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Research on Vehicle-to-Grid Interactive Strategies in High-Proportion Distributed Photovoltaic Distribution Networks

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WHAT IS ALREADY KNOWN ON THIS TOPIC?

- *Existing research on vehicle-grid (V2G) covers technical (e.g., optimal scheduling algorithms) and economic (e.g., demand response) aspects, but most planning algorithms fail to balance grid efficiency and electric vehicle (EV) economic interests. V2G games are categorized into cooperative and non-cooperative types, with non-cooperative ones causing interest conflicts and cooperative ones lacking targeted design for high-proportion renewable energy integration. Additionally, though EVs are recognized as mobile energy storage, existing studies focus on EV cluster scheduling or bidding rather than exploring their synergy with photovoltaic (PV) to mitigate output fluctuations.*

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ABSTRACT

The integration of high-penetration distributed photovoltaic (PV) systems has introduced challenges to distribution grids, including reverse power flow, distribution transformer overload, and voltage uplift. To address the challenges posed by high-penetration distributed PV grid connection and large-scale electric vehicle (EV) integration, this paper proposes a vehicle-grid cooperative interaction strategy based on a cooperative game model. A cooperative alliance between vehicles and the grid is established, with a collaborative interaction game model designed to maximize alliance profits. The profit distribution weights for both parties are determined based on their respective contributions to cooperative gains. Shapley values are applied to allocate interaction profits, yielding time-of-use electricity prices at different moments to guide EVs charging and discharging, thereby achieving coordinated operation between EVs and the grid. Simulation results demonstrate that after implementing the optimized cooperative interaction strategy: surplus PV power generation decreased by 939.10 kW, node voltage fluctuation rate reduced by 5.90%, mitigated the impact of PV fluctuations on the grid, enhanced PV power absorption capacity, and alliance cooperative profits increased by 606.91 yuan compared to non-cooperative grid scenarios.

Index Terms—Cooperative game theory, improved shapley value, time-of-use tariff, vehicle-grid coordination

I. INTRODUCTION

The proportion of distributed photovoltaics (PV) in distribution networks is increasing steadily. The grid integration of fluctuating PV output tends to induce issues such as reverse power flow, distribution transformer overload, and voltage elevation, which exert adverse impacts on the power quality of distribution networks [1,2]. According to statistics, among the distribution transformer areas with distributed PV connected in a certain region, approximately 78% have experienced PV reverse power flow, and about 96% have encountered voltage limit violations. The impact of distributed PV on distribution networks is becoming increasingly severe [3–4].

The large-scale deployment of electric vehicles (EVs) has provided distribution networks with abundant adjustable resources[5–7]. As mobile energy storage units, the charging and discharging behaviors of EVs exert a significant influence on the power balance of distribution networks. If EVs can engage in coordinated interaction with the power grid through orderly charging and discharging, it will help mitigate the impact of PV power fluctuations on distribution networks [8–10].

The collaborative interaction between EVs and the power grid leverages the mobile energy storage attribute of EVs, enabling them to serve as distributed flexible resources [11]. Current research on vehicle-grid interaction can be categorized into two dimensions: technical and economic. From the technical perspective, bidirectional interaction of Vehicle-to-Grid (V2G) technology is realized through approaches such as optimal scheduling algorithms [12–13], dynamic programming methods [14], or game theory [15–18]. From the economic perspective, price-based or incentive-based demand responses are employed to stimulate users to comply with

WHAT DOES THIS STUDY ADD ON THIS TOPIC?

- *Targeted cooperative game model for PV-integrated grids: Addressing the gap of ignoring renewable energy dynamics in existing studies, this study constructs a V2G cooperative framework tailored for PV-rich distribution networks, framing EVs and PV-integrated grids as a collaborative alliance.*
- *Equitable benefit allocation via improved Shapley value: To solve unbalanced interest prioritization, the study proposes an improved Shapley value method incorporating actual contribution factors (PV absorption capacity, EV charging/discharging power) for fair profit sharing, advancing beyond traditional abstract game structure-based methods.*
- *Synergistic optimization of EV capacity and PV output: Contrasting with EV-only scheduling studies, this study establishes an EV adjustable capacity model considering travel characteristics and develops a cyclic optimization strategy (genetic algorithm-updated time-of-use prices) to guide EV-PV synergy, enhancing PV absorption, reducing voltage fluctuations, and maximizing alliance profits.*

grid dispatching [19–21]. However, these planning algorithms often prioritize the interests of one party while neglecting those of the other. In contrast, game theory treats the vehicle and grid as equal entities and achieves coordinated operation by accounting for the mutual influence of their respective decisions.

As an effective analytical tool for vehicle-grid interaction research, vehicle-grid interaction games can be categorized into cooperative games and non-cooperative games. Non-cooperative games frame vehicles and the grid as opposing entities, with each party pursuing nothing but self-interest maximization. For example, [22–23] developed a two-layer game model based on leader-follower game theory to design real-time electricity pricing strategies that guide the orderly charging and discharging of EVs; [24] analyzed the interaction process between EVs and the grid using evolutionary game theory of public goods. In non-cooperative games, conflicting interests arise between vehicles and the grid, which hinders the long-term development of vehicle-grid interaction. In reality, the two interacting parties (vehicles and the grid) exhibit both cooperative and competitive attributes, thus enabling the formation of a cooperative game alliance. [25] derived an axiomatic equilibrium solution for electricity-carbon coupling transactions among multiple microgrids based on Nash bargaining theory; [26] leveraged virtual power plants as intermediaries, utilizing their cooperative ties with users and active distribution networks to establish a bilateral cooperative game model, aiming to maximize the benefits of the three stakeholders; [27] constructed a dynamic time-of-use electricity price-based charging and discharging model grounded in cooperative game theory, so as to facilitate positive interaction between EVs and the grid. Cooperative games typically adopt an alliance-centric perspective, taking into account the benefits of both vehicles and the grid, thereby boosting their enthusiasm for participation in cooperation [28].

In the context of high-penetration distributed PV integration into distribution grids, both PV output and EV charging/discharging exhibit volatility. However, EVs possess excellent charge/discharge controllability outside of limited usage periods, offering a viable means to mitigate the fluctuations of distributed PV. Currently, specific collaborative interaction strategies between EVs and distributed PV remain lacking. Most V2G scheduling research focuses primarily on EV scheduling, neglecting comprehensive consideration of distributed PV's dynamic characteristics. This oversight may result in poor synergy with PV systems and suboptimal regulation of power quality in distribution grids.

This paper views EVs and distribution grids incorporating distributed PV as a cooperative alliance from the perspective of synergistic interaction. It analyzes the coordinated response characteristics between EVs and distributed PV, optimizing for high distributed PV absorption rates, minimal PV-induced load variance, and low EV charging costs. The contribution of both parties to alliance benefits is examined. Shapley values are applied to allocate V2G alliance profits, determining optimal grid charging/discharging prices and corresponding EV energy volumes. Unlike existing game models mainly focusing on EV cluster scheduling or bidding, with less consideration of PV fluctuation synergy and bilateral benefit balance, this paper proposes a cooperative game-based V2G interaction strategy considering high-proportion distributed PV, focusing on alliance profit maximization and equitable benefit allocation via improved Shapley values. This mobilizes adjustable EV resources to absorb PV power fluctuations, mitigating grid impacts while maximizing alliance benefits.

II. THE COOPERATIVE GAME MECHANISM OF VEHICLE-TO-GRID COLLABORATIVE INTERACTION

In vehicle-grid interaction, a mutual dependence exists between the two parties: the benefit of each party is contingent on both its own strategic choices and those of the other. In the context of positive interaction, the total benefit derived from bilateral cooperation exceeds the sum of benefits each would attain through independent operation. Thus, the collaborative interaction between vehicles and the power grid can be framed as a cooperative game problem.

A. The Shapley Value-based Benefit Allocation Model

Positive interaction benefits both the vehicle and the grid. Thus, the interactive alliance formed by the two parties includes two members: the power grid (g) and the EV (v), and they jointly constitute the set $N=\{g,v\}$. The alliance $S=\{S_1,S_2,S_3,S_4\}\left(S_j\subseteq N,j\in\left[1,4\right]\right)$ represents all possible combinations of members, namely four cases: $S_1=\varnothing$, $S_2=\{v\}$, $S_3=\{g\}$ and $S_4=\{g,v\}$.

In cooperative game theory, the marginal contribution is employed to quantify the incremental increase in the overall contribution of a coalition due to the inclusion of member *i*. For the interactive coalition S_j, the marginal contribution made by any member *i* among the two parties (the vehicle side and the grid side) is:

$$\rho_i\left(S_j\right)=V\left(S_j\right)-V\left(S_j-\left\{i\right\}\right) \tag{1}$$

Where $\rho_i(S_j)$ denotes the marginal contribution of member *i* to coalition S_j, $V(S_j)$ represents the total payoff of coalition S, and $V\left(S_j-\left\{i\right\}\right)$ is the total payoff of coalition S when member *i* is excluded.

To mitigate the impact of the joining order on payoff allocation, it is essential to explore all possible sequences in which member *i* joins the coalition. Denote the payoff that the *i*-th member obtains from the coalition's joint payoff as $x\left(i\right)$:

$$x\left(i\right)=\sum_{\substack{j=1\\ i\in S}}^{4}\frac{\left(\left|S_j\right|-1\right)!\left(n-\left|S_j\right|\right)!}{n!}\left[V\left(S_j\right)-V\left(S_j-\left\{i\right\}\right)\right] \tag{2}$$

where $x(i)$ is the Shapley value, *n* is the total number of coalition participants, $\left|S_j\right|$ is the number of members in subset S_j.

Consequently, the payoff that the power grid obtains from the joint payoff of the vehicle-grid interactive coalition is:

$$x\left(g\right)=\frac{1}{2}\left[V\left(g\right)-V\left(\varnothing\right)\right]+\frac{1}{2}\left[V\left(g,v\right)-V\left(v\right)\right] \tag{3}$$

where $x\left(g\right)$ is the Shapley value of the power grid, $V\left(g\right)$ is the payoff of the power grid operating independently, $V\left(\varnothing\right)$ is the payoff of the empty coalition, $V\left(g,v\right)-V\left(v\right)$ is the marginal contribution of the power grid to the alliance formed with EVs.

The payoff that the EV fleet obtains from the joint payoff of the vehicle-grid interactive coalition is:

$$x\left(v\right)=\frac{1}{2}\left[V\left(v\right)-V\left(\varnothing\right)\right]+\frac{1}{2}\left[V\left(g,v\right)-V\left(g\right)\right] \tag{4}$$

where $x\left(v\right)$ is the Shapley value of the EV fleet, $V\left(v\right)$ is the payoff of the EV fleet operating independently, and $V\left(g,v\right)-V\left(g\right)$ is the marginal contribution of the EV fleet to the alliance formed with the power grid. $V\left(\varnothing\right)$, $V\left(v\right)$, $V\left(g\right)$, and $V\left(g,v\right)$ represent the joint payoffs of the vehicle-grid cooperation coalitions S_1, S_2, S_3, and S_4, respectively.

The influencing factors for the strategic choices of both the vehicle side and the grid side during the interaction process vary. Correspondingly, the gains obtained from the interaction also differ. In the interactive alliance, EVs absorb the output of distributed PVs in the vicinity during charging, thereby alleviating issues such as voltage rise and PV curtailment caused by excessive PV power generation. Thus, regarding the consumption of new energy, the contributions of the grid and the EV fleet to the alliance diverge. The contribution of EVs to the cooperative gains is primarily manifested in the power support provided through their charging and discharging operations. On the other hand, the grid's contribution to the cooperative gains mainly lies in enhancing the new energy consumption capacity through interactions [29]. To more accurately quantify their contributions to the alliance, different influencing factors are incorporated into the joint gain distribution weights, leading to the formation of a Shapley value-based gain distribution model.

In a distribution network featuring a high proportion of distributed PVs, consider the revenue-distribution weight $M=\left(\lambda_g,\lambda_v\right)$ of the vehicle-grid alliance. Among them, the revenue-distribution weight λ_g of the power grid is given by:

$$\lambda_g=\frac{P_{PV}}{P_{EV}+P_{PV}} \tag{5}$$

where λ_g is the revenue distribution weight of the power grid, P_{PV} is the total distributed PV power absorbed by the grid due to EV participation, and P_{EV} is the total discharging power of EVs to the grid.

The weight λ_v of the revenue distribution for the EV fleet during the interactive absorption process is:

$$\lambda_v=\frac{P_{EV}}{P_{EV}+P_{PV}} \tag{6}$$

where λ_v is the total discharging power of EVs to the grid.

Since different profit distributions will result in different power responses, the distribution weights of both the vehicle side and the grid side will be adjusted according to their response strategies until a stable state is finally achieved. The adjustment amount for each correction is:

$$\Delta\phi_i\left(V\right)=\left(\lambda_i-\lambda_0\right)\cdot V\left(S\right) \tag{7}$$

Where $\Delta\phi_i\left(V\right)$ is the weight adjustment amount of member *i*, $\lambda_i-\lambda_0$ is the adjustment coefficient, $V\left(S\right)$ is the sum of power contribution changes of all members.

The new revenue distribution result is thus expressed as:

$$\phi_i^{'}\left(V\right)=x\left(i\right)+\Delta\phi_i\left(V\right) \tag{8}$$

Where $\phi_i^{'}\left(V\right)$ is the adjusted revenue distribution weight of member *i*, and $x\left(i\right)$ is the initial revenue distribution weight of member *i*, $\Delta\phi_i\left(V\right)$ represents the adjustment amount of the Shapley value of member *i*. If $\Delta\phi_i\left(V\right)>0$, the benefit share of member *i* from the alliance will increase relative to its original benefit; conversely, if $\Delta\phi_i\left(V\right)<0$, the benefit share of member *i* from the alliance will decrease relative to its original benefit. λ_i is the distribution weight of the *i-th* member. *i* is a member of the alliance (g or v), where its identity is determined by the member's contribution to the alliance. λ_0 is the initial allocation weight, where all parties share the same initial allocation weight. $x\left(i\right)$ is the initial allocation of the alliance's joint benefit to the *i*-th member; $\phi_i^{'}\left(V\right)$ is the adjusted benefit of the *i*-th member.

The Shapley value-based cooperative revenue distribution model redistributes revenues in light of the actual contributions made by the power grid and the EV fleet to the interactive alliance. By taking into account the extent of contributions, a more equitable and reasonable distribution outcome is achieved. This not only safeguards the enthusiasm of both the vehicles and the grid to engage

in cooperation but also ensures the stable operation and long-term development of vehicle-grid interaction.

B. Constraint Conditions

The vehicle-grid interaction cooperative game model must satisfy the following constraint conditions:

1. The cooperative revenue of the vehicle-grid interaction alliance should be no less than the revenue of each member acting alone.

$$V\left(S_j\right) \geq V\left(S_j - \{i\}\right) \tag{9}$$

where $V\left(S_j\right)$ denotes the joint revenue of the cooperative alliance S_j, and $V\left(S_j - \{i\}\right)$ represents the joint revenue of the alliance $S_j - \{i\}$ when member *i* does not participate in the alliance.

2. Vehicle-grid power constraints:
Photovoltaic power generation output constraint:

$$P_{PV,\min} \leq P_{PV} \leq P_{PV,\max} \tag{10}$$

where, P_{PV} represents the power of PV power generation; $P_{PV,\max}$ and $P_{PV,\min}$ denote the upper and lower limits of the PV power generation power, respectively.
Power constraints for charging and discharging of EVs:

$$P_{EV,\min} \leq P_{EV} \leq P_{EV,\max} \tag{11}$$

where, $P_{EV,\max}$ and $P_{EV,\min}$ denote the upper and lower limits of the charging and discharging power of EVs, respectively.

3. Battery capacity constraints for EVs:

$$SOC_{\min} \leq SOC_i \leq SOC_{\max} \tag{12}$$

where, SOC_i represents the state-of-charge (SOC) of the EV battery; $SOC_{\max}$ and $SOC_{\min}$ denote the upper and lower limits of the SOC of the battery, respectively.

III. THE ADJUSTABLE CAPACITY IN VEHICLE-TO-GRID COORDINATED CONTROL

Vehicle-to-Grid interaction mainly leverages the charging and discharging of EVs to offer power support to the power grid. The available capacity of EVs is a crucial variable in V2G interaction. Establishing an accurate adjustable capacity is a prerequisite for the analysis of V2G interaction strategies.

Factors affecting the charging and discharging capacity of EVs encompass charging/discharging time and power. The charging/discharging time is determined by both the start time of charging/discharging and its duration. The initial available time of EVs conforms to a normal distribution [30]:

$$f_s\left(t\right) = \frac{1}{\sigma_s\sqrt{2\pi}} \exp\left[-\frac{\left(t\mu_s\right)^2}{2\sigma_s^2}\right] \tag{13}$$

where *t* denotes the end time of the last trip, that is, the initial available time; μ_s represents the average expected value of the trip end time; σ_s is the standard deviation of the statistically analyzed trip end time. Both μ_s and σ_s vary according to the different driving characteristics of various vehicle types.

The daily driving mileage of EVs conforms to a normal distribution [31]:

$$f_D\left(s\right) = \frac{1}{s\sigma_D\sqrt{2\pi}} \exp\left[-\frac{\left(\ln s\mu_D\right)^2}{2\sigma_D^2}\right] \tag{14}$$

Where *s* denotes the daily driving mileage (km); μ_D represents the average expected value of the vehicle's daily driving mileage; σ_D is the standard deviation of the statistically obtained daily driving mileage. Both μ_D and σ_D are associated with the vehicle type and usage demands.

The charging and discharging duration is associated with the expected SOC of the battery upon the completion of charging and discharging:

$$SOC_l = SOC_0 + \sum_{\tau=t}^{t_l}\left[\frac{P_{EV}\cdot\eta}{E}\left(\tau - t_l\right)\right] \tag{15}$$

Where SOC_l denotes the desired SOC, which is related to the daily driving demand of the EV in (14). SOC_0 represents the initial SOC. *E* is the battery capacity (kWh). P_{EV} is the charging and discharging power (kW). η is the charging and discharging efficiency. *t* is the starting time of charging and discharging, and t_l is the ending time of charging and discharging. The value of $\left(t_l t\right)$ represents the charging and discharging duration (h).

The schedulable thresholds for the charging and discharging of individual electric vehicles participating in V2G interactions are divided into the upward-adjustable capacity and the downward-adjustable capacity. Specifically, the upward-adjustable capacity is expressed as follows:

$$W_{up}\& = \left(SOC_{\max} - SOC_i\right)E = \sum_{\tau=t}^{t_l}\left[P_{EV}\cdot\eta\cdot\left(\tau - t_l\right)\right](P_{EV} > 0) \tag{16}$$

The downward-adjustable capacity is:

$$\begin{aligned} W_{down} &= \left(SOC_i - SOC_{\min}\right)E \\ &= \sum_{\tau=t}^{t_l}\left[P_{EV}\cdot\eta\cdot\left(\tau - t_l\right)\right](P_{EV} < 0) \end{aligned} \tag{17}$$

After the individual charging and discharging processes of EVs are completed, it is necessary to not only meet the travel requirements but also satisfy the battery capacity constraints:

$$SOC_l \cdot E \leq W_{down} + W_{up} + SOC_0 \cdot E \leq E \tag{18}$$

where SOC_i represents the current SOC of the EV. W_{up} and W_{down} denote the upward-adjustable and downward-adjustable electrical quantities of the EV battery respectively. *E* is the battery capacity (kWh). P_{EV} is the charging and discharging power (kW). When $P_{EV} > 0$, it represents the charging state; when $P_{EV} < 0$, it represents the discharging state; when $P_{EV} = 0$, it means that the vehicle is neither charging nor discharging. η is the charging and discharging efficiency.

IV. VEHICLE-TO-GRID COLLABORATIVE CONTROL STRATEGY

A. Practical Deployment Architecture of the Algorithm

To ensure the implementability of the proposed strategy in actual grid environments, a three-layer distributed deployment architecture

is designed, consisting of the grid dispatch center layer, EV aggregator layer, and edge computing node layer:

1. Grid dispatch center layer: Responsible for collecting real-time operation data of the distribution network (PV output, load, voltage, current), issuing global optimization objectives and constraint conditions, and verifying the feasibility of the scheduling results. It communicates with EV aggregators through the existing power dedicated communication network (IEC 61850 standard).
2. EV aggregator layer: Responsible for managing EV clusters in its jurisdiction, collecting EV status information (SOC, charging/discharging power, available time), receiving electricity price signals from the dispatch center, and solving the local optimal charging/discharging strategy.
3. Edge computing node layer: Deployed at charging piles, responsible for collecting real-time data of individual EVs, executing basic control instructions, and feeding back EV status information to the aggregator. The edge nodes have local computing capabilities, which can realize millisecond-level response to emergency control instructions.

The algorithm adopts a distributed computing mode to reduce the computational burden of the dispatch center: The grid dispatch center only calculates the global optimal electricity price signal, and the specific charging/discharging strategy of each EV is solved by the EV aggregator.

Compatibility with existing grid systems: The proposed strategy can be seamlessly integrated with the existing distribution management system and advanced metering infrastructure through standard communication protocols. It does not require large-scale transformation of existing grid equipment, only adding corresponding software modules to the dispatch center and EV aggregators, which significantly reduces the deployment cost.

The proposed peak-shaving algorithms are inherently designed to support bidirectional V2G power exchanges. The optimization model explicitly incorporates both EV charging and discharging power variables, enabling the algorithms to dynamically adjust V2G power flows based on real-time grid conditions, PV output, and EV availability. The three-layer distributed architecture allows for seamless integration of V2G power exchanges into the existing peak-shaving framework, with edge computing nodes providing millisecond-level response to support fast V2G power regulation.

B. Algorithm Implementation Steps

In cooperative games, EVs and the power grid serve as two interacting entities. Electric vehicles can not only act as producers, providing discharging support to the power grid, but also function as consumers, drawing power from the grid for charging to achieve power consumption.

During the interaction process, EV users can determine their available adjustable capacity by taking into account factors such as their individual transaction preferences, electricity consumption demands, and the SOC of their EVs. Subsequently, through the collaborative optimization of charging and discharging responses in conjunction with distributed PV systems, the electricity price, electricity volume, and revenue distribution are determined. This process is cycled until the optimal conditions are met, thereby obtaining the strategy that maximizes the alliance's profit.

The specific steps are as follows:

Step 1: Determine the adjustable capacity of EVs for each time period.

Based on the driving requirements of EVs (including daily driving mileage, trip end time, and desired SOC), combined with battery capacity constraints and charging/discharging power limits, calculate the upward-adjustable capacity (W_{up}) and downward-adjustable capacity (W_{down}) of each EV in each time period (1-hour interval) using (16)–(18). Summarize to obtain the total adjustable capacity of the EV fleet for each time period.

Step 2: Set initial parameters and iteration conditions.

Set the number of iterations k = 0, and specify the initial time-of-use electricity price (refer to the local grid's peak-valley time-of-use electricity price policy, with peak period (17:00–23:00) price set to 1.05 yuan/kWh, flat period (7:00–17:00) price set to 0.65 yuan/kWh, and valley period (0:00–7:00) price set to 0.35 yuan/kWh). Set the iteration termination condition: the relative change in alliance profit between two consecutive iterations is less than 1%, or the maximum number of iterations (set to 100) is reached.

Step 3: Solve EV charging and discharging strategies and verify alliance feasibility

Aiming to maximize the revenue of the alliance, establish an optimization model with the objective of maximizing $\phi_S = \phi(V) + \phi(G)$, and solve the charging and discharging power ($P_c(t), P_d(t)$) of the EV fleet in each time period under the current electricity price using IBM ILOG CPLEX Optimization Studio and YALMIP solver. Verify whether the constraint conditions ((9)–(12)) are satisfied: if satisfied, the alliance can be established; otherwise, adjust the initial electricity price and re-enter this step.

Step 4: Calculate the revenue of each entity in the alliance

Based on the solved charging and discharging power and current electricity price, calculate the revenue of the power grid and the EV fleet respectively:

Revenue of the power grid:

$$\phi_1(V) = \sum_0^t [c_c(t)P_c(t) - (c_f(t) + c_d(t))P_f(t) - c_t(t)P_{dc}(t) - F(t)] + \Delta\phi_1(V) \tag{19}$$

Revenue of the EV group:

$$\phi_2(V) = \sum_0^t (c_f(t) + c_d(t))P_f(t) - c_c(t)P_c(t) + c_t(t)P_{dc}(t) + \Delta\phi_2(V) \tag{20}$$

Where $c_c(t)$ and $c_f(t)$ is the charging and discharging prices of EVs (EVs) in time period *t*. $P_c(t)$ and $P_f(t)$ is the charging and discharging power of EVs in time period *t*. $c_d(t)$ is the battery degradation cost in time period *t*. $c_t(t)$ is the cost required for the power grid to shift peak load in time period *t*. $P_{dc}(t)$ is the peak load shifting power in time period *t*. $F(t)$ is the peak shaving cost of the power grid in time period *t*.

The weight adjustment amount $\Delta\phi_i(V)$ is obtained by optimizing the weights according to the benefits brought about by the alliance's greater absorption of new energy.

Step 5: Optimize revenue distribution weights and update time-of-use electricity prices.

According to the benefits brought by the alliance's increased absorption of new energy, calculate the weight adjustment amount $\Delta\phi_i(V)$ using (7), and substitute it into (8) to obtain the improved revenue distribution results. Based on the current grid load, use the genetic algorithm to iteratively update the time-of-use electricity prices: reduce the charging/discharging prices during PV peak generation periods (10:00–17:00) to encourage EV charging and absorb surplus PV power; increase the charging/discharging prices during grid peak load periods (17:00–23:00) to encourage EV discharging and support the grid.

Step 6: Recalculate user response and revenue distribution.

Under the guidance of the updated time-of-use electricity prices, resolve the EV users' charging and discharging strategies, and recalculate the revenue distribution results of the alliance based on the new distribution weights.

Step 7: Judge the iteration termination condition.

Check whether the relative change in alliance profit between the current iteration (k) and the previous iteration (k−1) is less than 1%:

$$\left|\frac{\phi_s(k)-\phi_s(k-1)}{\phi_s(k-1)}\right|<1\% \tag{21}$$

If yes, terminate the iteration; if no, set $k = k + 1$ and return to Step 3. If the maximum number of iterations is reached and the termination condition is still not met, output the results of the last iteration.

Step 8: Output the optimal solution.

Output the optimal time-of-use electricity prices, the optimal charging/discharging strategies of the EV fleet, and the optimal revenue values of the power grid, EV fleet, and alliance.

V. CASE STUDY

Taking a residential distribution transformer station in Nanchang, Jiangxi Province, China as an instance, this study analyzes the influence of the participation and interaction of EVs within the station on the consumption of distributed PVs and power quality in the distribution network. The structure of the distribution transformer station and the distribution of PVs are presented in Fig. 1. All optimization models are formulated and solved using YALMIP (version R20230918) with CPLEX (version 22.1.1) as the solver. The solver configuration is set as follows: the maximum solving time is 3600 seconds, the optimality tolerance is 1e-6, and the number of threads is set to 8 to balance solving efficiency and computational stability.

A. Input Data Description

1. The daily driving mileage of private cars follows a normal distribution $N(35,10^2)$ km, and the trip end time follows a normal distribution $N(18{:}30,1.5^2)$ hours; the daily driving mileage of taxis follows a normal distribution $N(150,30^2)$ km, and the trip end time follows a normal distribution $N(22{:}00,2^2)$ hours.
2. The typical daily PV output characteristics are: starting to generate power at 6:00, reaching the peak output (480 kW) at 12:00, and stopping power generation at 18:00.
3. Other basic data: The rated voltage of the distribution transformer station is 10 kV/0.4 kV, the rated capacity is 2000 kVA, the original load data (without EV interaction) is derived from the historical load monitoring data of the station, with a sampling interval of 1 hour. The battery replacement cost is 1200 yuan/kWh based on the market price survey of power lithium-ion batteries in 2024.

B. Basic Parameters of Electric Vehicles

The number of EVs within the distribution transformer station is set to 150. Based on their usage purposes, they are categorized into private cars and taxis. Taxis account for approximately 10% of the total number of EVs. The parameters and available charging/discharging times of these two types of EVs are presented in Table I.

Based on the data of the automotive travel survey, the initial SOC of taxicabs is predominantly distributed within the range of 20%–40%, while that of private passenger vehicles is mainly distributed in the interval of 70%–95% [32]. Consequently, the adjustable capacity of EVs is presented in Fig. 2. Taxicabs feature short charging durations and relatively low initial SOC values, leading to a substantial charging demand. However, their downward-adjustable capacity is limited. As a result, the probability of taxicab users engaging in charge-discharge scheduling is relatively low. On the other hand, private passenger vehicles have flexible charging times, relatively high initial SOC, and a long duration of being connected to the grid. After being connected to the grid, they exhibit the maximum upward-adjustable capacity. Therefore, on the premise of ensuring a full charge, the probability

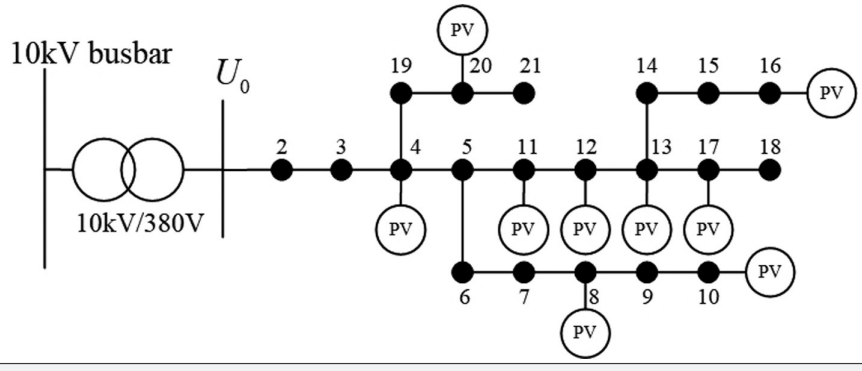

Fig. 1. Substation structure and photovoltaic distribution diagram of a distribution network.

TABLE I. ELECTRIC VEHICLE LOAD PARAMETERS

Type of EVs	Battery Capacity	Charging Power	Charging Time
Private passenger vehicle	45 kWh	7 kW	9:00–17:00 18:00–07:00
Taxicab	45 kWh	45 kW	2:00–4:00 11:00–14:00

of private passenger vehicle users participating in charge-discharge scheduling is relatively high.

C. The Influence of Electric Vehicle Coordinated Response on the Absorption of Distributed Photovoltaics

On the basis of the adjustable capacity of EVs, typical daily PV power generation data is collected. By means of cooperative game theory, private cars and a portion of taxis are induced to engage in the charging and discharging scheduling of V2G coordinated interaction. The time-of-use electricity price and the corresponding charging and discharging strategies of EVs are solved using the genetic algorithm and the CPLEX/YALMIP solver. The revenue distribution results of the V2G interaction alliance are derived to validate the V2G coordinated interaction strategy proposed in this study. The grid load conditions before and after the involvement of EVs in coordinated interaction are presented in Fig. 3.

As is observable from Fig. 3, prior to the optimization of the coordinated operation, EVs charged and discharged in accordance with their individual demands. During the peak electricity consumption period following the working hours, specifically from 17:00 to 23:00, the charging load of EVs and the grid load superimposed, creating a compound peak. This led to the grid's peak load during the peak period soaring to 1470.05 kW. In the noon period from 11:00 to 13:00, the PV power generation reached its apex. Meanwhile, the charging power of EVs was relatively minimal. Consequently, there was a substantial surplus of PV power generation, amounting to as much as 1672.78 kW, which was fed back into the grid. Subsequent to the optimization of the coordinated operation, EVs adjusted their charging behavior in response to the variations in PV power output. Between 10:00 and 17:00, the charging power of EVs was relatively high, enabling the absorption of the vast majority of the PV power generated. As a result, the surplus of PV power generation was decreased to 733.68 kW. During the peak electricity consumption period from 17:00 to 23:00 after the working hours, EVs discharged rather than charged. This action not only alleviated the peak load during the peak period but also provided power support to the grid. As a consequence, the power supplied by the grid during the peak period was reduced to 1019.80 kW. Evidently, through the optimization of the collaborative interaction, by leveraging the charging and discharging responses of EVs, peak shaving and valley filling of the grid load were effectively achieved. This led to a 13% reduction in the grid's power fluctuations. Simultaneously, the output of distributed PV was maximally absorbed, facilitating the local consumption of distributed PV power. As a result, the power fed back from distributed PV was decreased by 11%.

D. The Impact of Electric Vehicle Coordinated Response on Node Voltage

Under the vehicle-grid coordinated operation strategy described above within the given distribution area, an analysis is conducted on the impact of vehicle-grid collaborative interaction on the node voltages of this distribution network. Taking the terminal node 16 as an example, in accordance with the collaborative interaction strategy mentioned previously, during the PV power generation period, the variation of the voltage at the point of common coupling before and after the collaborative interaction is presented in Fig. 4.

As depicted in Fig. 4, in the scenario where EVs do not engage in coordinated interaction, the node voltage exhibits substantial fluctuations. During the peak PV power generation period from 10:00 to 13:00, the node voltage exceeds the nominal voltage of 220 V. This leads to voltage out-of-limit conditions and the occurrence of reverse power flow from PV systems. At 11:00, when the surplus PV power reaches its maximum value, the node voltage surges to 243.86 V, which is +10.85% higher than the nominal voltage. The elevation of the node voltage causes the surplus PV power to be fed back into the grid, thereby influencing the operational stability of the grid. Conversely, subsequent to the optimization of the coordinated interaction, the charging and discharging behaviors of EVs are adjusted in accordance with the PV

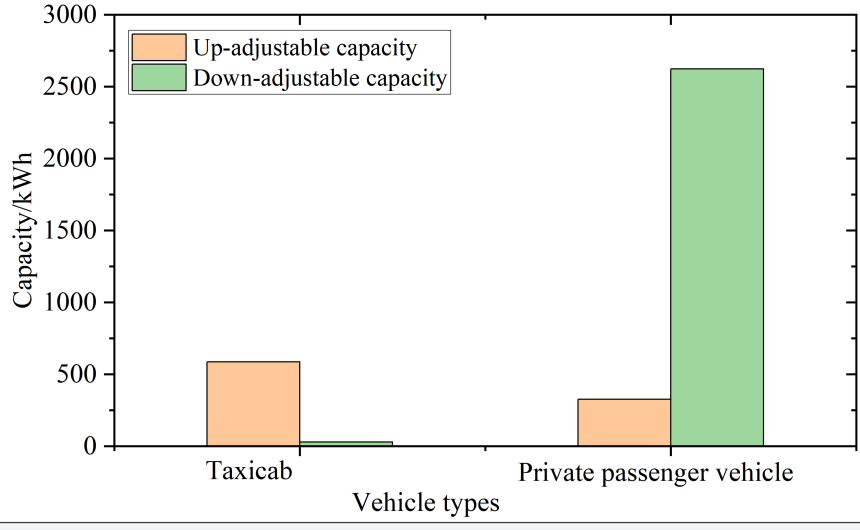

Fig. 2. Adjustable capacity of electric vehicles.

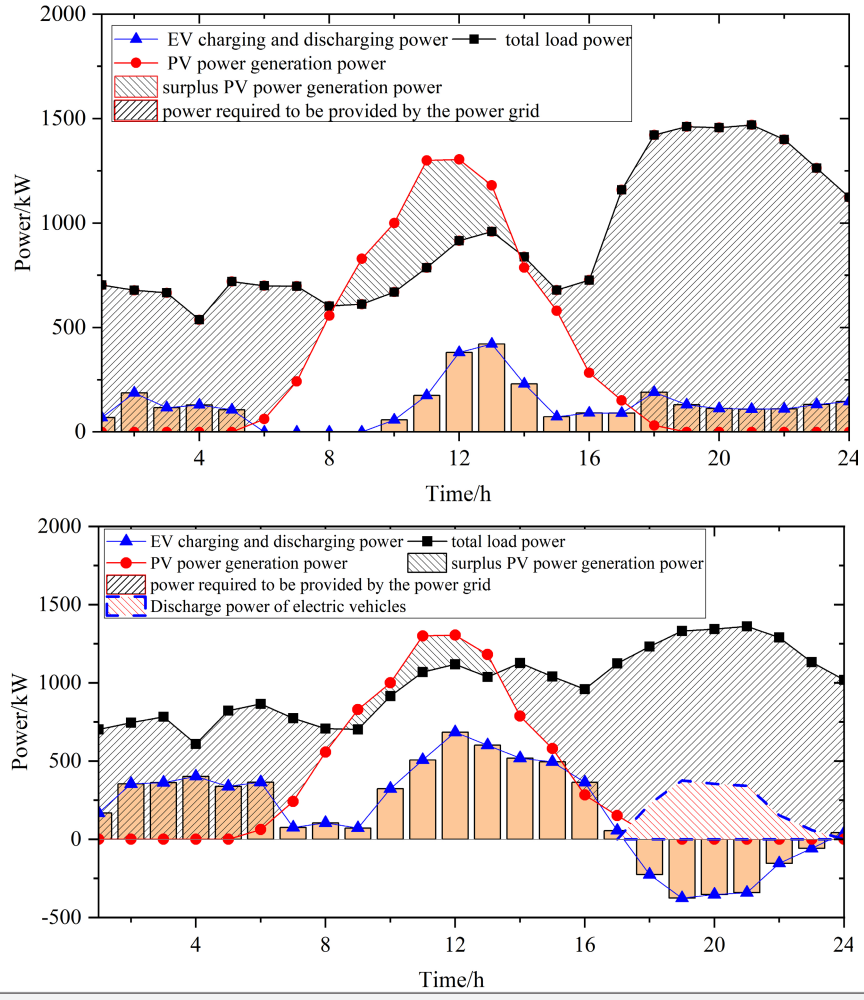

Fig. 3. (a) The load condition of the power grid prior to the participation of electric vehicles in the interaction. (b) The load condition of the power grid subsequent to the participation of electric vehicles in the interaction.

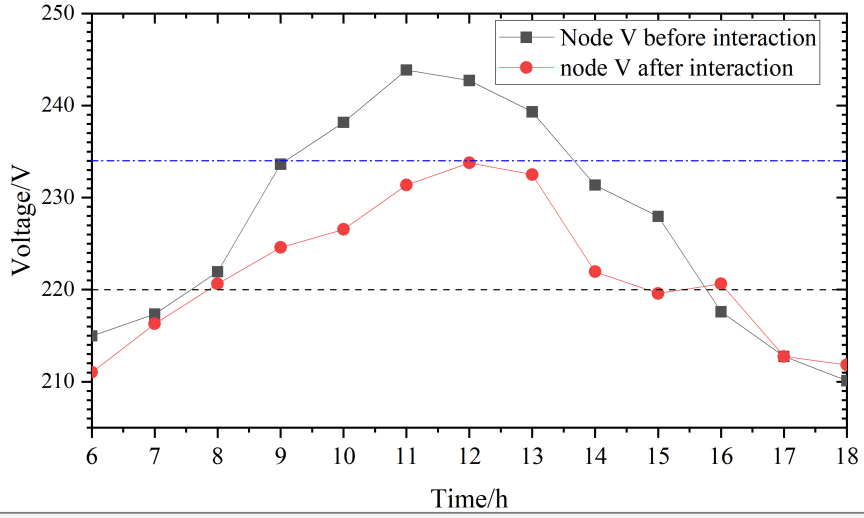

Fig. 4. Voltage changes at node 16 before and after synergistic interaction

power output. As a result, the fluctuation amplitude of the node voltage is significantly mitigated. During the PV power generation period from 6:00 to 18:00, the node voltage remains relatively stable at approximately 220 V, and no voltage out-of-limit situations occur. When the surplus PV power is at its peak, the node voltage registers at 233.77 V. Evidently, through the implementation of coordinated interaction, the issue of reverse PV power flow has been ameliorated. This effectively reduces the grid voltage fluctuations induced by the variability of PV power generation. Specifically, the voltage fluctuation rate decreases from 15.34% to 9.24%, thereby ensuring the stability of the voltage at the point of grid connection.

E. Analysis of the Benefits of Vehicle-Grid Collaborative Interaction

As demonstrated by the preceding analysis, the synergistic interaction between EVs and distributed PV systems enables on-site consumption of solar power. This approach reduces power backflow from distributed PV generation and mitigates voltage uplift at nodes caused by such backflow. These benefits translate into economic gains that can be distributed between participating parties. Such distribution effectively incentivizes both sides, fostering stable and sustainable positive interactions.

In accordance with the Shapley value calculation method described above, when EVs participate in the interaction, the total power of distributed PVs absorbed by the power grid amounts to 3709.3 kW, and the total power of EVs discharging into the grid is 1409.4 kW. By calculating according to the benefit weight distribution, the benefit distribution weight of the power grid is as follows:

$$\lambda_g = \frac{P_{PV}}{P_{EV} + P_{PV}} = \frac{3709.3}{1409.4 + 3709.3} = 0.72 \quad (22)$$

The benefit distribution weight of EVs is:

$$\lambda_v = \frac{P_{EV}}{P_{EV} + P_{PV}} = \frac{1409.4}{1409.4 + 3709.3} = 0.28 \quad (23)$$

Calculated according to the time-of-use electricity prices corresponding to the charging of EVs, the respective benefits of both the EVs and the power grid before and after the EVs' participation in the coordinated interaction are presented in Table II.

In Table II, the enhancement of benefits is calculated as revenue after interaction minus the revenue without interaction. It can be observed that when there is no interaction between the EV and the power grid, the EV only incurs costs for its own charging activities. Specifically, 1886.98 yuan represents the daily charging expenses of the EV. The only revenue the power grid can obtain is the charging fees paid by the EV. After the implementation of coordinated operation, the actual daily charging cost borne by the EV amounts to 1,793.82 yuan, indicating an increase in revenue of 93.16 yuan. This consists of a charging expenditure of 2403.50 yuan, a discharging revenue of 562.29 yuan generated by the EV during the night, and a coalition revenue of 47.39 yuan resulting from its participation in the coordinated operation. Meanwhile, the total revenue of the power grid reaches 2400.73 yuan, showing an increment of 513.75 yuan compared to the pre-optimization state. Among this increase, due to the collaborative optimization enhancing the absorption of distributed PV power output, the power grid has achieved a combined revenue of 437.67 yuan from reducing peak-shaving costs and decreasing the demand for load transfer. Additionally, the coalition-allocated revenue amounts to 121.85 yuan.

Overall, the revenue of the vehicle-grid interaction alliance has been enhanced. In comparison with the scenario without interactive response, the actual charging cost of EVs during the interaction is reduced. Thus, cooperative interaction can more effectively stimulate the enthusiasm of EV users to participate, thereby facilitating the sustained development of such interactions.

F. Summary of Simulation Results

To facilitate the comparison of scenarios before and after interaction, a summary table of key simulation results is added as follows in Table III:

The cooperation between PV and EVs affects the power grid in multiple dimensions: (1) Technical dimension: It reduces reverse power flow by 56.14%, mitigates voltage fluctuations by 39.76%, and lowers peak grid load by 30.63%, eliminating transformer overload risks and improving overall grid stability and power quality; (2) Economic dimension: It reduces grid peak-shaving costs by avoiding the deployment of expensive peaking power generation resources, increases grid revenue by 27.22% through optimized power trading, and lowers EV users' charging costs by 4.93% via V2G discharging revenue; (3) Environmental dimension: It increases PV local consumption rate from 43.86% to 83.86%, reducing carbon emissions associated with fossil fuel-based power generation and grid power transmission losses.

To validate the stability of the proposed strategy, the number of EVs was increased based on the original simulation case, and the

TABLE II. INCOME DISTRIBUTION OF VEHICLE-NETWORK INTERACTION/ CNY

	Revenue of EVs	Revenue of the Power Grid	Revenue of the Cooperative Alliance
Non-interaction	−1886.98	1886.98	–
Interactive response	−1793.82	2400.73	606.91
Enhancement of benefits	93.16	513.75	606.91

TABLE III. SUMMARY OF KEY SIMULATION RESULTS

Indicator	Without Interaction	With Coordinated Interaction	Change Amount	Change Rate, %
Peak grid load (kW)	1470.05	1019.80	−450.25	−30.63
Surplus PV power (kW)	1672.78	733.68	−939.10	−56.14
Node voltage at PV peak (V)	243.86	233.77	−10.09	−4.14
Voltage fluctuation rate (%)	15.34	9.24	−6.10	−39.76
EV fleet revenue (yuan/day)	−1886.98	−1793.82	+93.16	+4.93
Power grid revenue (yuan/day)	1886.98	2400.73	+513.75	+27.22
Alliance revenue (yuan/day)	–	606.91	+606.91	–

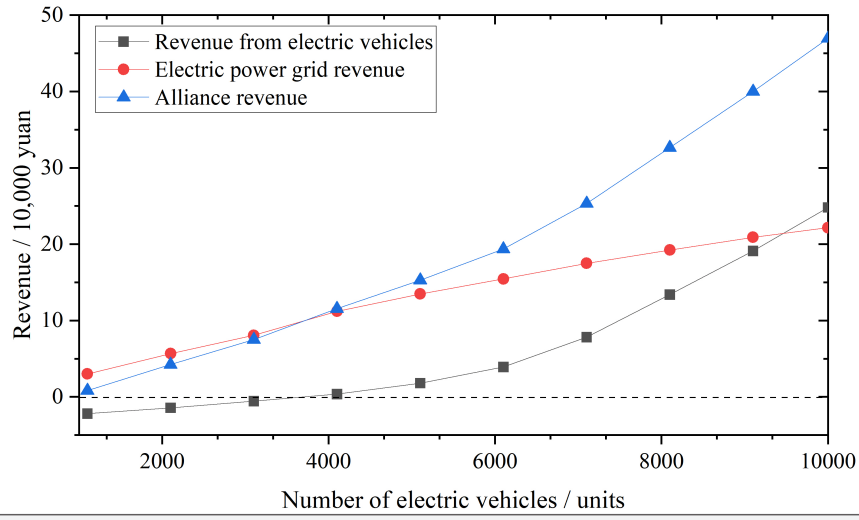

Fig. 5. The benefits of different numbers of electric vehicles participating in the cooperation.

revenue of vehicle-grid cooperative interaction was analyzed. The results are presented in Fig. 5. As the number of EVs increases, the revenue obtained by EVs gradually rises. When the number of EVs reaches a certain threshold, the revenue distribution weight $\lambda_v > \lambda_g$ in the vehicle-grid interaction, where the revenue distribution value of EVs exceeds that of the power grid. It can be concluded that the improved Shapley value-based revenue distribution can reasonably allocate revenue according to the contributions of both the EV side and the power grid side, thereby promoting more active participation of both parties in the cooperative alliance.

VI. CONCLUSION

After the coordinated operation between EVs and the power grid, the coordination between the charging and discharging behaviors of EVs and the output of distributed PVs has been achieved. Based on the cooperative game model, the strategy for coordinating vehicle-grid regulation has been derived. Leveraging the characteristics of the prosumer nature of EVs, this strategy fully stimulates the enthusiasm of the EV community, enabling EVs to shift the load of distributed PV power generation. Through verification using the simulation model, the following conclusions are drawn:

1. The power quality of the power grid has been enhanced. After the collaborative interaction, the peak-valley difference of the grid load has been mitigated. Specifically, the peak-valley difference rate has decreased from 56.8% to 35.4%, and the power fluctuation of the grid has been reduced by 13%. The surplus power of PV power generation has declined from 1,672.78 kW to 733.68 kW. As a result, peak-shaving and valley-filling of the grid load have been realized, along with the local absorption of distributed PV power.
2. The improvement in the elevation of nodal voltage has been achieved. Following the vehicle-grid joint optimization, the fluctuation range of nodal voltage has been narrowed and remains stable at around 220 V. Specifically, the voltage at the moment when the surplus power of PV power generation reaches its maximum has decreased from 243.86 V to 233.77 V. This not only reduces the investment cost of voltage regulation but also averts potential damage to electrical equipment caused by voltage out-of-limit conditions. Consequently, the stability of nodal voltage is effectively ensured.
3. The economic returns of the alliance have been augmented. The returns accrued by both EVs and the power grid within the alliance are markedly higher than those in the non-interactive scenario. Post-interaction, the aggregate returns of the EV fleet have increased by 93.16 yuan, while the returns of the power grid have risen by 513.75 yuan. By modifying the time-of-use electricity tariffs to direct the charging and discharging strategies of EVs and continuously fine-tuning the weights of both parties, the distribution of returns becomes more equitable and rational. This can effectively stimulate a mutually beneficial interaction between the two sides.

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