizing system operating costs and load fluctuations. At the same time, multiple constraints such as electric vehicle charging and discharging, photovoltaic output, and safe operation of the power grid are comprehensively considered to simulate and analyze the collaborative scheduling effect under various user behaviors. This study refers to the "Guidelines for Stability Evaluation of Distribution Network Operation" (DL/T 1970-2021) and defines the stability coefficient K_s to comprehensively evaluate the degree of voltage, current, and frequency fluctuations. The formula is shown in Eq. (12):

$$K_s = 1 - [(\Delta U/U_n) + (\Delta I/I_n) + (\Delta f/f_n)]/3 \quad (12)$$

Among them, ΔU represents the amplitude of voltage fluctuation, U_n represents the rated voltage, ΔI represents the amplitude of current fluctuation, I_n represents the rated current, Δf represents the amplitude of frequency fluctuation, and f_n represents the rated frequency.

4. Experimental results and analysis

Local self-made interactive strategy of a high proportion of vehicle-light connected to the distribution network based on vehicle-light collaboration is studied experimentally, which mainly uses the power generation data of vehicle-mounted photovoltaic systems, status data running status data of the distribution power load forecasting data. In the experiment, a high-precision smart meter, a data acquisition system, and a real-time monitoring platform are utilized for data acquisition. MATLAB/Simulink power system simulation software is employed for modeling and algorithm simulation. To ensure the efficiency and accuracy of experimental data processing, the experiment is also equipped with a high-performance computing server for large-scale data processing and model calculation. In addition, the application of a vehicle-optical collaborative scheduling optimization platform provides important support for strategy optimization, ensuring that the experiment has high operability and reliability in the actual effect analysis of the vehicle-optical collaborative strategy.

4.1 Grid stability under different vehicle-optical access ratios

This system has built a distribution network architecture that includes two levels of voltage: 35kV/10kV. The main network is connected to the 35kV busbar, and power is supplied to residential and commercial areas through two 10kV feeders. Configure photovoltaic power stations with a total installed capacity of 5MW in the system, distributed at the end of the feeder line and next to the charging station; Two charging stations are connected to a total of 200 electric vehicles, each

Table 1: Analysis of power grid stability under different access ratios of vehicle-optical collaboration.

Access ratio (%)	Stability coefficient	Voltage fluctuation amplitude (V)	Current fluctuation amplitude (A)
10%	0.92	5.5	3.2
30%	0.89	8.1	5.7
50%	0.85	10.3	8.4
70%	0.79	12.6	10.1

with a battery capacity of 50kWh and a charging power range of 5-15kW. Key monitoring points are set at the end node of the 10kV feeder line 2 and the charging station connection branch to track voltage and current fluctuations. The basic load of the system covers typical periods such as early peak of 8MW, noon peak of 5MW, and late peak of 12MW, which, together with parameters such as photovoltaic conversion efficiency and line resistance, form the simulation basis for vehicle photovoltaic collaborative optimization. The power grid stability analysis under different access ratios of vehicle-optical collaboration is shown in Table 1.

Vehicle-optical coordinated access, the stability coefficient of the power grid gradually decreases, indicating that a high proportion of access may hurt the power grid's stability. Especially when the access ratio reaches 70%, the stability coefficient decreases to 0.79, which shows that the voltage and current fluctuation amplitude of the system increases significantly under the high proportion of vehicle light access, which may lead to greater fluctuations in the power grid,

especially when the voltage fluctuation amplitude is close to 12.6 V.

To quantify the stability of the power grid under different vehicle to light access ratios, three key indicators were studied: stability coefficient K_s , voltage fluctuation amplitude, and current fluctuation amplitude. The latter two are defined as the maximum deviation of voltage and current relative to the rated value during steady-state operation of key monitoring nodes, namely $\Delta U = |U_{max} - U_{min}|$, $\Delta I = |I_{max} - I_{min}|$. All indicators are based on real-time monitoring platform sampling data at 1-second intervals and measured in different access ratio scenarios.

To demonstrate power changes on the load response of the explore the system operation when a high proportion of photovoltaics is connected, this paper analyzes the impact of different photovoltaic power outputs on the load response of the distribution network, and the results are shown in Fig. 5.

Specific data shows that the 'negative net load' in the curve indicates that the photovoltaic output is greater than the base

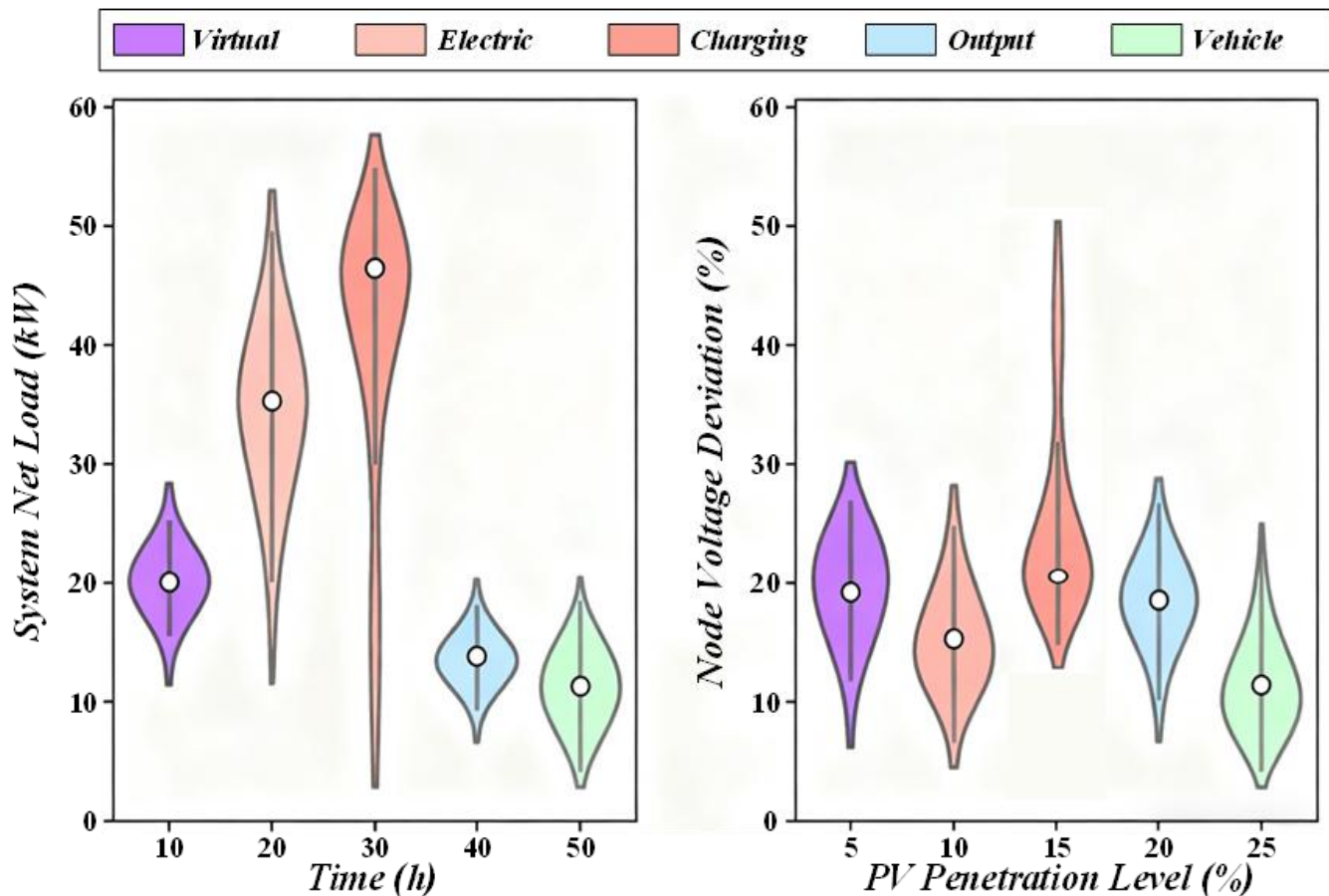


Fig. 5: Net load response curve of distribution network under different photovoltaic penetration rates.

load+charging load, and needs to be consumed through electric vehicle charging; 19: At 00, due to a sudden decrease in photovoltaic output (≈ 0) and the electric vehicle entering a peak charging period, V2G discharge scheduling needs to be triggered to smooth out fluctuations. When the photovoltaic penetration rate increases from 10% to 25%, the load peak-valley difference of the distribution network shows significant nonlinear changes: during the peak photovoltaic output period at 12:00 noon, the system's reverse power flow reaches 8.2 MW at 25% penetration rate, an increase of 137% compared with the 10% penetration rate, causing the 35kV bus voltage to rise to 1.07 p.u., exceeding the national standard $\pm 5\%$ limit; During the peak load period at 7:00 p.m., the sudden drop in photovoltaic output in high penetration scenarios caused the equivalent load of the system to surge by 19.3%, and the voltage at the end of the 10kV feeder dropped to 0.92 p.u., triggering the transformer overload protection action. It is worth noting that when the dynamic reactive power compensation device is used to adjust the power factor of the photovoltaic inverter from 0.95 to 0.98 ahead of time, the voltage fluctuation range during 12:00 is reduced to 1.03-1.05 p.u., and the system network loss during 19:00 is reduced from 7.8% to 5.3%, which verifies that the reactive power control of the photovoltaic inverter in vehicle-optical coordination can effectively suppress the voltage exceeding limit problem caused by high proportion of access. The load deviation of the power grid is shown in Eq. (13).

$$\Delta P = |P_{actual} - P_{forecast}| \tag{13}$$

The reliability of power supply is shown in Eq. (14).

$$Reliability = \frac{T_{operation} - T_{fault}}{T_{operation}} \times 100\% \tag{14}$$

To analyze the regulating effect of vehicle-mounted battery energy storage on distribution network load fluctuations and evaluate its efficiency under the access of a high proportion of renewable energy, this paper compares the regulating effect of vehicle-mounted battery energy storage on distribution network load, and the results are shown in Fig. 6.

Among them, VBE represents on-board battery energy storage, CPS represents charging and discharging power strategy, VFG represents vehicle-to-grid frequency modulation, and BSS represents battery energy storage system. According to the data chart, in the vehicle-light collaboration scenario, the adjustment effect of vehicle-mounted battery energy storage and conventional power supply under different operating parameters is significantly different: the figure on the left shows that when the operating parameter of VBE is about 3.5, the power output of the electric vehicle battery reaches the peak value. About 65kW, significantly higher than the output of CPS, indicating that the energy storage system has stronger discharge capabilities during peak load periods; The figure on the right further shows that when the load peak-to-valley difference reaches about 60kW, the adjustment time of VBE is significantly shorter than that of traditional fuel generators and building energy storage systems, and its response time is concentrated in a shorter range, indicating that vehicle-mounted energy storage can respond more quickly. Load changes effectively smooth the load curve of the distribution network and improve system operation stability.

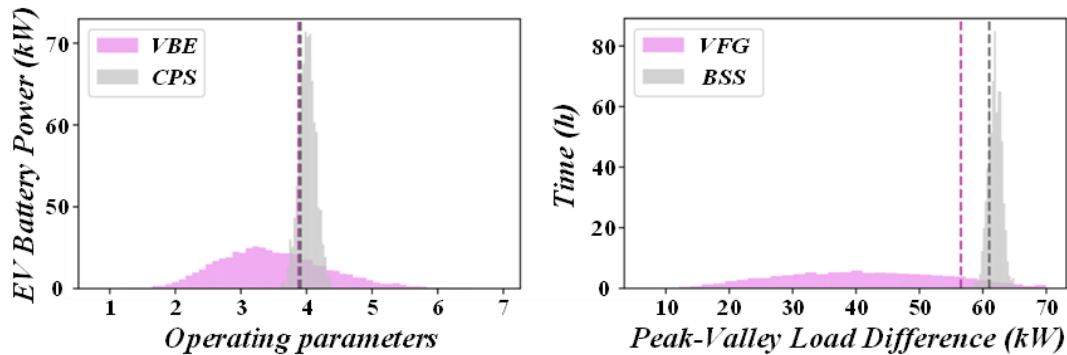


Fig. 6: Regulating effect of vehicle battery energy storage on distribution network load.

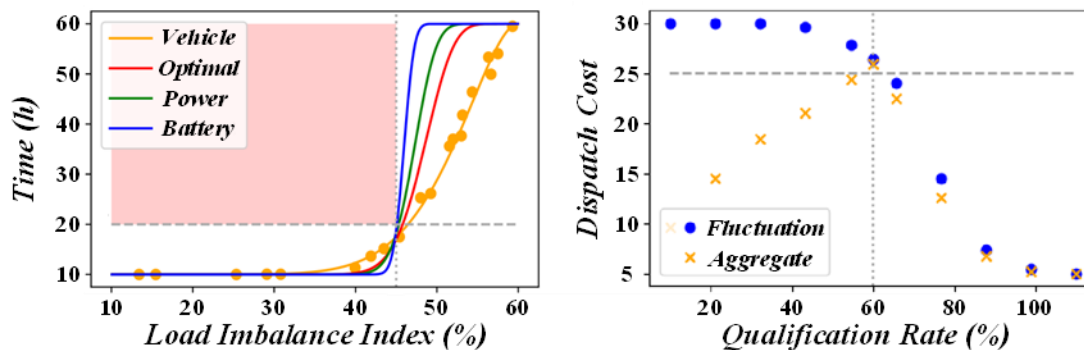


Fig. 7: Impact of collaborative optimal dispatching of photovoltaic and vehicle batteries on load balance of distribution network.

4.2 Impact of photovoltaic penetration on distribution network operation

To optimize the scheduling algorithm and demonstrate the impact of photovoltaic and vehicle battery collaboration on load balance, this paper analyzes the effect of collaborative optimal scheduling between photovoltaic and vehicle batteries on the load balance of the distribution network, as shown in Fig. 7.

It can be seen from the figure that in the vehicle-light collaborative optimization scheduling, with the increase of the load imbalance index, the vehicle response time is initially low but rises rapidly, and the optimization strategy can effectively suppress this upward trend. When the load imbalance index reaches 50%, the optimization strategy controls the response time within about 20 hours, which is more stable than simply relying on battery or power supply power adjustment; In terms of qualification rate, when the qualification rate exceeds 60%, the fluctuation cost in the dispatching cost is significantly reduced to close to 5, and the aggregation cost also tends to be stable, indicating that a high proportion of vehicle-optical collaborative optimization dispatching can effectively reduce the cost caused by load imbalance and improve the load balancing level of the distribution network. The impact of local self-made interaction strategy on power grid load response is shown in Table 2.

From the data in the table, it can be seen that with the increase of load change rate, the response time of local self-made interactive strategy also shows an increasing trend. Specifically, when the load change rate increases from 5% to 20%, the response time increases from 15 seconds to 24 seconds, indicating that under high load changes, the response

capability of the power grid will be limited to some extent. In addition, power grid load deviation and power supply reliability will also have a negative impact with the increase of load changes, especially the power supply reliability will drop significantly, with a maximum drop of nearly 5%.

In order to analyze the impact of different photovoltaic access ratios on the reliability of distribution network, especially at peak load, this paper analyzes ratios on the reliability of distribution network, and the results are shown in Fig. 8.

From the figure, it can be seen that in the simulation, this article simulated a distribution network fault event, with a fault clearing time set to 50-150s, to evaluate the impact of photovoltaic access on the success rate of recovery, that under the background of vehicle-light collaboration, with the increase of photovoltaic penetration rate, the fault interruption frequency and fault recovery success rate of the distribution network show different trends. When the photovoltaic penetration rate is in the range of 25%-50%, the reliability data points are relatively concentrated, and the interruption frequency is roughly between 20%-40%, while the interruption frequency in microgrid mode is relatively scattered, with some points as high as about 70%; In terms of fault recovery success rate, when the fault clearance time is within the range of 50-150 seconds, the success rate corresponding to reliability is mostly 30%-60%. The success rate in microgrid mode is widely distributed, and some can reach more than 70%. It shows that reasonable control of the photovoltaic access ratio can help improve the reliability of the distribution network, and the microgrid mode has great differences in fault response performance under different photovoltaic penetration rates.

Table 2: Impact of local self-made interaction strategy on power grid load response.

Load change rate (%)	Local self-made response time (s)	Grid load deviation (kW)	Power supply reliability (%)
5%	15	3.2	98.4
10%	18	5.8	97.1
15%	21	7.5	95.3
20%	24	9.3	93.8

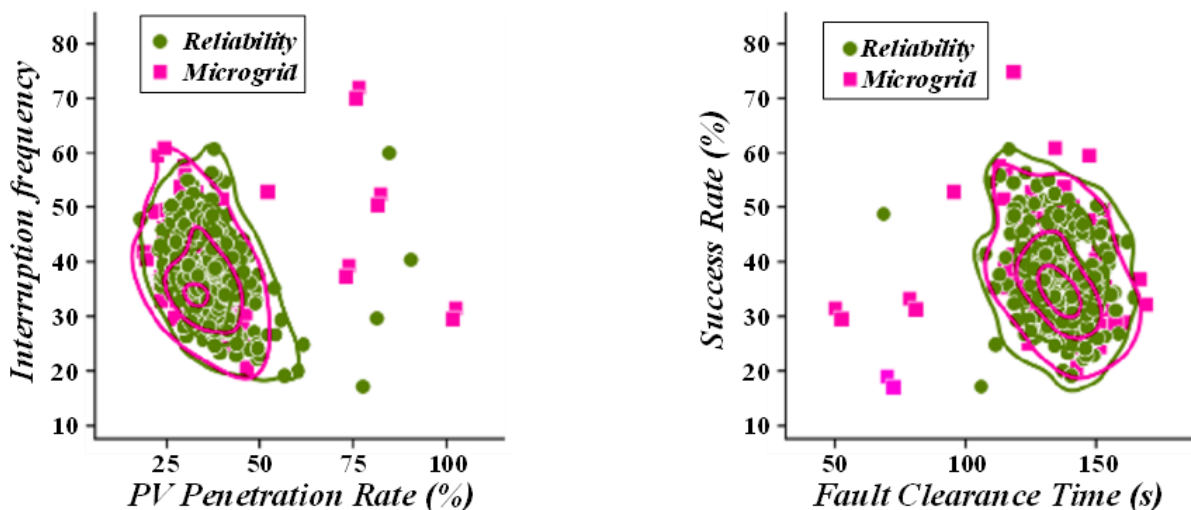


Fig. 8: The impact of photovoltaic access ratio on the success rate of fault recovery in distribution networks.

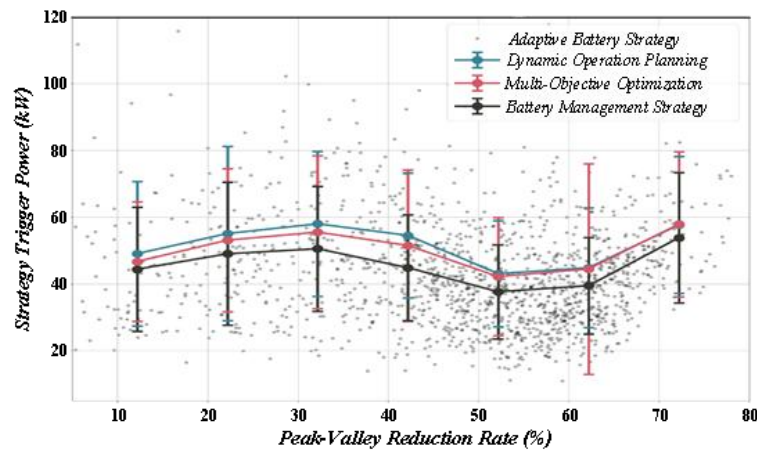


Fig. 9: Charging and discharging strategies of vehicle batteries under different load conditions.

In order to show vehicle batteries under different load conditions and analyze their contribution to power grid stability, this paper analyzes the charging and discharging strategies of vehicle batteries under different load conditions, and the results are shown in Fig. 9.

Data analysis shows that under the scenario that a high proportion of vehicle-light collaboration is connected to the distribution network, when the load peak-to-valley difference rate is in the range of 10%-80%, the strategy trigger power of the adaptive battery strategy is concentrated at around 50-60kW, and the dynamic operation planning is similar but fluctuates slightly; The trigger power of the multi-objective optimization strategy is slightly lower and relatively stable, about 55kW; The trigger power of the battery management strategy is the lowest, about 45kW, and the data points of each strategy are discrete to a certain extent. The error bar shows its fluctuation range, indicating that different strategies have different regulation effects on vehicle battery charging and discharging under different peak-valley difference rates.

In order to show the fluctuation of photovoltaic power generation under different meteorological conditions and analyze, this paper analyzes the fluctuation under different meteorological conditions, and the results are shown in Fig. 10.

The data shows that in the context of coordinated vehicle-light access to the distribution network, photovoltaic output power and volatility are significantly affected by total solar irradiance and fluctuation density. The figure on the left shows

that when the total solar irradiance changes in the range of 10-80W/m², the photovoltaic output power under actual weather conditions fluctuates periodically, with a peak value of about 75kW, and the power fluctuation corresponds to it; The figure on the right shows that when the fluctuation density is about 2-7, the volatility varies in the range of 40%-70%, and the volatility after smoothing is significantly reduced. For example, the volatility after smoothing at the red arrow decreases from about 65% to about 50%, indicating that meteorological conditions have a greater impact on the stability of photovoltaic power generation, and the smoothing strategy can effectively reduce its fluctuation. The comparison of the cooperative optimization effects of off-bus light under different access strategies is shown in Table 3.

The table shows that the high-efficiency vehicle-optical collaboration solution has shown obvious advantages in optimizing grid efficiency, and the grid efficiency has increased by 7%. Among them, the minimum power loss is reduced from 250kWh to 200kWh, showing the effective reduction of power loss by vehicle-light coordination. At the same time, the maximum load fluctuation has also been reduced, indicating that the efficient vehicle-optical collaboration strategy has played a positive role in reducing the burden and fluctuation of the power grid. After the introduction of local interaction strategy, the optimization effect is further enhanced, especially in load fluctuation control and power loss reduction.

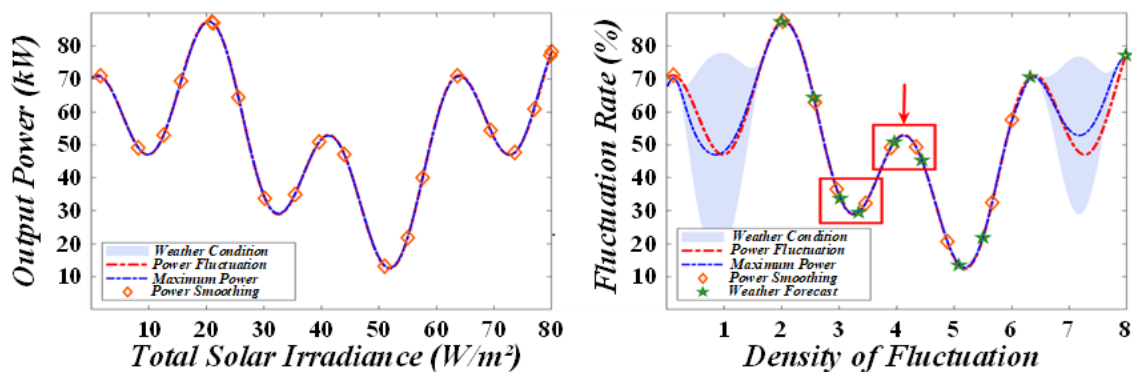


Fig. 10: Analysis of photovoltaic power generation fluctuation under different meteorological conditions.

Table 3: Comparison of optical collaborative optimization effect of different access strategies.

Access policy	Optimized grid efficiency (%)	Maximum load fluctuation (kW)	Minimum electrical energy loss (kWh)
Traditional access	85	15.3	250
Efficient vehicle-light collaboration	92	12.7	220
Efficient vehicle-light collaboration + local interaction	95	10.2	200

In order to demonstrate the accuracy of load forecasting under vehicle-light cooperative scheduling and evaluate the reliability of the forecasting model in practical application, this paper analyzes the accuracy of load forecasting under vehicle-light cooperative scheduling, and the results are shown in Fig. 11.

It can be seen from the figure that in the dispatching scenario of vehicle-optical collaborative access to the distribution network, the load forecasting errors and confidence intervals of different strategies behave differently with the change of forecasting conditions. In the percentage error diagram, the peak error of each strategy is concentrated around 30%-40%, and the error of collaborative strategy is relatively low; In the time domain diagram, as the time range changes from 1 hour to 9 hours, the confidence interval width of each strategy shows a trend of first increasing and then decreasing, reaching a peak of about 25-30kW in about 3 hours, indicating that under vehicle-light collaborative scheduling, different strategies have differences in load forecasting accuracy on different time scales, and collaborative strategies

help to improve forecasting accuracy.

In order to study the change of power system frequency stability under the situation of high, this paper analyzes the frequency stability of power system under high proportion of photovoltaic access, and the results are shown in Fig. 12.

The figure shows that the system frequency stability is affected by the initial value of the system frequency and the disturbance scale in the case of vehicle-optical coordinated access to the. When the system frequency is in the range of 10Hz to 90Hz, the distribution of frequency and integrated data points shows that the frequency fluctuation range of the system is roughly within ± 2 s at different initial frequencies; When the disturbance scale increases from 0MW to 70MW, the frequency value is relatively stable at a low disturbance scale, fluctuating around 5-10Hz. As the disturbance scale increases, the frequency fluctuation intensifies, but the overall situation remains within a certain range, indicating that with a high proportion of photovoltaic access, the power system has certain frequency stability capabilities under different working conditions, but it is also affected by the disturbance scale.

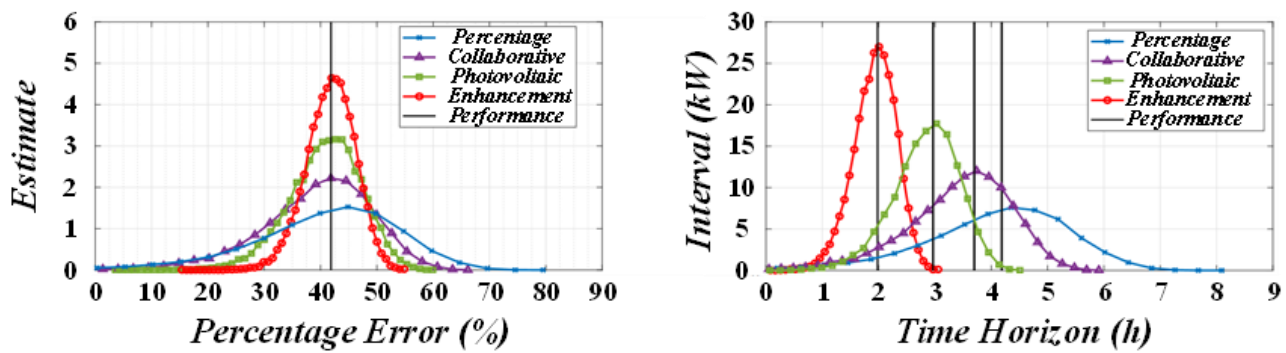


Fig. 11: Accuracy analysis of load forecasting under vehicle-light cooperative scheduling.

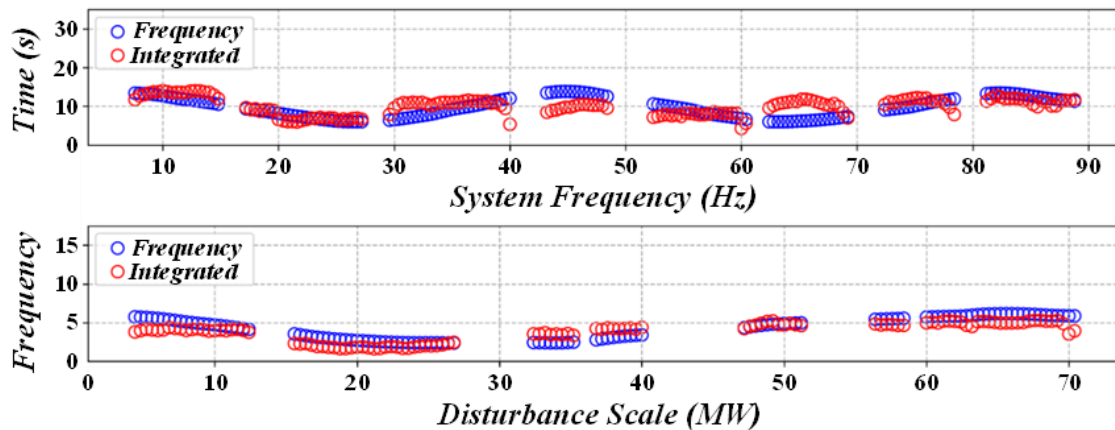


Fig. 12: Frequency stability analysis of power system under high proportion of photovoltaic access.

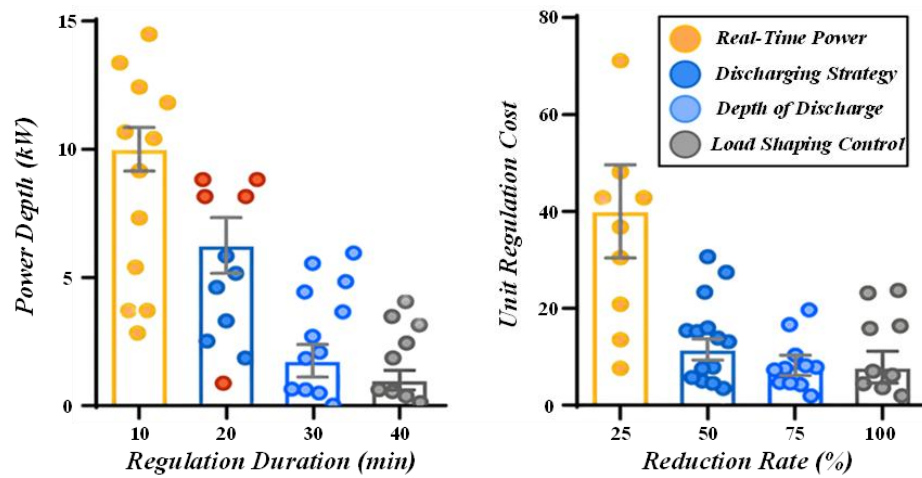


Fig. 13: Short-term load regulation capability of vehicle battery to distribution network.

In order to analyze the adjustment ability of vehicle battery in short-term load fluctuation and evaluate its role in rapid load change, this paper analyzes the short-term load adjustment ability of vehicle battery in distribution network, and the results are shown in Fig. 13.

The figure shows that in the scenario where a high proportion of vehicle-optical collaboration is connected to the distribution network, vehicle batteries exhibit different regulation characteristics. When the adjustment time is 10 minutes, the power depth of real-time power can reach about 10kW, which is significantly higher than other strategies; As the conditioning time increases to 40 minutes, the power depth of each strategy decreases significantly, such as the discharge strategy decreases to about 2kW. In terms of reduction rate, when the reduction rate is 25%, the unit adjustment cost is about 40, while when the reduction rate reaches 100%, the cost drops to about 30, indicating that the adjustment capacity and cost of vehicle batteries are different under different adjustment times and reduction rates, and reasonable selection of strategies can optimize the adjustment effect.

In order to show the changes of energy consumption and cost under vehicle-light collaborative scheduling and evaluate its economy, this paper analyzes the energy consumption and cost optimization under vehicle-light collaborative scheduling, and the results are shown in Fig. 14.

Among them, TCO represents total cost optimization, ECO represents energy consumption optimization, NPV represents net present value, and LCO represents levelized operating cost. The figure shows that under the dispatching mode of vehicle-light collaborative access to the distribution network, different economic indicators show significant differences with changes in photovoltaic penetration rate and vehicle-mounted battery energy storage power. When the photovoltaic penetration rate increases from 20% to 80%, the median operating cost corresponding to the net present value increases from about 32 to about 48, while economic costs and life cycle costs also have a similar upward trend; When the energy storage power is 15kW, in terms of investment payback period, the median LCO is about 3.5 years, which is higher than about 1 year for TCO. This indicates that the increase in photovoltaic penetration will increase operating costs, while different economic indicators have different cost performance and investment recovery characteristics under vehicle-light collaborative scheduling, which need to be comprehensively considered to achieve optimization.

In order to demonstrate the effect of vehicle-optical collaboration system on improving the load safety margin of distribution network, this paper analyzes the impact of vehicle-optical collaboration system on the load safety margin of distribution network, and the results are shown in Fig. 15.

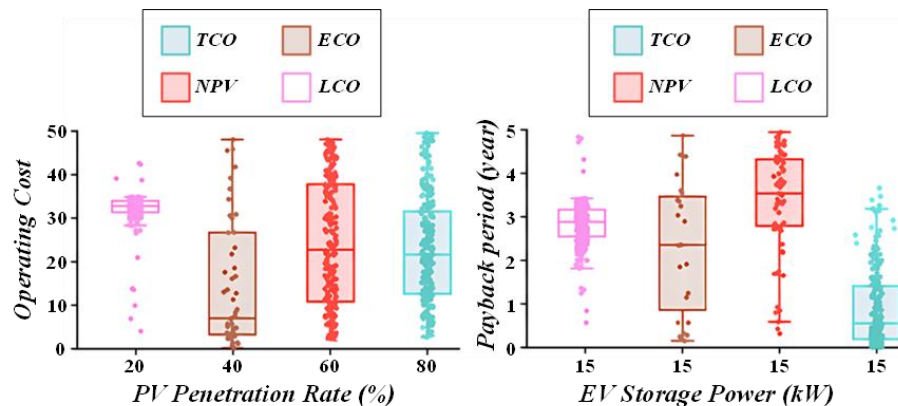


Fig. 14: Energy consumption and cost optimization analysis under vehicle-light collaborative scheduling.

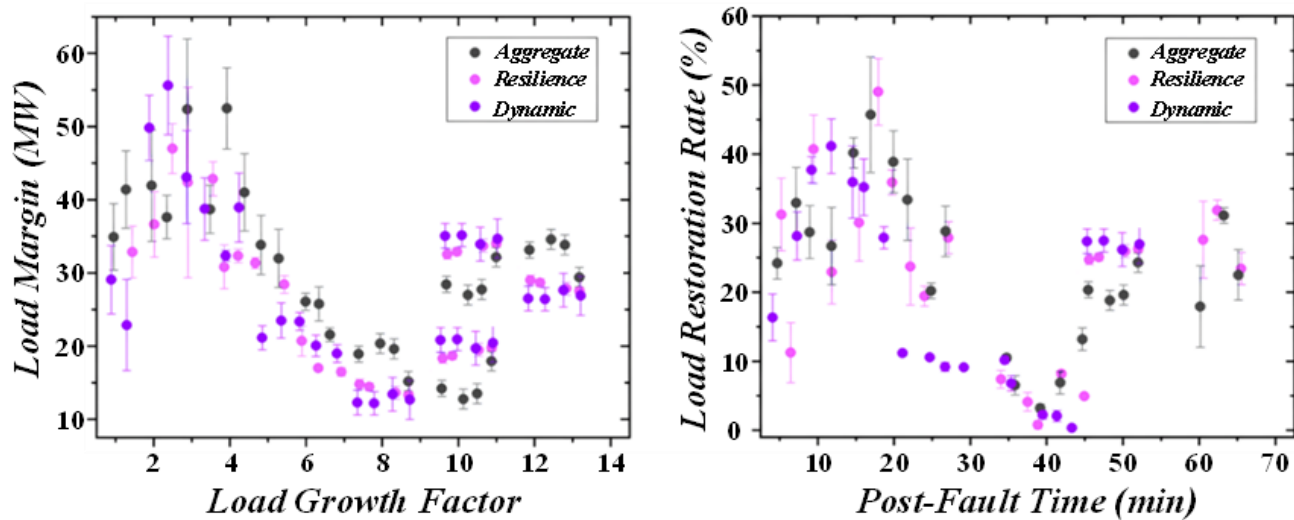


Fig. 15: Influence of vehicle-optical collaborative system on load safety margin of distribution network.

The figure shows that under the scenario of vehicle-optical collaborative access to the distribution network, as the load growth factor increases, the load safety margins in the three modes of aggregation, elasticity, and dynamic all show fluctuations. When the load growth factor is 2, the load safety margins of the three modes are all around 30-40MW. When the growth factor reaches about 10, the margin drops to around 20MW; In terms of post-fault time, as the time increases from 10 minutes to 70 minutes, the load recovery rate gradually increases, and the recovery rate of elastic mode can reach about 50% at 70 minutes, indicating that the vehicle-optical collaborative system has different effects on the load safety margin and recovery ability of distribution network in different load growth and fault recovery stages.

5. Conclusion

This study explores how to improve the stability of power distribution systems through local self-organizing vehicle photovoltaic coordination mechanisms in the context of a high proportion of electric vehicles and photovoltaic integration into the grid. Research has confirmed that electric vehicles, as energy storage units, can effectively stabilize grid load fluctuations and improve system reliability and economy when combined with photovoltaic power generation. Experiments have shown that the proportion of photovoltaic access and the scheduling mode of electric vehicles are crucial for load management, especially when there are large load fluctuations. Optimizing the vehicle photovoltaic coordination strategy can significantly enhance grid stability, reduce energy loss and system interference.

From the experimental results, with the increase of the proportion of vehicle-optical collaborative access, the stability of the power grid gradually decreases. For example, when the access ratio is 10%, the stability coefficient of the grid is 0.92, the voltage fluctuation amplitude is 5.5 V, and the current fluctuation amplitude is 3.2 A. As the access ratio increases to 70%, the stability coefficient decreases to 0.79, the voltage

fluctuation range increases to 12.6 V, and the current fluctuation range is 10.1 A. This indicates that the high proportion of access presents significant challenges to the stability of the power grid. A high proportion of vehicle-optical collaborative access requires effective scheduling strategies to avoid system instability.

Experiments show that the proportion of photovoltaic access has a significant impact on the response of the grid load. When the photovoltaic penetration rate increased from 10% to 25%, the photovoltaic output reached 8.2 MW at 12 noon, causing the system's reverse power flow to increase by 137%, and causing the voltage to rise to 1.07 p.u., exceeding the national standard limit. During the peak load period at night, the sudden drop in photovoltaic output caused the system load to surge by 19.3%. Through the reactive power compensation strategy, the voltage fluctuation of the power grid can be effectively reduced, and the network loss can be reduced from 7.8% to 5.3%, which proves the important role of reactive power regulation.

The role of vehicle battery energy storage in load regulation has also been verified. When the load peak-to-valley difference is large, vehicle-mounted battery can reach 65kW, which is significantly higher than that of conventional energy storage equipment. When the load fluctuates greatly, the vehicle-mounted energy storage system can respond quickly, and the adjustment time is significantly shorter than that of traditional fuel generators and building energy storage systems, further proving its effectiveness in the vehicle-optical collaborative distribution network.

This study demonstrates the potential and challenges of high vehicle-optical collaborative access to the distribution network, particularly in improving grid stability, optimizing dispatching strategies, and reducing energy losses. In the future, with the further development of electric vehicles and photovoltaic power generation technology, the local, self-made interactive strategy of vehicle-light collaboration will become a key strategy for realizing the optimal operation of smart grids.

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Conflict of Interest

All authors declare that they have no conflict of interest.

Supporting Information

Not applicable.

CRedit Statement

Huiming Zhang: Write the original draft; **Taoyong Li:** Data collection; **Jincheng Liu:** Formal analysis, Validation; **Fengkai Gao:** Review & edit the original draft, Supervision. All authors read and approved the final manuscript.

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