Highlights

Cooperative V2G-Enabled Vehicle-to-Vehicle Sharing in Energy and Reserve Markets: A Coalitional Approach

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- A coalitional approach-based V2V sharing for energy and reserve markets is proposed.
- A mathematical V2V sharing formulation suited to a coalitional approach is provided.
- The prerequisite condition for a coalitional approach is first proven theoretically.
- A two-stage payoff allocation problem is proposed with a fast decomposition solution.

Cooperative V2G-Enabled Vehicle-to-Vehicle Sharing in Energy and Reserve Markets: A Coalitional Approach

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ABSTRACT

The dynamics of electric vehicles (EVs) charging significantly influence the current power system dynamics. However, with advancements in battery technology and charging infrastructure, EVs can also serve as energy storage systems through vehicle-to-grid (V2G) technology. This opens up possibilities for novel approaches, such as a coalition-based V2G-enabled vehicle-to-vehicle (V2V) energy and reserve sharing mechanism. Unlike traditional transactive energy models that often under-utilize EVs due to mismatches with smaller renewable outputs and peak loads, the proposed cooperative V2V sharing mechanism aims to maximize the use of EVs' charging and discharging capabilities. It forms a grand coalition of EV users to optimize energy and reserve market participation. The model introduces mathematical formulations to describe how EVs collaborate in both energy and reserve markets. It ensures fairness and stability in pay allocations among users within the cooperative framework. The theoretical foundation includes proof of balance in the coalition approach and a two-stage imputation method to achieve fair and optimal payoff distribution. This minimizes incentives for users to defect from the coalition, ensuring stability. To address scalability challenges inherent in coalition formation problems, a decomposition algorithm is proposed. This algorithm enhances efficiency in solving problems that grow exponentially with the number of users. The effectiveness and superiority of this approach are validated through applications to various community energy systems of different sizes. The proposed plan can increase 22.21% of the total payoff in 10-users case and 22.39% in 30-users case. The computation time scales near-linearly with the number of users, although the computation scales exponentially with it. These demonstrations highlight its capability in modeling and solving complex energy sharing scenarios.

1. Introduction

The rise in electric vehicle (EV) adoption, driven by their eco-friendly nature [1], has spurred concurrent mass construction of EV infrastructures [2]. The charging dynamics of these EVs exert a significant influence on the existing power system dynamics due to their unique load characteristics, which are intermittent and distributed [3]. These effects manifest primarily in load and voltage concerns. The increased load from EVs can lead to higher active power losses and congestion in the existing distribution grid infrastructure [4], potentially causing equipment degradation and failures by overloading transformers or lines. Voltage issues resulting from EV charging can degrade service quality for end-users [5], causing voltage drops and phase imbalances beyond the grid's capacity. The severity of these impacts varies based on various factors such as EV adoption rates, grid configuration, user behavior, and pricing schemes. The uncertain nature of these impacts places significant pressure on power system operations.

Addressing these challenges of integrating charging stations has spurred exploration of various solutions in both research societies and practical engineering communities. For fast-charging stations, researchers have proposed methods to coordinate traffic flow and power usage. These include implementing commute fees and charging scheduling fees to manage traffic and mitigate impacts on the power grid [6]-[7]. At the practical community level, efforts have focused on slow charging to ease grid strain. An effective strategy is the EV smart charging scheme, which shifts the charging load to off-peak periods, thereby preventing overloads [8]. Furthermore, smart charging has been shown to synergize with photovoltaic (PV) generation by aligning EV charging with solar energy availability, thereby reducing the overall impact of EV integration on power grids. For instance, in [9], a smart charging scheme minimized net-load variability in residential buildings equipped with PV systems. Similarly, [10] assessed the combined hosting capacity of PV and EVs in a residential low-voltage distribution grid.

While smart charging schemes effectively reduce the impact of EV integration on power systems, they just represent just the beginning of exploring EV charging and discharging behaviours. EVs contribute substantial load to the power system but also offer significant potential for flexibility [11]. On one hand, with individual EV battery capacities now exceeding 100 kWh and advancements in charging technologies, EVs can actively participate in power system operations as effective energy storage units [13],

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facilitated by vehicle-to-grid (V2G) technology [14; 15]. On the other hand, from a temporal standpoint, EVs spend a significant amount of time idle, more than 80 % [12], and can typically recharge their average daily consumption within 1 to 2 hours using a standard 7 kVA home charger. Therefore, it is crucial to synchronize the charging and discharging patterns of EVs with power system operations. This process can transform EVs from mere energy consumers into producers and providers of flexibility, maximizing the value and potential of EV batteries due to their large capacity and extended idle periods. This capability significantly bolsters the resilience and efficiency of power system operations.

More recently, researchers have focused on coordinating V2G-enabled EVs with power systems, proposing diverse methods to optimize EV dispatch and harness their V2G capabilities. In [16] and [17], deep learning techniques have been introduced to utilize domestic EVs for tasks like peak shaving, valley filling, and enhancing photovoltaic (PV) self-consumption. Meanwhile, [18] explored leveraging electric taxis in large numbers to provide effective load support. To address transactive energy challenges such as power imbalances, [19] advocated managing EVs' charging and discharging dynamics through multiple aggregators to coordinate their actions effectively. Additionally, to uphold privacy concerns, [20] proposed a blockchain-based method for EV dispatching that reduces data overhead and ensures secure content delivery. Although these methods significantly bolster power system operations by stabilizing frequency and balancing power, they predominantly prioritize benefits to the power system and may overlook advantages for EV users.

In contrast, some researchers focus on studying charging and discharging strategies through the lens of the energy market, emphasizing the benefits to EV users. Transactive energy, including peer-to-peer energy trading, is particularly suited for energy consumers with PV systems or EVs in community energy setups, enabling each participant to optimize their gains in a market-driven manner [21]. Numerous studies have contributed to this field, proposing various modes of transactive energy mechanisms. These include auction-based methods [22]-[23], bilateral negotiation approaches [24]-[25], and game theory-based strategies [26]-[27]. Further advancements consider decentralized and privacy-preserving techniques using the alternating direction method of multipliers [28] and blockchain technologies [29]. Additionally, deep reinforcement learning approaches have been explored to model community energy trading involving EVs, taking into account uncertainties from distributed energy resources [30].

Despite these efforts to better serve the interests of EV users compared to grid-centric energy management approaches, existing studies on transactive energy and peer-to-peer trading often do not fully address the specific needs of EVs. This is primarily because traditional methods like auctions, price matching, bilateral negotiations, and game theory do not fully exploit the potential of EVs. Given that EV batteries can store up to 100 kWh and home chargers can deliver 7 kW or more, surpassing the peak load and PV capacities of individual users in community energy systems, conventional peer-to-peer methods may under-utilize the flexibility potential of EVs. Thus, there is a pressing need to develop specialized mechanisms that maximize the value of EVs as providers of flexibility.

This paper proposes a novel coalitional approach-based vehicle-to-vehicle (V2V) sharing mechanism tailored for V2G-enabled EVs. Under this framework, all participants form a large coalition to exchange energy and reserves, allowing a single EV owner to provide these services to multiple neighboring users seeking flexibility. This approach optimizes the charging power and energy storage capacity of EVs, particularly leveraging their high charging capabilities. In summary, this paper makes the following contributions:

1. Proposes a specialized coalitional approach-based V2G-enabled V2V sharing mechanism designed for energy and reserve markets. This innovative approach contrasts with conventional transactive energy methods that often under-utilize EVs' robust charging capabilities and battery capacities when paired with smaller PV outputs and peak loads. Based on this, demonstrates a grand coalition of EV users under this cooperative V2V sharing mechanism, facilitating effective engagement of EVs in both energy and reserve markets.
2. Provides theoretical proofs and a solution methodology to ensure the existence and achievability of a fair and stable payoff allocation scheme for all coalition members within the cooperative V2V sharing framework. Establishes the balance condition required for the coalitional approach in solving the V2V sharing problem.
3. Presents a two-stage imputation method to determine a fair and optimal payoff allocation scheme, minimizing incentives for coalition members to defect. Then, introduces a decomposition algorithm to iteratively solve complex problems that grow exponentially with the number of users, ensuring efficiency in finding stable solutions.

These contributions collectively aim to enhance the integration of EVs into energy systems by maximizing their role as flexible energy providers, thereby supporting overall grid stability and efficiency.

The remaining paper is organized as follows. Sec. II will describe the coalitional approach for cooperative V2V sharing. The payoff allocation for cooperative V2V sharing will be addressed in Sec. III. The solution algorithm of imputation determination will be stated in Sec. IV. Numerical studies will be presented in Sec. V. Finally, some conclusions are made in Sec. VI.

2. Coalitional-based cooperative V2V sharing

In this section, the cooperative V2V sharing among a coalition is modeled. The users play both consumer and prosumer roles in the energy and reserve trading according

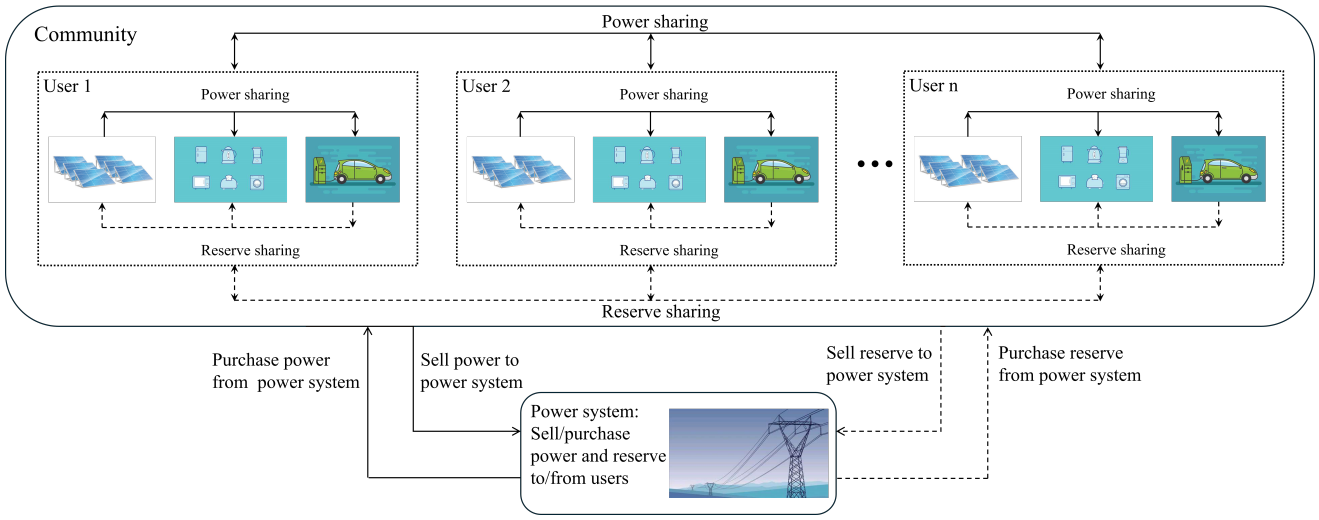

Figure 1: The trading mechanism between users and power system.

to the price of buying and selling energy and reserve. Moreover, the charging and discharging dynamic model of EVs which considers the power reserve is proposed in this section to meet the reserve requirement and maximize the payoff of users in the reserve market.

2.1. Framework of cooperative V2V sharing

In a modern residential community, the household microgrid (MG) consists of residential loads, household generation like PV systems, and EVs which can act as either uncertain loads or energy storage systems. Users can optimize their benefits by adjusting power consumption plans, including intra-household power and reserve sharing, as depicted in Fig. 1. Typically, EVs function as loads, but advancements in charging station technology enable them to discharge and provide Vehicle-to-Grid (V2G) services when necessary for urgent power supply needs from users or the power grid. PV systems, as uncontrollable generators, primarily supply electricity to their owners, with surplus electricity sold to the grid at lower prices during periods of excess generation. Each household user is solely responsible for their profits or losses, and the flexibility of EVs is often underutilized under these conditions.

To fully leverage the flexibility of EVs, an energy coordinator is introduced to manage energy distribution within the household MG. Users can achieve higher profits by operating as a unified coalition. For instance, EVs typically arrive during peak customer power consumption times when electricity prices are highest. By utilizing surplus energy from EVs during peak periods, users can significantly reduce EV charging costs. The energy coordinator engages in trading with both the power grid and users to maximize user benefits while meeting grid backup requirements. This Peer-to-Peer (P2P) trading mode consolidates all users into a cohesive group, enhancing profitability. In this framework, each user c_n belongs to a grand coalition C, where every member ($c \in C := \{1, 2, \ldots, l\}$) cooperates. Additionally, subsets S can form within grand coalition C, comprising various smaller coalitions of users from C (thus $S \subseteq C$).

2.2. Objective function of V2V sharing coalition

The energy coordinator's objective is to maximize the payoff for each user. This translates to maximizing the total benefits of users before the second round of payoff distribution. If a user chooses not to participate in the coalition S, the payoff of this user remains a fixed value. Therefore, the objective of the energy coordinator can be reconverted to maximize the total payoff of users within coalition S. The objective function $O(S) : 2^R \rightarrow \mathbb{R}$ of coalition S can be expressed as follows:

$$O(S) = \max R^S \tag{1}$$

where R^S represents the total payoff for users in coalition S, and 2^C denotes the power set of coalition S within the grand coalition C.

The total payoff function R^S comprises several components, including electricity load revenue for users and electricity costs:

$$R^S = \sum_{i \in S} \sum_t U_{i,t}^{cl} - \sum_t F_t + \sum_t F_t^r \tag{2}$$

Here:

1. $U_{i,t}^{cl}$ denotes the revenue from electricity consumption for user i at time t, defined as:

$$U_{i,t}^{cl} = \lambda_i^{cl} PL_{i,t}^{cl} - \beta_i^{cl} \left(PL_{i,t}^{cl} \right)^2 \quad \forall i \in S, \forall t \in T \tag{3}$$

2. F_t represents the electricity costs incurred by users at each time interval:

$$F_t = \sum_{i \in S} \left(p_t^{buy} z_{i,t}^{buy} - p_t^{sell} z_{i,t}^{sell} \right) \quad \forall t \in T \tag{4}$$

3. F_t^r accounts for users' payoffs from participating in the reserve market:

$$F_t^r = \sum_{i\in S}\left(r_{i,t}^{sell+} z_t^{rs+} + r_{i,t}^{sell-} z_t^{rs-}\right) - \sum_{i\in S}\left(r_{i,t}^{buy+} z_t^{rb+} + r_{i,t}^{buy-} z_t^{rb-}\right) \quad \forall t \in T \tag{5}$$

The quadratic term in $U_{i,t}^{cl}$ is linearized using piece-wise linear methods [7]. This involves dividing the function into $(H-1)$ segments with H points, ensuring each segment is linear:

$$U_{i,t}^{cl} = \sum_{h=1}^{H}\left(w_{i,t,h}\cdot U_{i,t,h}^{cl}\right) \tag{6}$$

$$PL_{i,t}^{cl} = \sum_{h=1}^{H}\left(w_{i,t,h}\cdot PL_{i,t,h}^{cl}\right) \tag{7}$$

where $w_{i,t,h}$ are weighting coefficients satisfying $\sum_h^H w_{i,t,h} = 1$ and $0 \le w_{i,t,h} \le 1$. The selection of segments is determined by binary variables $an_{i,t,h}$, ensuring the constraints:

$$\sum_{h=1}^{H-1} an_{i,t,h} = 1, \quad an_{i,t,h} \in \{0,1\} \tag{8}$$

$$w_{i,t,h+1} \le an_{i,t,h} + an_{i,t,h+1}, \quad \forall h = 2,\dots,H-2 \tag{9}$$

$$w_{i,t,1} \le an_{i,t,1}, \quad w_{i,t,H} \le an_{i,t,H-1} \tag{10}$$

(8) guarantees only one segment can be selected, (9) and (10) restrict that the selection of $w_{i,t,H}$ is within the ends of this segment. These formulations ensure efficient linearization of the quadratic term $\beta_i^{cl}\left(PL_{i,t}^{cl}\right)^2$ within $U_{i,t}^{cl}$, optimizing the calculation process while maintaining accuracy.

2.3. Charging and discharging dynamics of EVs in V2V sharing

After arriving home, EVs can be connected to charging stations, allowing the control center to schedule optimal charging and discharging plans to maximize revenue. EVs are capable of providing V2G services by discharging electricity back to the power system when necessary. This capability transforms EVs into flexible and reliable power sources while they are parked at home. The dynamics of EVs considering their charging and discharging actions within the residence are described by equations (11)-(17):

$$SOC_{i,t} = SOC_{i,1} + \frac{1}{E_i}\sum_{t_s=1}^{t}\left(\eta P_{i,t_s}^{\mathrm{ch}} + \frac{1}{\eta}P_{i,t_s}^{\mathrm{dis}}\right)\Delta t, \quad \forall t_s \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \tag{11}$$

$$SOC_{t_{i,\mathrm{arr}}} = SOC_{t_{i,\mathrm{dep}}} - \Delta SOC_i \quad \forall i \in C \tag{12}$$

$$SOC_{\min} \le SOC_{i,t} \le SOC_{\max}, \quad \forall i \in C, \forall t \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \tag{13}$$

$$SOC_{i,1} = SOC_{t_{i,T}} + \frac{1}{E_i}\left(\eta P_{i,1}^{\mathrm{ch}} + \frac{1}{\eta}P_{i,1}^{\mathrm{dis}}\right)\Delta t \tag{14}$$

$$0 \le P_{i,t}^{\mathrm{ch}} \le P_{\max}^{\mathrm{ch}}, \quad \forall i \in S, \quad \forall t \in T \tag{15}$$

$$0 \le P_{i,t}^{\mathrm{dis}} \le P_{\max}^{\mathrm{dis}}, \quad \forall i \in S, \quad \forall t \in T \tag{16}$$

$$P_{i,t}^{\mathrm{EV}} = P_{i,t}^{\mathrm{ch}} - P_{i,t}^{\mathrm{dis}}, \quad \forall i \in S, \quad \forall t \in T \tag{17}$$

Here:

1. $SOC_{i,t}$ denotes the State of Charge (SOC) of the ith EV at time t, accumulated from the initial SOC $SOC_{i,1}$ in equation (11).
2. $P_{i,t}^{\mathrm{ch}}$ and $P_{i,t}^{\mathrm{dis}}$ represent the active power for charging and discharging at time t respectively.
3. $t_{i,\mathrm{dep}}$ and $t_{i,\mathrm{arr}}$ represent the departure time and arrival time of the ith EV respectively.
4. η is the charging/discharging efficiency coefficient of the EV battery.
5. E_i denotes the rated battery capacity of the ith EV.

It is worthy of mentioning that equations (12)-(16) impose constraints on SOC levels, continuity of charging/discharging schedules, and limits on active power based on the maximum and minimum values. On the other hand, the interaction between EVs and the power grid is directly captured by equation (17), ensuring that at any given time t, either $P_{i,t}^{\mathrm{ch}}$ or $P_{i,t}^{\mathrm{dis}}$ must be zero, reflecting the physical limitations of EV operations.

Conventionally, the power system mandates that renewable energy and MGs must provide power reserves to stabilize fluctuations and support the grid during faults. These reserves are categorized into three types based on time scales: primary reserve (within 30 seconds), secondary reserve (between 10-15 minutes), and tertiary reserve (up to hourly scale) [37]. With the introduction of energy coordinators and the increasing adoption of EVs, households with EVs have the potential to act as reserve suppliers due to EVs' rapid charging/discharging capabilities. The battery capacity and flexible power management of EVs enable them to function as viable energy storage systems participating in reserve markets.

In recent years, several European countries have established reserve markets coordinated with transmission system

operators [38]. In this study, the power system requires households to provide reserves for their loads and PV generation, corresponding to daily demand and PV output. Additionally, the power system acts as a buyer, purchasing excess reserves from households. Another advantage of EV participation in reserve markets is their ability to supply both upward and downward reserves simultaneously. The reserve market model is structured as follows:

$$r_{i,t}^{+} = r_{i,t}^{\mathrm{ch}} - r_{i,t}^{re+}, \quad \forall i \in S, \quad \forall t \in T \tag{18}$$

$$r_{i,t}^{-} = r_{i,t}^{\mathrm{dis}} - r_{i,t}^{re-}, \quad \forall i \in S, \quad \forall t \in T \tag{19}$$

$$r_{i,t}^{re+} = \alpha_{l}^{+} PL_{i,t}^{cl} + \alpha_{PV}^{+} P_{i,t}^{PV}, \quad \forall i \in S, \quad \forall t \in T \tag{20}$$

$$r_{i,t}^{re-} = \alpha_{l}^{-} PL_{i,t}^{cl} + \alpha_{PV}^{-} P_{i,t}^{PV}, \quad \forall i \in S, \quad \forall t \in T \tag{21}$$

$$\begin{aligned} P_{i,t}^{\mathrm{ch}} + r_{i,t}^{\mathrm{ch}} &\le P_{\max}^{\mathrm{ch}}, \\ P_{i,t}^{\mathrm{dis}} + r_{i,t}^{\mathrm{dis}} &\le P_{\max}^{\mathrm{dis}}, \\ \forall i \in S, \quad \forall t \in \left[1, t_{i,\mathrm{dep}}\right] &\cup \left(t_{i,\mathrm{arr}}, T\right] \end{aligned} \tag{22}$$

$$r_{i,t}^{\mathrm{ch}} = 0, \quad r_{i,t}^{\mathrm{dis}} = 0, \quad \forall i \in S, \quad \forall t \in \left(t_{i,\mathrm{dep}}, t_{i,\mathrm{arr}}\right] \tag{23}$$

$$\begin{aligned} SOC_{i,t} \cdot E_i + \mu \left(P_{i,t}^{\mathrm{ch}} + r_{i,t}^{\mathrm{ch}}\right) \Delta t &\le SOC_{\max} \cdot E_i, \\ \forall i \in S, \quad \forall t \in \left[1, t_{i,\mathrm{dep}}\right] &\cup \left(t_{i,\mathrm{arr}}, T\right] \end{aligned} \tag{24}$$

$$\begin{aligned} SOC_{\min} \cdot E_i \le SOC_{i,t} \cdot E_i - \frac{1}{\mu} \left(P_{i,t}^{\mathrm{dis}} + r_{i,t}^{\mathrm{dis}}\right) \Delta t, \\ \forall i \in S, \quad \forall t \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \end{aligned} \tag{25}$$

Here:

1. $r_{i,t}^{+}$ and $r_{i,t}^{-}$ denote the upward and downward reserves that each user can supply; users must purchase reserves if these values are negative.
2. $r_{i,t}^{re+}$ and $r_{i,t}^{re-}$ represent the upward and downward reserves that users are required to supply based on their daily load and PV generation described by equations (20) and (21) respectively.
3. α coefficients ($\alpha_{l}^{+}, \alpha_{l}^{-}, \alpha_{PV}^{+}, \alpha_{PV}^{-}$) are used to calculate the required reserves.
4. $r_{i,t}^{\mathrm{ch}}$ and $r_{i,t}^{\mathrm{dis}}$ represent the reserves provided by EVs. These reserves are regulated by equation (22) to ensure that EV charging and discharging stay within acceptable limits for the subsequent interval.

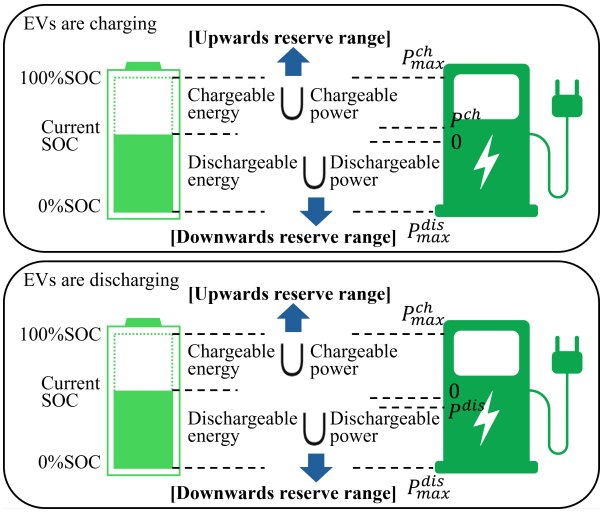

Figure 2: Possible upwards/downwards reserve

5. $P_{i,t}^{\mathrm{PV}}$ represents the active power output produced by the PV system, while $P_{i,t}^{\mathrm{EV}}$ denotes the active power consumed by the EV load.

Fig. 2 depicts the constraints on the reserves that each user can utilize. The range of reserves that each EV can provide is limited by its current charging/discharging power, the SOC of its battery, and the maximum charging/discharging power. Consequently, under these conditions, equation (23) guarantees that EVs do not charge or discharge while they are away from the residence. Additionally, equations (24) and (25) ensure that the SOC of EV batteries remains within optimal ranges for future intervals.

2.4. Load dynamic of users

The constraints governing the total load of each user are detailed in this subsection. For each household, the daily load comprises of the combined contributions from PV generation and EV dynamics. Based on this total load, users devise their plans for purchasing and selling electricity. The daily load of each user falls within a specified range, with lower and upper bounds determined by empirical values of rated daily load.

$$\rho_{\min} PL_{i,t}^{\mathrm{clr}} \le PL_{i,t}^{\mathrm{cl}} \le \rho_{\max} PL_{i,t}^{\mathrm{clr}}, \quad \forall i \in S, \quad \forall t \in T \tag{26}$$

Here, $\rho_{\min}$ and $\rho_{\max}$ denote the lower and upper coefficients defining the range of daily load. $PL_{i,t}^{\mathrm{clr}}$ represents the rated daily load. The total load can then be expressed as:

$$PL_{i,t}^{z} = PL_{i,t}^{\mathrm{cl}} + P_{i,t}^{\mathrm{EV}} - P_{i,t}^{\mathrm{PV}}, \quad \forall i \in S, \quad \forall t \in T \tag{27}$$

Under this framework, EVs can operate in one of the following two modes when connected to the charging station: (i) charging mode, where they act as a load; and (ii) discharging mode, where they can function as a power source to support the user's daily load.

2.5. Reserve and electricity sharing

As previously mentioned, each user has the option to either buy or sell electricity and reserves within a specified time interval. This process can be represented by the following constraints (28)-(30):

$$p_t^{buy} - p_t^{sell} = \sum_{i \in S} PL_{i,t}^{z} \quad \forall t \in T \tag{28}$$

$$r_t^{sell+} - r_t^{buy+} = \sum_{i \in S} r_{i,t}^{+} \quad \forall t \in T \tag{29}$$

$$r_t^{sell-} - r_t^{buy-} = \sum_{i \in S} r_{i,t}^{-} \quad \forall t \in T \tag{30}$$

Under the coordination of a central entity, all users within the coalition S can engage in trading electricity and reserves as a unified entity. Users can exchange electricity or reserves amongst themselves, reducing the overall cost of procuring electricity and reserves from the central power system.

3. Payoff allocation for cooperative V2V sharing

In this section, payoff allocation for cooperative V2V sharing will be addressed. First, theoretical proof of the appropriateness of the coalitional approach will be discussed. Then, a formulation of two-stage imputation problem will be presented.

3.1. Theoretical proof of the appropriateness of the coalitional approach

In the previous section, we have introduced the cooperative payoff for all users in coalition S. The total payoff for users in the grand coalition can be computed similarly. This subsection aims to demonstrate that the maximum payoff for all users occurs when every user participates in a single coalition (the grand coalition). Subsequently, it will address the allocation problem of distributing the payoff among individual users.

Definition 1. *(Imputation) Define the payoff of the user when they all participate in the grand coalition C is denoted as b. Therefore, the payoff of each user can be expressed as a vector* $\boldsymbol{b}$. $\boldsymbol{b}$ *is called an imputation if the following conditions are held:*

- *Efficiency: If the total payoff of the grand coalition satisfies the relationship* $\sum_{i \in C} b_i = O(C)$*, then the payoff allocation* $\boldsymbol{b}$ *is efficiency. In this condition, all the payoff is allocated to the users.*
- *Individual Rationality: The payoff of each user under the condition of participating in the grand coalition should be no less than trading with the power system individually* $b_i \geqslant O(\{i\})\ \forall i \in C$*. Under this circumstance, each user will prefer to stay in the grand coalition rather than leave.*

Note that the above two criteria ensure that each user can achieve greater payoff by not acting individually, yet they still have the option to join other coalitions S to potentially increase their payoff. Therefore, the following definitions are introduced.

Definition 2. *(Excess) Define the total payoff of users in coalition S when every user consists of a grand coalition C as o(S), and it has* $o(S) = \sum_{i \in S} b_i$*. And the gap between o(S) and O(S) is defined as the excess* ε *of coalition S.*

$$\varepsilon(S) = O(S) - o(S) \tag{31}$$

The excess ε denotes the satisfaction of users willing to join the grand coalition C. The higher value of the $\varepsilon(S)$ means that users are more likely to consist of a smaller coalition S to obtain more benefit.

Definition 3. *(Core) If a set of payoff* $\boldsymbol{b}$ *can guarantee each user are more willing to participate in the grand coalition c (obtain the maximum payoff), this set of payoff* $\boldsymbol{b}$ *is defined as core. Core should meet the following equation:*

$$\boldsymbol{b} \in Y, \quad where\ Y = \{\boldsymbol{b} \mid \varepsilon(S) \leqslant 0, \quad \forall\ S\} \tag{32}$$

For the core $\boldsymbol{b}$, the excess of every smaller coalition should be no more than 0.

Definition 4. *(Balanced Game) If the core* $\boldsymbol{b}$ *exists in the grand coalition, Then the following balanced game holds [39],[40]:*

$$\sum_{S \in 2^C} \gamma(S) O(S) \leqslant O(C) \tag{33}$$

where $\gamma(S) : 2^C \rightarrow [0, 1]$ *is the balanced map and is obtained by the following equation:*

$$\sum_{S \in 2^C} \gamma(S) \mathrm{I}_i^S = 1 \quad \forall i \in C \tag{34}$$

where I_i^S *is a binary variable. If the value is* 1*, the i-th user belongs to coalition S; if not, the value is* 0*. It should be noted that this balanced game is a cooperative game.*

After introducing several notations, the following theorem shows that the cooperative game is indeed balanced.

Theorem 1. *The cooperative game is balanced and stable.*

Before proving the above main theorem, some lemmas will be stated first.

Lemma 1. *The objective function of coalition described by (1) is a linear problem. Therefore,* $a \cdot O(S) = O(aS)$

Lemma 2. *The objective of the energy coordinator is maximizing the payoff of each user which can be expressed as (1), and (1) is equal to* $O(S) = -\min\left(-R^S\right)$*. Since* $-R^S$ *is a convex problem, we have:*

$$\min\left(-R^{S_1+S_2}\right) \leqslant \min\left(-R^{S_1}\right) + \min\left(-R^{S_2}\right) \tag{35}$$

where S_1 and S_1 are two non-overlapping coalitions belonging to the grand coalition. Moreover, by using (1), we have

$$O\left(S_1 + S_2\right) \geqslant O\left(S_1\right) + O\left(S_2\right) \tag{36}$$

Proof of Theorem 1: By employing the above two lemmas, the left side of (33) can be re-written as:

$$\sum_{S\in 2^C} a(S)O(S) = \sum_{S\in 2^C} v(a(S)\cdot S) \leqslant O\left(\sum_{S\in 2^C} a(S)\cdot S\right) \tag{37}$$

Meanwhile, the right side of (37) can be derived as:

$$\begin{aligned} &O\left(\sum_{S\in 2^C} a(S)\cdot S\right) = O\left(\sum_{S\in 2^C} a(S)\cdot \sum_n I_i^S\{i\}\right) \\ &= O\left(\sum_n \sum_{S\in 2^C} a(S) I_i^S\{i\}\right) = O\left(\sum_i \{i\}\right) = O(C) \end{aligned} \tag{38}$$

By combining (37) and (38) together, the cooperative game described by (33) is shown to be balanced and stable as stated in [41].

3.2. Formulation of two-stage imputation problem

In the previous subsection, it has been established that the maximum payoff for every user is achieved only when participating in the grand coalition. The next step involves determining the allocation that minimizes the highest excess. Given a specific set $\boldsymbol{b}$, we can identify the coalition with the highest excess which is referred to as the *worst coalition*.

To address this issue, a two-stage optimization problem is formulated to determine the allocation of payoffs:

$$\min_{\mathbf{b}} \max_{\mathbf{q}} \left(R - \sum_{i\in C} q_i b_i\right) \tag{39}$$

where $\mathbf{q}$ is a binary variable indicating whether each user i belongs to the coalition with the highest excess.

In the first stage, the vector $\boldsymbol{b}$ is adjusted to minimize the excess in the second stage. The objective function R and its constraints are based on the household MG model introduced in sec. 2. It is worthy of mentioning that R here also represents the total payoff of these users who tend to form a sub-coalition, which is the same as R^S. However, the components of the sub-coalition will change under different imputations. Therefore, R is used to represent the total revenue of any sub-alliance. An additional constraint (40) is included to ensure the efficiency of $\boldsymbol{b}$, and the variables in (39) are expressed as (41)-(47). To handle the nonlinear terms in (41) and (45)-(47), binary variables $\mathbf{q}$ are introduced in (39), and these are linearized using the big-M method. Constraints (65)-(72) represent the linearized forms where $k_{i,t}^1, k_{i,t}^2, k_{i,t}^3, k_{i,t}^4$ replace the original nonlinear terms, ensuring the entire problem remains within the framework of the grand coalition C.

$$\sum_i b_i = O(C), \mathrm{O_i} \geqslant 0 \tag{40}$$

$$R = \sum_{i\in C}\sum_t q_i U_{i,t}^{cl} - \sum_t F_t + \sum_t F_t^r \tag{41}$$

$$U_{i,t}^{cl} = \lambda_i^{cl} PL_{i,t}^{cl} - \beta_i^{cl}\left(PL_{i,t}^{cl}\right)^2 \forall i \in C, \forall t \in T \tag{42}$$

$$F_t = \sum_{i\in C}\left(p_t^{buy} z_{i,t}^{\mathrm{buy}} - p_t^{sell} z_{i,t}^{sell}\right) \forall t \in T \tag{43}$$

$$\begin{aligned} F_t^r = &\sum_{i\in C}\left(r_{i,t}^{sell+} z_t^{rs+} + i, t_t^{sell-} z_t^{rs-}\right) \\ &- \sum_{i\in C}\left(r_{i,t}^{buy+} z_t^{\mathrm{rb+}} + r_{i,t}^{buy-} z_t^{\mathrm{rb\text{-}}}\right) \quad \forall t \in T \end{aligned} \tag{44}$$

$$p_t^{buy} - p_t^{sell} = \sum_{i\in C} q_i PL_{i,t}^z \quad \forall t \in T \tag{45}$$

$$r_t^{sell+} - r_t^{buy+} = \sum_{i\in C} q_i r_{i,t}^+ \quad \forall t \in T \tag{46}$$

$$r_t^{sell-} - r_t^{buy-} = \sum_{i\in C} q_i r_{i,t}^- \quad \forall t \in T \tag{47}$$

Compared to the objective function (1) described in Sec. 2, the binary variable q_i is introduced in the current objective function (39) to capture the worst coalition. It should be noticed that every constraint in this two-stage problem is under the grand coalition C. Therefore, the remaining constraints can be re-written as:

$$\rho_{min} PL_{i,t}^{clr} \leq PL_{i,t}^{cl} \leq \rho_{max} PL_{i,t}^{clr} \quad \forall i \in C, \forall t \in T \tag{48}$$

$$PL_{i,t}^z = PL_{i,t}^{cl} + P_{i,t}^{EV} - P_{i,t}^{PV} \quad \forall i \in C, \forall t \in T \tag{49}$$

$$\begin{aligned} SOC_{i,t} = SOC_{i,1} + \frac{1}{E_i}\sum_{t_s=1}^{t}\left(\eta P_{i,t_s}^{\mathrm{ch}} + \frac{1}{\eta} P_{i,t_s}^{\mathrm{dis}}\right)\Delta t \\ \forall i \in C, \forall t_s \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \end{aligned} \tag{50}$$

$$SOC_{t_{i,\mathrm{arr}}} = SOC_{t_{i,\mathrm{dep}}} - \triangle SOC_i \quad \forall i \in C \tag{51}$$

$$\begin{aligned} SOC_{\min} \leq SOC_{i,t} \leq SOC_{\max} \\ \forall i \in C, \forall t \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \end{aligned} \tag{52}$$

$$\begin{aligned} SOC_{i,1} = SOC_{t_{i,T}} + \frac{1}{E_i}\left(\eta P_{i,1}^{\mathrm{ch}} + \frac{1}{\eta} P_{i,1}^{\mathrm{dis}}\right)\Delta t \\ \forall i \in C \end{aligned} \tag{53}$$

$$0 \le P_{i,t}^{\mathrm{ch}} \le P_{\max}^{\mathrm{ch}}, \quad \forall i \in C, \quad \forall t \in T \tag{54}$$

$$0 \le P_{i,t}^{\mathrm{dis}} \le P_{\max}^{\mathrm{dis}}, \quad \forall i \in C, \quad \forall t \in T \tag{55}$$

$$P_{i,t}^{EV} = P_{i,t}^{\mathrm{ch}} - P_{i,t}^{\mathrm{dis}}, \quad \forall i \in C, \quad \forall t \in T \tag{56}$$

$$r_{i,t}^{+} = r_{i,t}^{\mathrm{ch}} - r_{i,t}^{re+}, \quad \forall i \in C, \quad \forall t \in T \tag{57}$$

$$r_{i,t}^{-} = r_{i,t}^{\mathrm{dis}} - r_{i,t}^{re-}, \quad \forall i \in C, \quad \forall t \in T \tag{58}$$

$$r_{i,t}^{re+} = \alpha_l^{+} PL_{i,t}^{cl} + \alpha_{PV}^{+} P_{i,t}^{PV}, \quad \forall i \in C, \quad \forall t \in T \tag{59}$$

$$r_{i,t}^{re-} = \alpha_l^{-} PL_{i,t}^{cl} + \alpha_{PV}^{-} P_{i,t}^{PV}, \quad \forall i \in C, \quad \forall t \in T \tag{60}$$

$$\begin{gathered} P_{i,t}^{\mathrm{ch}} + r_{i,t}^{\mathrm{ch}} \le P_{i,t}^{\mathrm{ch}}, P_{i,t}^{\mathrm{dis}} + r_{i,t}^{\mathrm{dis}} \le P_{i,t}^{\mathrm{dis}} \\ \forall i \in C, \quad \forall t \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \end{gathered} \tag{61}$$

$$\begin{gathered} r_{i,t}^{\mathrm{ch}} = 0, \quad r_{i,t}^{\mathrm{dis}} = 0 \\ \forall i \in C, \quad \forall t \in \left(t_{i,\mathrm{dep}}\, t_{i,\mathrm{arr}}\right] \end{gathered} \tag{62}$$

$$\begin{gathered} SOC_{i,t} \cdot E_i + \mu \left(P_{i,t}^{\mathrm{ch}} + r_{i,t}^{\mathrm{ch}}\right) \Delta t \le SOC_{max} \cdot E_i \\ \forall i \in C, \quad \forall t \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \end{gathered} \tag{63}$$

$$\begin{gathered} SOC_{min} \cdot E_i \le SOC_{i,t} \cdot E_i - \frac{1}{\mu}\left(P_{i,t}^{\mathrm{dis}} + r_{i,t}^{\mathrm{dis}}\right) \Delta t \\ \forall i \in C, \quad \forall t \in \left[1, t_{i,\mathrm{dep}}\right] \cup \left(t_{i,\mathrm{arr}}, T\right] \end{gathered} \tag{64}$$

Note that constraints (48)-(64) are the linear constraints, while constraint (41) and constraints (45)-(47) contain the nonlinear items. For constraint (41), the first item of the right side of the equation is a binary variable multiple with a continuous variable, and this variable contains quadratic terms. Therefore, the continuous variable $U_{i,t}^{cl}$ should be linearized first by (6)-(10), then applied with the big M method as described by (65)-(66) [42]. The right side of these constraints (45)-(47) can also implement with big M method to complete the linearization as shown in constraints (67)-(72) below:

$$\begin{gathered} -M_1(1-q_i) \le k_{i,t}^{1} - U_{i,t}^{cl} \le M_1(1-q_i) \\ \forall i \in C, \quad \forall t \in T \end{gathered} \tag{65}$$

$$-M_1 \le k_{i,t}^{1} \le M_1 \quad \forall i \in C, \quad \forall t \in T \tag{66}$$

$$\begin{gathered} -M_2(1-q_i) \le k_{i,t}^{2} - PL_{i,t}^{z} \le M_2(1-q_i) \\ \forall i \in C, \quad \forall t \in T \end{gathered} \tag{67}$$

$$-M_2 \le k_{i,t}^{2} \le M_2 \quad \forall i \in C, \quad \forall t \in T \tag{68}$$

$$\begin{gathered} -M_3(1-q_i) \le k_{i,t}^{3} - r_{i,t}^{+} \le M_3(1-q_i) \\ \forall i \in C, \quad \forall t \in T \end{gathered} \tag{69}$$

$$-M_3 \le k_{i,t}^{3} \le M_3 \quad \forall i \in C, \quad \forall t \in T \tag{70}$$

$$\begin{gathered} -M_4(1-q_i) \le k_{i,t}^{4} - r_{i,t}^{-} \le M_4(1-q_i) \\ \forall i \in C, \quad \forall t \in T \end{gathered} \tag{71}$$

$$-M_4 \le k_{i,t}^{4} \le M_4 \quad \forall i \in C, \quad \forall t \in T \tag{72}$$

where M_1-M_4 are big enough numbers, $k_{i,t}^{1}$-$k_{i,t}^{4}$ are equal to $q_i U_{i,t}^{cl}$, $q_i PL_{i,t}^{z}$, $q_i r_{i,t}^{+}$, $q_i r_{i,t}^{-}$ respectively. They can substitute the origin nonlinear items in constraint (41) and constraints (45)-(47). It should be noted that in constraints (25)-(28), $U_{i,t}^{cl}$ is a linear continuous variable.

4. Solution techniques of imputation determination

In Sec. 3, the cooperative and allocation problem is converted as a two-stage optimization problem. In this section, a solution technique based on the column constraints generation algorithm is implemented to solve this problem [43]. The master problem aims at minimizing the excess of the worst case obtained by the sub-problem, while the sub-problem will search for the worst case with the imputation obtained by the master problem in each iteration. Technical details of both the master problem and the sub-problem will be described as follows.

4.1. Master problem

The master problem can be established as follows:

$$\min \ \phi \tag{73}$$

$$\text{s.t. } \phi \geqslant R_m^{*} - \sum_{i \in C} q_{i,m}^{*} b_i \quad \forall m \in M, \text{ and} \tag{74}$$

$$\sum_i b_i = O(C), \ b_{\mathrm{i}} \geqslant 0 \tag{75}$$

The master problem aims at minimizing the excess of the worst case obtained by the sub-problem. ϕ is an auxiliary variable to guarantee the latest imputation b_i can cover all the worst cases obtained by the sub-problem. M represents the aggregation of the worst cases in the previous iterations. The right side of (74) denotes the excess of the worst case, and after each iteration, a new worst case as well as its constraint (74) is appended to the master problem. Constraint (75) ensures the efficiency of the updated imputation.

4.2. Sub-problem

The objective of each sub-problem is to search for the worst case with the imputation obtained by the master problem in each iteration. The sub-problem is set as (76)-(77):

$$\max_{q} \left(R - \sum_{i \in C} q_i b_i^* \right) \tag{76}$$

$$\text{s.t. } (48) - (72) \tag{77}$$

where b_i^* is the imputation obtained by the master problem in this iteration. Through the sub-problem, the users who are dissatisfied with the current allocation plan b_i^* can be obtained, which is represented by q_i.

4.3. Solution algorithm

The solution algorithm of this two-stage algorithm can be outlined as follows:

(1) Initialize all parameters, set m as 0.
(2) Set all elements in $q_{i,0}^*$ as 1, calculate the total payoff of the grand coalition.
(3) Make an initial imputation $b_{i,0}$ by solving the master problem. Here the total payoff can be allocated to each user randomly. In this step, (74) is not included yet.
(4) Update the imputation $b_{i,m}$ (the first is $b_{i,0}$) to the sub-problem to search for the worst case ($q_{i,m+1}$) with the updated imputation. Set $m = m + 1$.
(5) Update the worst case $q_{i,m}$ to the master problem, and obtain a new imputation $b_{i,m}$.
(6) Go back to Step (4) to obtain a new worst case with $q_{i,m}$. If the $q_{i,m}$ remains stable and all users participate in the grand coalition, the best imputation $b_{i,m}$ is achieved. If not, go to Step (5) and continue iteration.

The flowchart of the solution process is shown in Fig. 3.

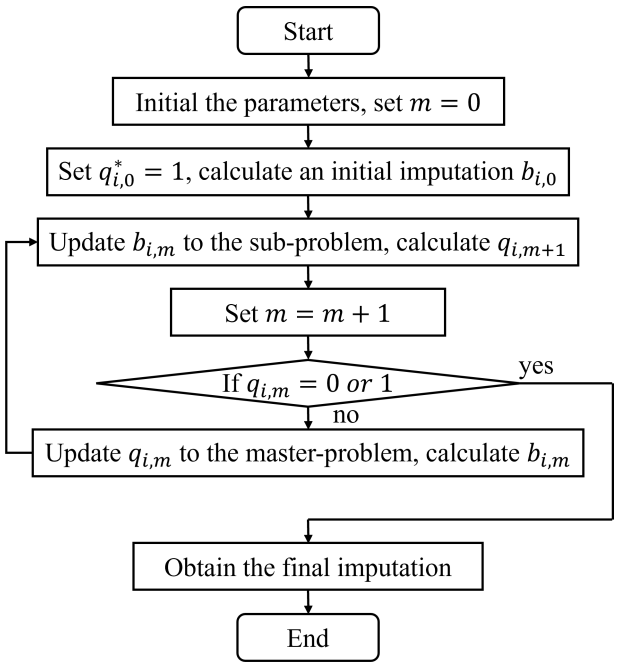

Figure 3: Flowchart of the solution algorithm.

5. Numerical validations

The proposed optimization model is applied to various residential communities to assess its effectiveness. The electricity pricing follows a tiered structure: 32.094¢/kWh from 5 p.m. to 10 p.m., and 16.723¢/kWh during all other time periods. The selling price of electricity from users to the power system is set at one-third of the purchasing price. Similarly, the pricing for purchasing and selling reserves mirrors that of electricity.

The charging and discharging efficiency of EVs are both assumed to be 0.95. 40% users possess EVs and 60% users are implemented with PV. Initially, a random distribution of EVs and PVs is carried out to ensure the model's general applicability. In this setup, users may have both an EV and PV system installed at their residence. The capacity of each EV is a random value between 40 and 80, and the max charging/discharging power is set as 7 KW. The arrival time and the departure time of these EVs are obtained through the empirical probability density function (PDF) sampling. Each day is divided into 24 one-hour time intervals.

5.1. A small-scale V2V sharing residential community

Initially, a small-scale residential community with 10 users is utilized to validate the efficiency of the proposed optimization strategy under the supervision of a power coordinator. Fig. 4 illustrates the payoff allocation for each user trading individually with the power system compared to their participation in the grand coalition. The results clearly demonstrate that each user achieves higher payoff when part of the grand coalition. This improvement is facilitated through coordinated actions as follows:

(1) During several time intervals, the output power from PV exceeds the users' electricity demand as shown in Fig. 5, notably peaking between 10 a.m. and 4 p.m.. Users with PV systems can directly sell surplus electricity to those without PV systems if they are part of the grand coalition. In contrast, trading individually would force them to sell surplus electricity to the power system at

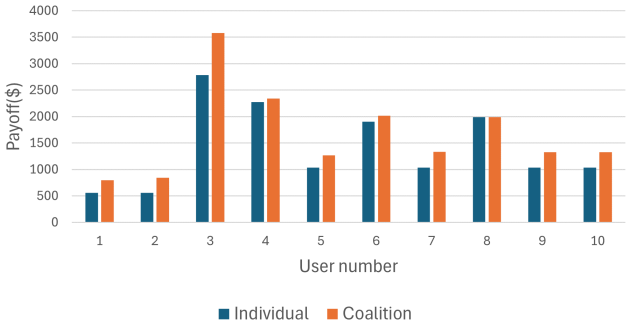

Figure 4: Payoff of user trade individually and jointly (10 users).

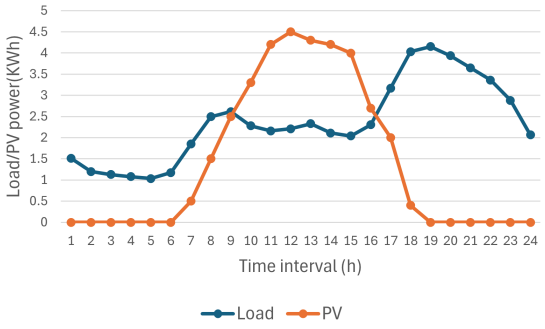

Figure 5: Power output of PV and load (10 users).

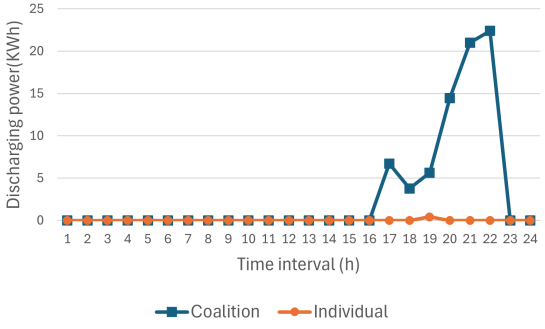

Figure 6: Total V2G power of EVs with/without coalition approach (10 users).

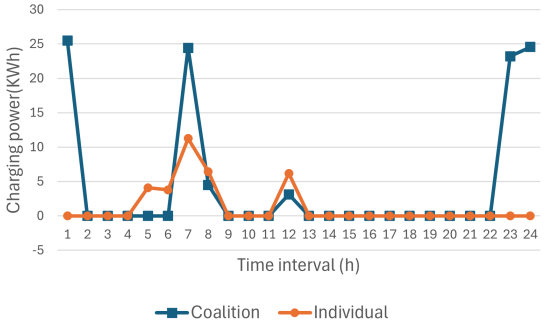

Figure 7: Total charging power of EVs with/without coalition approach (10 users).

a significantly lower price than the purchasing price of electricity.

(2) Between 5 p.m. and 10 p.m., electricity prices reach their peak, coinciding with peak domestic electricity consumption when people return home. Users with EVs can optimize their electricity usage by utilizing EV battery power during this period and charge the EVs during off-peak hours when prices are lower. Typically, an EV's battery capacity can sufficiently supply a user for an extended period, allowing surplus electricity from EVs to be shared with users without EVs within the grand coalition. This peer-to-peer electricity trade can increase overall payoff. Fig. 6 illustrates the total discharging power of EVs engaged in V2G scenarios under both individual trading and within a grand coalition. Users benefit from using cheaper electricity from EVs between 5 p.m. and 10 p.m., and those with EVs also gain revenue by selling electricity during this peak-priced period. The assumption is that EV batteries can recharge after 10 p.m., leveraging lower electricity prices more cost-effectively. Then after 10 p.m., EVs are charging immediately when the electricity price decreases to the off-peak value, which can illustrated in Fig. 7. EVs take full advantage of the off-peak price period to save the total cost with our plan being implemented.

(3) Each user must provide reserve capacity related to their load and PV generation. Users with EVs can supply both upward and downward reserves, akin to energy storage systems. However, users without EVs must purchase reserves from the power system if they opt for individual trading. Thus, participating in a coalition for reserve trading ensures higher revenue. Fig. 8 and Fig. 9 depict the total upward and downward reserves supplied by all users within the grand coalition, respectively. It should be noted that forming a grand coalition may reduce the total reserves supplied compared to individual trading scenarios. However, the total cost or payoff related to reserves in a coalition may not necessarily be lower, as users with EVs absorb reserves that users without EVs would otherwise need to purchase.

To validate the effectiveness of the proposed cooperative allocation model, a comparison of four scenarios is established:

- sc(i): Each user trades individually with the power system without considering reserve requirements.
- sc(ii): Each user trades as a grand coalition with the power system without considering reserve requirements.
- sc(iii): Each user trades individually with the power system, considering reserve requirements.
- sc(iv): Each user trades as a grand coalition with the power system, considering reserve requirements.

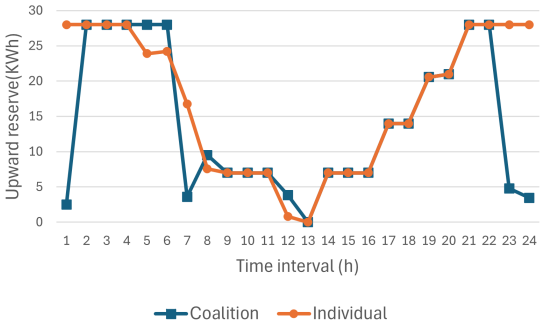

Figure 8: Total upward reserve with/without coalition approach (10 users).

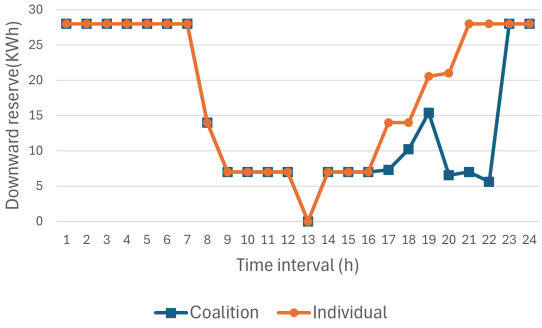

Figure 9: Total downward reserve with/without coalition approach (10 users).

The model proposed in this study corresponds to scenario sc(iv). Table 1 illustrates the total payoff for all users in these scenarios. It shows that whether or not reserve requirements are considered, the total revenue for all users is higher when they form a grand coalition. Additionally, even though some users may not individually meet reserve requirements, the collective approach of the grand coalition can still generate higher revenue from reserves.

Table 1
Total payoff for all users in four scenarios

item	sc (i)	sc (ii)	sc (iii)	sc (iv)
Total payoff ($)	14323.58	15713.32	14213.42	17370.36
Electricity cost($)	9709.96	8320.23	10609.04	9045.93
Revenue($)	24033.54	24033.55	24034.54	24034.55
Reserve payoff($)	0	0	787.92	2381.74

The iterative process is depicted in Table 2. $q_i = \{c_1, c_2, \cdots, c_{10}\}$ shows whether each user is willing to join the grand coalition under the payoff allocation plan in the $i-th$ iteration. Initially, at the start of the solution process, the payoff is evenly distributed among all users as the initialization of the imputation. Subsequently, using this initial imputation, the sub-problem identifies the maximum excess and determines the corresponding $q_{i,0}$, as shown in the second row of Table 2. Upon updating $q_{i,0}$ in the master problem, the solution process continues by searching for another imputation and iterates according to the procedure outlined in Sec. 4.3 until achieving the optimal imputation.

Table 2
The iteration process of q_i.

Iteration	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}
1	0	0	1	1	0	1	0	1	0	0
2	1	1	0	1	1	1	1	1	1	1
3	1	1	1	0	1	1	1	1	1	1
4	1	1	1	1	1	1	1	0	1	1
5	1	1	1	1	1	0	1	1	1	1
6	1	1	0	0	0	1	1	1	1	1
7	0	1	0	0	1	1	1	1	1	1
8	1	1	0	0	1	1	1	1	1	0
9	1	0	0	0	1	1	1	1	1	1
10	1	1	0	0	1	1	1	1	0	1
11	1	1	0	0	1	1	0	1	1	1
12	0	0	0	0	0	0	0	0	0	0

5.2. A large-scale V2V sharing residential community

To demonstrate the applicability of the proposed cooperative allocation model in a larger-scale residential community, the optimal imputation is presented in Fig. 10. It shows that each user achieves significantly higher payoffs when they participate in a grand coalition. When users trade individually with the power system, those with EVs tend to refrain from supplying V2G services, as indicated by the orange line in Fig. 11, but they contribute more to reserves, as shown by these orange lines in Fig. 13 and Fig. 14. Conversely, users with EVs actively participate in V2G systems to take advantage of the flexibility in charging and discharging their EVs. This engagement can be illustrated by these blue lines in Fig. 11 and Fig. 12. As a result, these users contribute less to the reserve supply, as shown by these blue lines in Fig. 13 and Fig. 14.

Fig. 15 depicts the total load trading dynamics between users and the power system. A notable distinction between individual and coalition-based load trading is evident from 6 p.m. to 10 p.m., corresponding to peak electricity prices. During this period, users opt to utilize their EVs as their primary energy source instead of selling reserves to the power system. Notably, within the grand coalition, the total user load peaks between 11 p.m. and 1 a.m. the following day. This observation underscores the effectiveness of the proposed cooperative allocation model in efficiently coordinating user behaviors.

5.3. Computational performance under various scales of residential communities

Finally, the iteration of the excess in this case is depicted in Fig. 16, demonstrating the method's convergence. Additionally, the simulation time is illustrated in Fig. 17. The computational complexity increases exponentially with the number of users. In greater detail, without the proposed method, the relationship between computation burden and

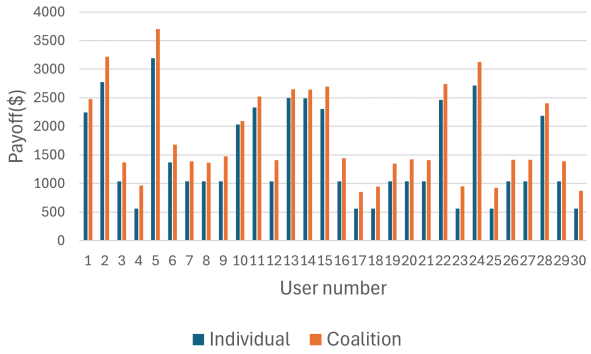

Figure 10: Payoff of user trade individually and jointly (30 users).

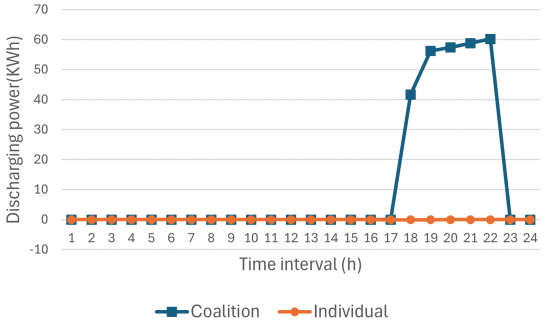

Figure 11: Total V2G power of EVs with/without coalition approach (30 users).

the number of users is given by $f(CB) \sim 2^C$, where $f(CB)$ represents the computation burden. Fig. 17 shows the complexity as the common logarithm of the computation burden. Since the computation time increases near-linearly, this result highlights the method's efficient convergence rate and computation time.

6. Conclusion

This study introduces a novel coalitional mechanism for V2G-enabled V2V sharing in energy and reserve markets. The cooperative V2V sharing approach consolidates EV users into a grand coalition to maximize the utilization of EVs' substantial charging and discharging capabilities. The modeling of V2V sharing is provided, detailing how EVs collaboratively engage in both energy and reserve markets through mathematical formulations. The study offers theoretical proofs and a solution methodology to establish a fair and stable pay allocation scheme within this cooperative framework. The feasibility of the coalitional approach is initially validated theoretically. Subsequently, a two-stage imputation problem is formulated to achieve an equitable and optimal payoff allocation. A decomposition algorithm is proposed to efficiently solve the exponentially growing problems associated with increasing numbers of users.

Comparing the total payoff between users trading individually with the power system and those in a grand coalition, the proposed method shows a significant increase

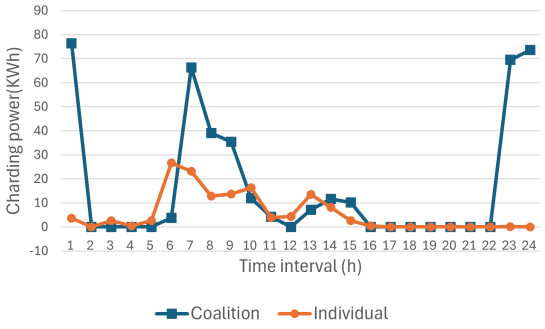

Figure 12: Total charging power of EVs with/without coalition approach (30 users).

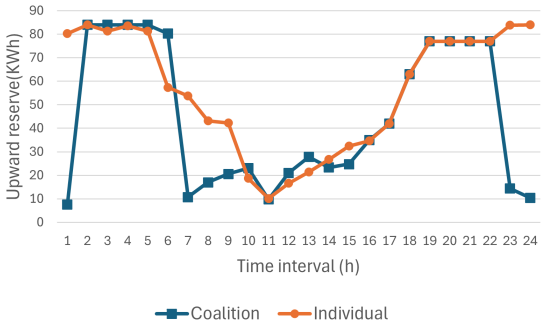

Figure 13: Total upward reserve with/without coalition approach (30 users).

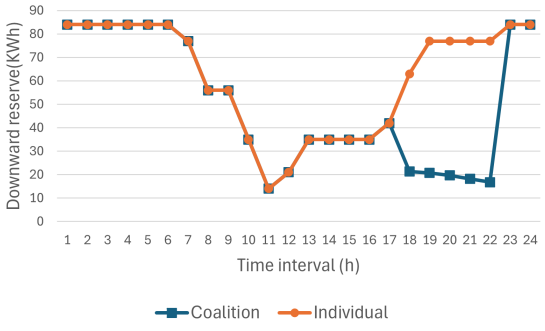

Figure 14: Total downward reserve with/without coalition approach (30 users).

in total payoff: a 22.21% increase for 10 users and a 22.39% increase for 30 users. In the case of 10 users, the proposed method also achieves a 14.73% reduction in total electricity costs and a remarkable 202.28% improvement in total reserve payoff. These results underscore the method's capability to fully leverage users' potential in power reserve management. Furthermore, the solution time of the proposed method scales near-linearly despite the system's complexity growing exponentially with the number of users. This highlights the efficient performance of the proposed method in delivering satisfactory solutions. In future work, we will investigate the dynamic interactions between the residential electric network and the power system. Our goal is to develop a more detailed model that accurately reflects the dynamics of this coupled system.

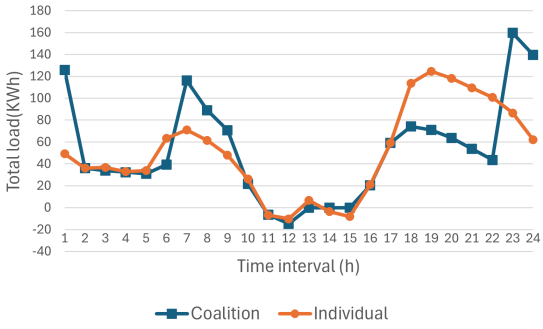

Figure 15: Total load of users with/without coalition approach (30 users).

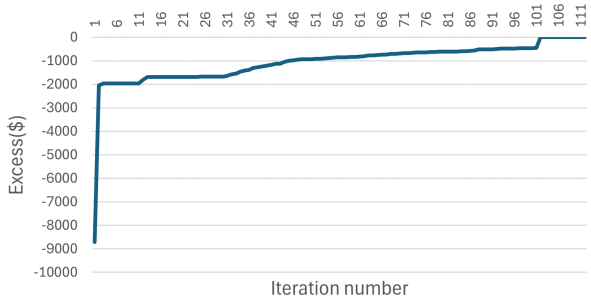

Figure 16: Iteration process of 30-user case.

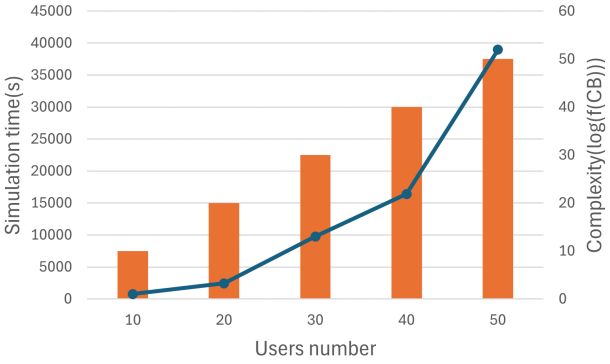

Figure 17: Simulation time and the complexity of various cases.

References

[1] Visaria A A, Jensen A F, Thorhauge M, et al. User preferences for EV charging, pricing schemes, and charging infrastructure. Transp Res Part A Policy Pract 2022;165:120-43.

[2] Int. Energy Agency. Global EV Outlook 2024. Available from: https://www.iea.org/reports/global-ev-outlook-2024.

[3] Patil H, Kalkhambkar V N. Grid integration of electric vehicles for economic benefits: A review. J Mod Power Syst Clean Energy 2020;9(1):13-26.

[4] Venegas F G, Petit M, Perez Y. Active integration of electric vehicles into distribution grids: Barriers and frameworks for flexibility services. Renew. Sust. Energ. Rev .2021;145:111060.

[5] CENELEC. EN 50160: 2010 voltage characteristics of electricity supplied by public electricity networks. Available from: https://standards.iteh.ai/catalog/standards/clc/18a86a7c-e08e-405e-88cb-8a24e5fedde5/en-50160-2010

[6] Wang H, Xu X, Chen Y, et al. Stochastic optimization of coupled power distribution-urban transportation network operations with autonomous mobility on demand systems. IEEE Trans. Smart Grid 2024;15(3):3040-53.

[7] Gan W, Shahidehpour M, Guo J, et al. Two-stage planning of network-constrained hybrid energy supply stations for electric and natural gas vehicles. IEEE Trans. Smart Grid 2020;12(3):2013-26.

[8] Ghazvini M A F, Lipari G, Pau M, et al. Congestion management in active distribution networks through demand response implementation. Sustain. Energy Grids Netw. 2019;17:100185.

[9] Ayyadi S, Bilil H, Maaroufi M. Optimal charging of electric vehicles in residential area. Sustain. Energy Grids Netw. 2019;19:100240.

[10] Fachrizal R, Ramadhani U H, Munkhammar J, et al. Combined PV–EV hosting capacity assessment for a residential LV distribution grid with smart EV charging and PV curtailment. Sustain. Energy Grids Netw. 2021;26:100445.

[11] Eid C, Codani P, Perez Y, et al. Managing electric flexibility from distributed energy resources: A review of incentives for market design. Renew. Sust. Energ. Rev. 2016;64:237-47.

[12] Wargers A, Kula J, Ortiz de Obregón F, et al. Smart charging: integrating a large widespread of electric cars in electricity distribution grids. EDSO for Smart Grids 2018.

[13] Qian T, Ming W, Shao C, et al. An edge intelligence-based framework for online scheduling of soft open points with energy storage. IEEE Trans. Smart Grid 2024;15(3):2934-45.

[14] Gan W, Wen J, Yan M, et al. Enhancing resilience with electric vehicles charging redispatching and vehicle-to-grid in traffic-electric networks. IEEE Trans Ind Appl, 2023, 60(1): 953-965.

[15] Sun Y, Yue H, Zhang J, et al. Minimization of residential energy cost considering energy storage system and EV with driving usage probabilities. IEEE Trans. Sustain. Energy 2018;10(4):1752-63.

[16] Shang Y, Li S. FedPT-V2G: Security enhanced federated transformer learning for real-time V2G dispatch with non-IID data. Appl. Energy 2024;358:122626.

[17] Zhang J, Che L, Shahidehpour M. Distributed training and distributed execution based Stackelberg multi-agent reinforcement learning for EV charging scheduling. IEEE Trans. Smart Grid 2023.

[18] Yu Q, Wang Z, Song Y, et al. Potential and flexibility analysis of electric taxi fleets V2G system based on trajectory data and agent-based modeling. Appl. Energy 2024;355:122323.

[19] Xu J, Huang Y. The short-term optimal resource allocation approach for electric vehicles and V2G service stations. Appl. Energy 2022;319:119200.

[20] Miglani A, Kumar N. Blockchain-based co-operative caching for secure content delivery in CCN-enabled V2G networks. IEEE Trans. Veh. Technol. 2023;72(4):5274-89.

[21] Zeng M, Leng S, Zhang Y, et al. QoE-aware power management in vehicle-to-grid networks: A matching-theoretic approach. IEEE Trans. Smart Grid 2016;9(4):2468-77.

[22] Lin J, Pipattanasomporn M, Rahman S. Comparative analysis of auction mechanisms and bidding strategies for P2P solar transactive energy markets. Appl. Energy 2019;255:113687.

[23] Bandara KY, Thakur S, Breslin J. Flocking-based decentralized double auction for P2P energy trading within neighborhoods. Int J Electr. Power Energy Syst. 2021;129:106766.

[24] Imran K, Zhang J, Pal A, Khattak A, Ullah K, Baig SM. Bilateral negotiations for electricity market by adaptive agent-tracking strategy. Electr. Power Syst. Res. 2020;186:106390.

[25] Khorasany M, Paudel A, Razzaghi R, Siano P. A new method for peer matching and negotiation of prosumers in peer-to-peer energy markets. IEEE Trans. Smart Grid 2020;12(3):2472-83.

[26] Lee WP, Han D, Won D. Grid-oriented coordination strategy of prosumers using game-theoretic peer-to-peer trading framework in energy community. Appl. Energy 2022;326:119980.

[27] Izanlo A, Sheikholeslami A, Gholamian SA, Verij Kazemi M, Hosseini SN. A new model for matching asks and bids in P2P energy trading: Game theory method. Electr. Power Components Syst. 2024:1-13.
[28] Zhang J, Che L, Wan X, et al. Distributed hierarchical coordination of networked charging stations based on peer-to-peer trading and EV charging flexibility quantification. IEEE Trans. Power Syst. 2021;37(4):2961-75.
[29] Luo Q, Zhou Y, Hou W, et al. A hierarchical blockchain architecture based V2G market trading system. Appl. Energy 2022;307:118167.
[30] Yan L, Chen X, Chen Y, et al. A hierarchical deep reinforcement learning-based community energy trading scheme for a neighborhood of smart households. IEEE Trans. Smart Grid 2022;13(6):4747-58.
[31] Nasiri N, Zeynali S, Najafi Ravadanegh S, Kubler S. Moment-based distributionally robust peer-to-peer transactive energy trading framework between networked microgrids, smart parking lots and electricity distribution network. IEEE Trans. Smart Grid 2024;15(2):1965-77.
[32] Zhao K, Zhang M, Lu R, et al. A secure intra-regional-inter-regional peer-to-peer electricity trading system for electric vehicles. IEEE Trans. Veh. Technol. 2022;71(12):12576-87.
[33] Liu Y, Wang Y, Li Y, et al. Multi-agent based optimal scheduling and trading for multi-microgrids integrated with urban transportation networks. IEEE Trans. Power Syst. 2020;36(3):2197-2210.
[34] Hoque MM, Khorasany M, Azim MI, Razzaghi R, Jalili M. Dynamic operating envelope-based local energy market for prosumers with electric vehicles. IEEE Trans. Smart Grid 2024;15(2):1712-24.
[35] Zhang Z, Li R, Li F. A novel peer-to-peer local electricity market for joint trading of energy and uncertainty. IEEE Trans. Smart Grid 2019;11(2):1205-1215.
[36] Maharjan S, Zhu Q, Zhang Y, et al. Demand response management in the smart grid in a large population regime. IEEE Transactions on Smart Grid, 2015, 7(1): 189-199.
[37] Wang Z, Bian Q, Xin H, et al. A distributionally robust co-ordinated reserve scheduling model considering CVaR-based wind power reserve requirements. IEEE Trans. Sustain. Energy, 2015, 7(2): 625-636.
[38] Ucte operations handbook:P1–policy 1: Load-frequency control and performance. Version: v3. 0 rev, vol. 15, no. 01.04, 2009.
[39] Shapley L, On Balanced Sets and Cores, (Memorandum Rand Corporation). Santa Monica, CA, USA: Rand Corporation; 1965.
[40] Baeyens E, Bitar EY, Khargonekar PP, Poolla K. Coalitional aggregation of wind power. IEEE Trans. Power Syst. 2013;28(4):3774–84.
[41] Suijs J, Borm P, De Waegenaere A, et al. Cooperative games with stochastic payoffs. Eur. J. Oper. Res. 1999;113(1):193-205.
[42] Gan W, Shahidehpour M, Yan M, Guo J, Yao W, Paaso A, et al. Coordinated planning of transportation and electric power networks with the proliferation of electric vehicles. IEEE Trans. Smart Grid, 2020;11(5):4005–16.
[43] Ding T, Liu S, Yuan W, et al. A two-stage robust reactive power optimization considering uncertain wind power integration in active distribution networks. IEEE Trans. Sustain. Energy, 2016;7(1):301–11.