An Incentivized Auction-Based Group-Selling Approach for Demand Response Management in V2G Systems

Ming Zeng, Supeng Leng, *Member, IEEE*, Sabita Maharjan, *Member, IEEE*, Stein Gjessing, *Member, IEEE*, and Jianhua He, *Senior Member, IEEE*

***Abstract*—Vehicle-to-grid (V2G) system with efficient demand response management (DRM) is critical to solve the problem of supplying electricity by utilizing surplus electricity available at electric vehicles (EVs). An incentivized DRM approach is studied to reduce the system cost and maintain the system stability. EVs are motivated with dynamic pricing determined by the group-selling-based auction. In the proposed approach, a number of aggregators sit on the first-level auction responsible to communicate with a group of EVs. EVs as bidders consider quality of energy (QoE) requirements, and report interests and decisions on the bidding process coordinated by the associated aggregator. Auction winners are determined based on the bidding prices and the amount of electricity sold by the EV bidders. We investigate the impact of the proposed mechanism on the system performance with maximum feedback power constraints of aggregators. The designed mechanism is proven to have essential economic properties. Simulation results indicate that the proposed mechanism can reduce the system cost and offer EVs significant incentives to participate in the V2G DRM operation.**

***Index Terms*—Auction, demand response management (DRM), group-selling, vehicle-to-grid (V2G).**

I. Introduction

THE CURRENT power grid has raging infrastructures. With increasing demand of electricity, it faces many problems such as blackouts and grid reliability. Rolling blackouts have been implemented in many countries such as China and South Africa, which has restrict the Gross Domestic Product (GDP) growth significantly and made huge economical losses to these countries. Smart grid has been widely regarded as an excellent long-term solution to the global energy crisis, with enhanced electricity generation capacity, integrated digital communication, more efficient demand-side management, and load balancing for efficiency improvement.

Parallelly with increasing concerns on fossil-fuel emission and global warming EVs are widely accepted to be a key solution for future road transport systems. The exponentially increasing number of EVs is expected to generate huge electricity demands and make the energy crisis even more worse. Vehicle-to-grid (V2G) is a promising solution to the problem by reducing the peak-to-average ratio of the electric grid load curve and balancing supply and demand. EVs are mobile electricity storage units in a V2G system. Surplus electricity stored in EVs can be fed back into the grid, which can mitigate the pressure of building new electricity generator while satisfying imminent electricity demands [1]. However, one key problem to solve when integrating V2G systems into the electricity market is the efficient management of the demand response.

There is a requirement on the coordination among the electricity market, the EVs, and the grid to trade surplus electricity of EVs. But it is very challenging to balance the objectives of the involved parties, due to the following reasons. On one hand, the amount of deficit power of the grid changes dynamically over time, due to the reasons such as inaccurate day-ahead consumption prediction and uncertain electricity output from renewable sources like wind and solar energy. The grid needs to decide a proper amount of electricity to purchase from the EVs with an objective of minimizing the payment for the electricity from the EVs in the open electricity market. From a long-term point of view, the payment to buy the surplus electricity of the EVs should not be higher than that for buying the same amount of electricity produced by power generators. On the other hand, the unit price for feedback electricity from each EV may be different. A necessary condition that an EV is willing to sell its surplus electricity is that the price is higher than the charging cost. To balance the benefits of the grid and the EVs, demand response management (DRM) becomes a critical component of the V2G system for determination of electricity transaction amounts between the EVs and the grid with proper prices for the electricity bought from the EVs.

In the existing mechanisms for DRM, optimal centralized solutions are widely used. But in order to balance the demand

Manuscript received October 30, 2014; revised July 07, 2015; accepted August 31 2015. Date of publication September 27, 2015; date of current version December 02, 2015. This work was supported in part by the National Natural Science Foundation of China under Grant 61374189, in part by the Information Technology Research Projects of Ministry of Transport of China under Grant 2014364X14040, in part by the Fundamental Research Funds for the Central Universities under Grant ZYGX2013J009, and in part by the EU FP7 Project Cross-Layer Investigation and Integration of Computing and Networking Aspects of Mobile Social Networks (CLIMBER) under Grant PIRSES-GA-2012-318939. Paper no. TII-15-0543. *(Corresponding author: Supeng Leng.)*

M. Zeng and S. Leng are with the School of Communication and Information Engineering, University of Electronic Science and Technology of China, Chengdu 611731, China (e-mail: spleng@uestc.edu.cn).

S. Maharjan is with Simula Research Laboratory, Fornebu 1364, Norway (e-mail: sabita@simula.no).

S. Gjessing is with Simula Research Laboratory, Fornebu 1364, Norway, and also with the Department of Informatics, University of Oslo, Oslo 1325, Norway (e-mail: steing@simula.no).

J. He is with Aston University, Birmingham B4 7ET, U.K. (e-mail: j.he7@aston.ac.uk).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TII.2015.2482948

and the supply of the grid, these solutions are not scalable and practical for the DRM problem in V2G system due to the large number of participating EVs. Decentralized control schemes using game theory have been applied to the charging scheduling problem of EVs [9], [10]. Fundamentally, the DRM problem in V2G systems is an electric energy resource allocation problem with a large number of electricity providers and consumers. In order to balance the benefits of both EVs and the grid in V2G systems, we believe a sophisticated auction mechanism could be a promising solution. Auction is a decentralized market mechanism which can adaptively allocate electricity feedback opportunities in an efficient and fair way. Since a single EV can only provide limited electric energy resources, the proposed auction-based mechanism should offer enough incentive to encourage a large number of EVs to participate in the V2G system. Inspired by Groupon for spectrum auction [2], we propose a group-selling strategy for the V2G DRM problem. In the proposed strategy, a feedback-based price scheme is designed to motivate the EVs to participate the auctions by taking into account the cost of electric energy generation and the charging costs of the EVs. Moreover, as the power grid is the only buyer and the EVs are the multiple sellers, reverse auction matches this scenario. Therefore, we use an incentivized reverse auction for the group-selling approach. The design objective is to reduce the cost of balancing the supply and the demand of the grid, while making more profit for the EVs to stimulate them to participate in the V2G system.

In this paper, we have the following major contributions.

1) We introduce a group-selling mechanism for the DRM problem in the V2G systems, and formulate the DRM problem as a two-level auction model. In the first level, we have an auction process between the EVs and the aggregators; while we have an auction between the aggregators and the electric grid in the second level.
2) We propose a group-selling formation (GSF) algorithm and a group determination (GD) algorithm to implement the auctions for the DRM model efficiently. The GSF algorithm is further extended to power constrained GSF (PC-GSF) algorithm, for the scenarios where the aggregators have constraints on the maximum feedback power.
3) We prove with theoretical analysis that the proposed group bidding mechanism possesses economic properties, and simulation results verify the convergence of the GD algorithm. Moreover, simulations are conducted to investigate the impact of the aggregator's maximum feedback power constraint on the profit of the EVs. Simulation results demonstrate the efficiency of the proposed approach.

This paper is organized as follows. Section II presents the related research work. In Section III, we propose the system model, the feedback-based price scheme, as well as the cost function of the grid. The optimization problem for DRM in V2G system is formulated in Section IV. Section V presents the group bidding mechanism in detail. Then, we analyze the economic properties of the proposed mechanism, such as truthfulness, individual rationality, and ex post budget balance. Simulation results presented in Section VI indicate that the proposed mechanism is able to reduce the cost of the grid for supplying its deficit power and obtain more profit for the EVs participating in the V2G system. Finally, Section VII concludes this paper.

II. Related Work

DRM is a key issue in V2G systems. There are some works studying DRM for EV charging and discharging in smart grids. Ref. [3] goes over the mathematical models in demand response programs in smart grids and summarizes the approaches such as convex optimization, game theory, dynamic programming, Markov decision process, stochastic programming, and particle swarm optimization. In [4], a multiobjective optimization problem is formulated to schedule charging and discharging for each EV in microgrids. Ant-colony-optimization-based heuristic scheduling algorithm is designed to minimize cost for EVs and reduce negative impacts on microgrids due to the fluctuation of renewable distributed energy resources output. In [5], priority-based policy is proposed for Quality of Service (QoS) differential scheduling in cognitive-radio-based smart grid networks. The system is modeled as a semi-Markov decision process problem and dynamic programming is applied to find a solution. Ref. [6] proposes an optimal centralized scheduling method via a mixed integer linear programming (ILP), to jointly control charging and discharging of plug-in EVs and electricity consumption of home appliances. In [7], a distributed strategy based on distributed dynamic programming algorithm is proposed to optimally allocate the total power demand among different generation units.

Quite a few literatures apply game theory in DRM problems in smart grid. Ref. [8] introduces the architecture of EV fasting charging and proposes resource allocation scheme jointly considering power and customer allocation via Stackelberg game model. Network operator is leader in the game while EV customers are followers. Through a noncooperative Stackelberg game model, the authors in [9] investigate the benefits of distributed energy resources using an energy management scheme for a smart community which consists of a large number of residential units and a shared facility controller. In [10], the DRM problem is addressed in a network of multiple utility companies and consumers using a Stackelberg game to maximize the revenue of each utility company and the payoff of each user. Ref. [11] presents a noncooperative game theoretic consumption scheduling framework based on mixed integer programming optimization technique to schedule the energy consumption at household level. In [12], the interaction between utility companies and residential users is modeled as a two-level game, where the competition among utility companies is a noncooperative game and the interaction among residential users is an evolutionary game. Ref. [13] models the interaction between selfish and foresighted electricity consumers as a repeated energy scheduling game and proposes a novel framework for determining optimal nonstationary DSM strategies.

The most related work to ours is literature [14] which designs an auction mechanism to trade energy in the smart

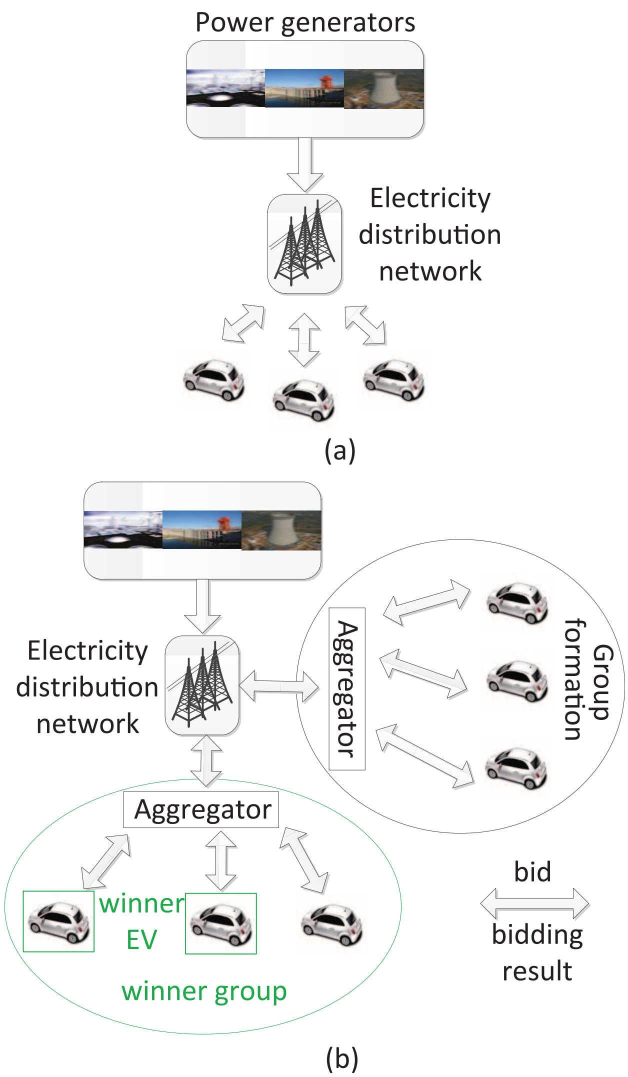

Fig. 1. Two auction-based mechanisms for DRM in V2G systems. (a) Single bidding mechanism. (b) Group bidding mechanism.

grid. However, our approach has the following distinguishing features which make it different from the work in [14].

1) We first introduce a group-selling mode for the auction mechanism design in V2G system, according to the fact that surplus electricity provided by a single EV is far lower than the amount that the grid demands.
2) Our proposed DRM approach is based on a two-level reverse auction model, while [14] applied a double auction mechanism.
3) Our work focuses on the energy trade between electric vehicles (EVs) and the grid in which mobility and quality of energy (QoE) guarantee of EVs is considered, while [14] studied energy trade between general distributed energy resources and consumers.

III. System Model

In this paper, we consider a two-level auction-based mechanism for DRM in V2G systems as shown in Fig. 1. The single bidding mechanism in Fig. 1(a) entitles EVs to submit their sealed bids directly to the grid. The grid then decides which EVs win and may feedback electricity. In the group bidding mechanism shown in Fig. 1(b), each EV first submits its sealed bid to an aggregator which organizes an electricity feedback group, and relay the electricity from EVs toward the grid. The aggregator should be located in the reachable range of its group members. The remaining electricity in the EV must support it to reach the aggregator as the group organizer. After receiving bids from a certain number of EVs, the aggregator forms a sealed group bid to the grid, which describes the amount of electricity that the electricity feedback group can offer, and the unit price of feedback electricity from this group. In this group bidding mechanism, auction processes are conducted twice to solve the DRM problem. Aggregators as group organizers decide the winner EVs in their groups, and the grid determines the winner aggregators. Winner EVs from the groups of the winner aggregators finally win the opportunities to feed their surplus electricity back to the grid.

We let $\mathbf{W}$ denote the set of final winner EVs. The auction process usually contains two stages, i.e., allocation and payment. Auction winners are determined in the allocation stage and the payment to each auction winner is made in the payment stage. Suppose we have N EVs and A aggregators. Let $\mathbf{N} = \{1, 2, \ldots, N\}$ denote the set of the EVs, and $\mathbf{A} = \{1, 2, \ldots, A\}$ denote the set of aggregators. Suppose that the whole operation time in 1 day is divided into N_t time slots. The length of each time slot is configurable as required (e.g., 30 min). At the beginning of each time slot, according to the supply and demand relationship of the last time slot and the supply and demand prediction for current slot, the grid decides how much electricity should be bought from the EVs if the supply of the grid is less than the demand. Let D denote the amount of deficit power of the grid, i.e., the difference between the demand and the supply offered by the power generators in the grid.

Let $C_{\mathrm{grid}}(S)$ define the cost function as the sum of the expenses paid to the EVs for buying their electricity and the extra operational costs, which includes monetary cost here referring to the cost for the different amounts of electricity between the demands of the grid and the total electricity trading volume S, and time cost referring to the cost due to the delay until the power can be provided. We have the following formula for the calculation of cost function:

$$C_{\mathrm{grid}}(S) = g(|D - S|) + \sum_{i \in \mathbf{W}} \bar{p}_i \bar{q}_i \tag{1}$$

where $\bar{p}_i$ is the negotiated prices between the grid and each winner EV, $\bar{q}_i$ is the trading volume between the grid and each winner EV, and $g(\cdot)$ is the generation cost function of the grid including construction investment cost, fuel cost, operation cost, maintenance cost, and environment cost, etc. [23]. Different amounts of electricity between D and S may be reduced but always exist after adopting V2G program, and it will be generated by power generators if $S < D$. On the contrary, if $S > D$, the extra cost is also needed to balance D and S, and the curve of extra cost should be similar to the generation cost curve shown in Fig. 2(a).

The objective of the DRM in the electric grid focuses on the minimization of the cost function expressed by (1). However, EVs are expected to be paid with more than their charging costs

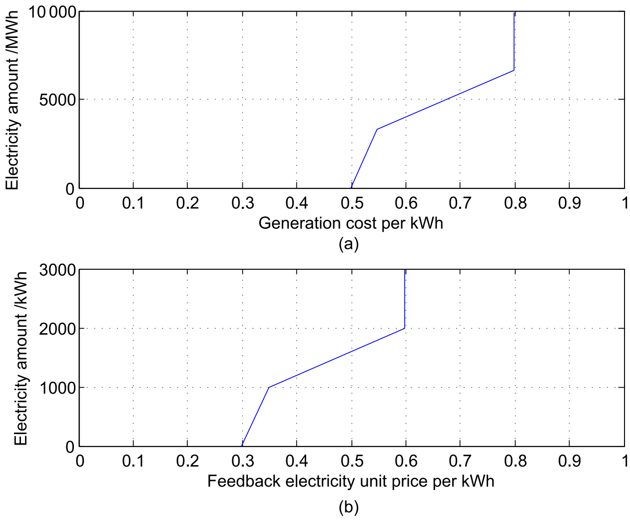

Fig. 2. Pricing mechanism in the proposed group bidding mechanism.

TABLE I
PEAK-VALLEY TIME-OF-USE (ToU) TARIFF IN FUJIAN PROVINCE IN CHINA [16]

Amount of electricity consumption per month (kWh)	Peak-valley ToU tariff per kWh	
	Peak period (8:00–22:00)	Valley period (22:00–24:00 and 00:00–8:00)
< 200	0.5283	0.2983
≥ 200 < 400	0.5783	0.3483
≥ 401	0.8283	0.5983

and the payment from the grid should cover the cost due to the degradation of EVs' batteries after every charging/discharging cycle. Consequently, incentive mechanism should offer profit to EVs. Moreover, a large number of EVs should be encouraged to participate in the V2G system, since surplus electricity provided by a single EV is far lower than the amount that the grid demands.

We design a feedback-based price scheme for the power grid. The bidding price is a function of the amount of electricity that the bidder can supply. The feedback electricity unit price paid by the grid should be lower than the unit price of the generation cost of the grid during peak period but higher than the unit price of the charging cost of EVs. Fig. 2 shows an example of the feedback-based price scheme. The feedback electricity unit price is a piecewise linear function of the amount of electricity, denoted by $g_p(\cdot)$. It is reasonable that the curve of the feedback-based electricity unit price has the same shape as the generation cost of the grid. The values of the specific unit prices in Fig. 2 are set according to real data of the electricity market in Fujian Province, China, which is shown in Table I. In this case, EVs that consume less than 200 kWh electricity per month can make a profit if they charge their batteries during the valley period and sell their surplus electricity with an unit price above 0.2983 per kWh [15].

IV. AUCTION MECHANISM DESIGN

Auction mechanisms used for DRM in V2G systems should achieve the following design goals.

1) The operation cost of the electric grid is reduced by incorporating V2G systems rather than generating more energy.
2) EVs gain profit from participating in V2G systems and do not experience any inconveniences beyond their acceptable levels, i.e., avoiding a detour or the shortage of electric energy on a trip.
3) Auction mechanisms should possess economic properties, such as ex post budget balance, individual rationality, and truthfulness.
4) The mechanisms should have low time complexity.

A. Single Bidding Mechanism

We first illustrate a single bidding mechanism as shown in Fig. 1(a) which will be used to compare the performance of the proposed group bidding mechanism. In this simple approach, aggregators do not participate in the auction and they only offer interfaces for auction winner EVs to complete electricity feedback. During the auction, bids from EVs are directly submitted to the grid.

It is supposed that each EV sends a two-tuple bid $B_i = (p_i, q_i^{\max}), i \in \{1, 2, \ldots, N\}$ to the grid, where p_i is the bid price of EV i and $q_i^{\max}$ represents the maximum offered electric energy of EV i. $q_i^{\max}$ takes into account the state of charge (SoC) at the plugging time and the departure time of EV i since we assume the discharging rate of EV i is fixed. $\mathbf{W_s}$ denotes the set of winner EVs. The optimization of the single bidding mechanism aims at the minimization of the cost of the grid. An ILP model is deployed to describe the optimal problem in the allocation stage of the single bidding mechanism. The decision variables in the ILP model are binary, i.e., $y_i, i \in \{1, 2, \ldots, N\}$. $y_i = 1$ if EV i wins the auction, 0 otherwise. Given the above definitions and notations, the ILP that models the problem can be expressed as follows:

$$\min C_{\text{grid}} \left(\sum_{i=1}^{N} y_i q_i^{\max} \right) \quad (2)$$

$$\text{s.t. } y_i \in \{0, 1\} \quad \forall i \in 1, 2, \ldots, N \quad (3)$$

$$y_i = 0 \quad \forall i \notin \mathbf{W_s};\; y_i = 1 \quad \forall i \in \mathbf{W_s}. \quad (4)$$

The objective function (2) minimizes the cost that will balance the difference between demand and supply. Constraints (3) and (4) ensure the integrality of the binary decision variables.

The optimization problem expressed by (2)–(4) can be solved by CPLEX when the number of EVs participating in the V2G system is small. However, the optimal problem is NP-hard. The computation time increases drastically with the number of EVs in the system.

Truthfulness is crucial for auction mechanisms. The payment stage in an auction mechanism has great influence on truthfulness. The Vickrey–Clarke–Groves (VCG) auction mechanism is the well known for ensuring truth-telling of bidders [20]–[22]. Applying the VCG auction mechanism, unit price paid to each winner EVs, $\bar{p}_i^{\text{VCG}}$ can be calculated as

$$\bar{p}_i^{\text{VCG}} = -\frac{C_{\text{grid}}(S, N\backslash i) - C_{\text{grid}}(S', N\backslash i)}{q_i^{\max}}, \quad i \in \mathbf{W_s} \quad (5)$$

where S' represents the electricity trading volume if EV i does not submit its bid to the auction. However, the above process of calculation suffers from high computational complexity.

Algorithm 1 (GSB, Greedy Single Bidding algorithm) is proposed to complete the allocation stage in the single bidding mechanism with lower complexity and gives truthfulness guaranteed pricing to auction winners. The time complexity of GSB is $\mathscr{O}(N)$. However, $\mathscr{O}(N)$ is still not acceptable if EVs take the place of most gasoline vehicles. For instance, it is reported that there had been 3.3494 million vehicles in Fujian Province in China by 2012 [17].

Algorithm 1. GSB: Greedy Single Bidding algorithm

Initialization:

D; $B_i = (p_i, q_i^{max})$; $i \in \{1, 2, \ldots, N\}$; $\mathbf{W_s} = \varnothing$

Iteration:

$L_s \Leftarrow Sort(\frac{p_i}{q_i^{max}}, "non-decreasing")$;
for all $i \in L_s$ **do**
  if $D > 0$ **then**
    $D = D - q_i^{max}$;
    $\mathbf{W_s} = \mathbf{W_s} \bigcup \{i\}$;
  end if
end for

Output:

$\mathbf{W_s}, max(p_i, i \in \mathbf{W_s})$

B. Group Bidding Mechanism

In this section, we propose an incentivized auction-based group bidding mechanism for V2G systems.

The auction is conducted in two levels. In the first-level auction, EVs join in feedback electricity groups managed by different aggregators in order to obtain higher feedback electricity unit prices. Each EV bids the bidding price according to its expectation for the feedback electricity unit price after joining the group. The negotiated price is related to the amount of electricity that each EV's group could offer to the grid. Each EV sends one sealed bid to one aggregator. Aggregator j decides the set of winner EVs $\mathbf{W_j^f}$ in the first-level auction according to the bids it receive. On behalf of these winning bids, the aggregators submit the group bids to the grid, including the expected unit price and the amount of electricity to be provided. In this second-level auction, aggregators become sellers and the grid is the buyer. The grid will notify all members of the set of winner aggregators $\mathbf{W_a}$ in the second-level auction. And aggregator $j, j \in \mathbf{W_a}$ is paid with unit price $\bar{p_j^g}$. Then, the winner aggregators publish bidding results to the EV winners of the first-level auction in their groups. Finally, those EVs join the electricity feedback and get the payment with unit price $\bar{p_{ij}}$. EVs that do not participate in the two-level auction will not be authorized to access discharging interfaces of aggregators. Meanwhile, winner EVs who do not fulfill their discharging commitment may have negative credit record as penalty.

In this paper, the utility of EV i is defined as

$$U_i = \begin{cases} \bar{p_{ij}} - p_{ij}, & \text{if } i \in \mathbf{W_j^f} \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

The utility of the auctioneer is defined as

$$U_j^a = \begin{cases} \bar{p_j^g} - \bar{p_{ij}}, & \text{if } j \in \mathbf{W_j^a} \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

1) *First-Level Auction:*

In the first-level auction, we design an algorithm for the formation of feedback electricity group. Aggregators as group organizers calculate the amount of feedback electricity and unit prices for their groups. These calculation results will then be the crucial elements of the two-tuple bids in the second-level auction.

$\mathbf{N_j}$ denotes the set of EVs which send their bids to aggregator j (i.e., group j), and N_j represents the number of bids. Since, we assume each EV only sends one bid to one aggregator, N_j also represents the number of EVs which participate in the feedback electricity group j. Each EV bidder sends its two-tuple sealed bid $B_i = (p_{ij}(Q_{ij}), q_{ij}^{\max}), i \in \mathbf{N_j}, j \in \mathbf{A}$ to an aggregator which is in its reachable range, where $\mathbf{A}$ denotes the set of aggregators as feedback electricity group organizers and A is the number of aggregators. Q_{ij} is the amount of electricity that the group that EV i belongs to is expected to offer. Unit price p_{ij} asked by EV i is determined under the feedback-based price scheme. For example, if EV i expects the unit price paid by aggregator j for its electricity is 0.5983 per kWh, the amount of electricity provided by its group is expected to be no less than 2000 kWh.

Other denotations in the group bidding mechanism are the same as that in the single bidding mechanism. Algorithm 2 (GSF algorithm) presents the details of feedback electricity group formation process.

Algorithm 2. GSF: Group-Selling Formation algorithm

Initialization:

$B_i = (p_{ij}(Q_{ij}), q_{ij}^{max})$; j; η_j; N_j; $\mathbf{W_j^f} = \varnothing$

Iteration:

$Q_s \Leftarrow Sort(q_{ij}^{max}, "non-increasing")$;
$q_j^c = Q_s(\lceil \eta_j * N_j \rceil)$;
$Q_{ss} \Leftarrow Sort(Q_{ij}, "non-decreasing")$;
for $k = \lceil \eta_j * N_j \rceil - 1 \; to \; 1$ **do**
  if $Q_{kj} \le (\lceil \eta_j * N_j \rceil - k) * q_j^c$ **then**
    $\mathbf{W_j^f} = [1:k]$;
    $q_j^g = sizeof(\mathbf{W_j^f}) * q_j^c$;
    $p_j^g = g_p(Q_{(k+1)j})$;
    $break$;
  end if
end for

Output:

q_j^g, p_j^g

The GSF algorithm is proposed to obtain group-selling electricity amounts and group-selling unit prices. The basic idea of the GSF algorithm is to remove those V2G EVs which ask for high prices beyond certain limits or which can only supply the amount of electricity less than the threshold value, aggregator forms a feedback EV group with as much electricity as possible. η_j is a parameter used by each aggregator j to decide the threshold amount of electricity q_j^c. Different aggregators could have either the same or different η_j. EVs are first sorted by the quantity of electricity they can provide in nonincreasing order, and EVs that could only sell less than q_j^c are removed. Then, among the remaining EVs, those with unreachable high unit price for their feedback electricity lose the auction. The GSF algorithm is executed independently by each aggregator. The tuple (p_j^g, q_j^g) forms the bid B_j^a of aggregator $j, j \in \mathbf{A}$, and this bid will be sent to the grid to compete for the second-level auction. Auction results of the first level are not published by aggregators immediately, because EV $i, i \in \mathbf{W_j^f}$ is not the final winner in the two-level auction, and p_j^g is not the final unit price. If aggregator j wins the second-level auction, EV winners belonging to winner groups in the second-level auction are the EVs which will feedback electricity to the grid.

2) Second-Level Auction: The second-level auction is conducted between the aggregators and the electric grid. Bid $B_j^a = (p_j^g, q_j^g)$ is submitted by aggregator j to the grid. $\mathbf{W_a}$ is the set of aggregators that are the second-level auction winners. The allocation stage of the second-level auction can also be formulated as an ILP. The decision variables in the ILP are binary variables $x_j, j \in \mathbf{A}$, and $x_j = 1$ if the group j wins the second-level auction, 0 otherwise. The optimal in the allocation stage of the second-level auction attempts to minimize the cost of the grid. Given above definitions and notations, the optimization problem is formulated as an ILP, i.e.

$$\min C_{\text{grid}} \left(\sum_{j=1}^{A} x_j q_j^g \right) \tag{8}$$

$$\text{s.t. } x_j \in \{0, 1\} \quad \forall j \in \mathbf{A} \tag{9}$$

$$x_j = 0 \quad \forall j \notin \mathbf{W_a};\ x_j = 1 \quad \forall j \in \mathbf{W_a}. \tag{10}$$

The objective function (8) minimizes the cost to balance the difference between demand and supply of the grid. Constraints (9) and (10) ensure the integrality of the binary decision variables.

The complexity to find the optimal solution of the above problem is high if the classic VCG auction mechanism is used [20]. We propose Algorithm 3 (GD) to determine the winner groups in the second-level auction. This algorithm retains the property of truthfulness of the VCG auction mechanism.

Algorithm 3. GD: Group Determination algorithm

Initialization:
D; $B_j^a = (p_j^g, q_j^g)$; $j \in \mathbf{A}$; $\mathbf{W_a} = \varnothing$
Iteration:
1: $L_g \Leftarrow Sort(\frac{p_j^g}{q_j^g}, "non-decreasing")$;
2: **for all** $j \in L_g$ **do**
3: **if** $D > 0$ **then**
4: $D = D - q_j^g$;
5: $\mathbf{W_a} = \mathbf{W_a} \bigcup \{j\}$;
6: **end if**
7: **end for**
Output:
$\mathbf{W_a}, max(p_j^g, j \in \mathbf{W_a})$

In the GD algorithm, aggregators are first sorted in nondecreasing order by $\frac{p_j^g}{q_j^g}$. Then, the grid goes through the aggregators in the sorted list. For each aggregator, the grid examines whether the total electricity demand has been satisfied. The loop ends until the electricity demand is satisfied. Otherwise, the aggregator in this round becomes an auction winner and the electricity demand is updated. The unit price paid to all winner aggregators is the maximum unit price that aggregators belonging to $\mathbf{W_a}$ request.

The electric grid now publishes the aggregator winners, and the EV winners of the two-level auction can also be announced. At this time, each EV winner i $(i \in \mathbf{W_j^f}, j \in \mathbf{W_a})$ is required to feed q_j^c units of electricity through aggregator j toward the grid. Aggregators charges the grid with the unit price $\bar{p_j^g}$ and each aggregator pays to its winner EVs with the unit price $\bar{p_{ij}}$.

3) Optimization in a Practical Scenario: In the above schemes, we considered the special case that the maximum feedback power of each aggregator is unbounded. The maximum feedback power of an aggregator is a key factor when the aggregators organize the feedback from EV groups. Similar to the power control in communication networks, in order to protect the operation of the grid and the aggregators, we consider a practical scenario where the amount of feedback electricity of each aggregator may feedback cannot exceed a maximum value during each unit time. We also develop an algorithm for this scenario. Assume that each aggregator maximally can feedback the power $P_j^a, j \in \mathbf{A}$. Feedback EVs in the same group parallelly connect to the electricity feedback interfaces of the aggregator. Each EV submits its electricity feedback power requirement P_{ij} to the aggregator with its bidding information. The PC-GSF for each aggregator j can be modeled as a constraint knapsack problem as follows:

$$\max q_j^g \tag{11}$$

$$\text{s.t. } y_{ij}^g \in \{0, 1\} \tag{12}$$

$$\sum_{i \in \mathbf{N_j}} P_{ij} y_{ij}^g \leq P_j^a. \tag{13}$$

The decision variables in the above optimal problem are binary $y_{ij}^g, i \in \mathbf{N_j}$, and $y_{ij}^g = 1$ if EV i is in the group j, 0 otherwise. The constraint knapsack problem is NP-hard. Algorithm 4 (PC-GSF algorithm) is an extended version of the GSF algorithm used to resolve the allocation problem with power constraints.

Different with the GSF algorithm, under the PC-GSF algorithm, if constraint (13) is not satisfied, the amount of electricity threshold q_j^c should be updated iteratively until constraint (13) is satisfied. Since the kernel of the PC-GSF and the GSF algorithms is the same, both of them guarantee the truthfulness of the group bidding mechanism.

C. Complexity Analysis of Group Bidding Mechanism

1) GSF Algorithm: In the GSF algorithm, the two sortings are both $\mathscr{O}(N_j \log N_j)$ [3] and the loop takes at most $\mathscr{O}(\lceil \eta_j * N_j \rceil - 1)$ time. The complexity of the GSF algorithm is hence $\mathscr{O}(N_j \log N_j)$.

Algorithm 4. PC-GSF: Power Constrained Group-Selling Formation algorithm

Initialization:

$B_i = (p_{ij}(Q_{ij}), q_{ij}^{max}, P_{ij})$; j; η_j; N_j; P_j^a; $\mathbf{W_j^f} = \varnothing$

Iteration:

$Q_s \Leftarrow Sort(q_{ij}^{max}, \text{"}non-increasing\text{"})$;
$q_j^c = Q_s(\lceil \eta_j * N_j \rceil)$;
$Q_{ss} \Leftarrow Sort(Q_{ij}, \text{"}non-decreasing\text{"})$;
r=1;
for $k = \lceil \eta_j * N_j \rceil - r \ to \ 1$ **do**
  if $Q_{kj} \leq (\lceil \eta_j * N_j \rceil - k) * q_j^c$ **then**
    $\mathbf{W_j^f} = [1:k]$;
    if $\sum_{i \in \mathbf{W_j^f}} P_{ij} \leq P_j^a$ **then**
      $q_j^g = sizeof(\mathbf{W_j^f}) * q_j^c$;
      $p_j^g = g_p(Q_{(k+1)j})$;
      $break$;
    else
      $q_j^c = Q_s(\lceil \eta_j * N_j \rceil - r)$;
      $r = r + 1$;
    end if
  end if
end for

Output:

q_j^g, p_j^g

2) GD Algorithm: The time complexity of the GD algorithm is $\mathscr{O}(A)$, where $A \ll N$.

3) PC-GSF Algorithm: For the PC-GSF algorithm, the complexity of the same part in the GSF algorithm is $\mathscr{O}(N_j \log N_j)$. Besides, examining whether the feedback power constraint of each aggregator has been satisfied will lead to the update of the electricity amount threshold of all EVs. If the feedback power constraint has not been satisfied, the same part contained in the GSF algorithm will be executed again. Thus, this part will be executed at most $\lceil \eta_j * N_j \rceil - 1 - \frac{P_j^a}{\max(P_{ij})}$ times. However, $\lceil \eta_j * N_j \rceil - 1 - \frac{P_j^a}{\max(P_{ij})} < N_j$, hence, the overall complexity of the PC-GSF algorithm is $\mathscr{O}(N_j \log N_j)$.

D. Economic Properties of Group Bidding Mechanism

As the proposed group bidding mechanism is a two-level auction process, all the economic robustness properties such as truthfulness, individual rationality, and ex post budget balance [20] must essentially be guaranteed. In this section, we will prove that the proposed mechanism does posses the economic robustness of auction mechanisms.

Definition 1: Truthfulness
An auction is truthful, if each buyer or seller cannot improve its own utility by bidding higher or lower than its true value. In the proposed mechanism, truthfulness can be realized only if all EV sellers to report their true values on their expected values of group size and the maximum amount of electricity they can offer.

Definition 2: Individual Rationality
A reverse auction is individually rational if no auction winner is paid less than what it bids. This property provides incentives for EVs to participate in a reverse auction-based V2G system.

Definition 3: Ex Post Budget Balance
An auction is ex post budget balanced if the auctioneer's utility is not less than 0. This property ensures that aggregators have incentives to set up auctions and organize the groups for electricity feedback.

Theorem 1: The proposed group bidding mechanism is individually rational, i.e., $\bar{p_{ij}} \geq p_{ij}$ and $\bar{p_j^g} \geq p_j^g$.

Proof: In the GSF algorithm, we sort the bidding prices of EVs (or aggregators) in a nondecreasing order, and pay the first-level auction winner EV $i, i < k$ (or the second-level auction winner aggregator $j, j < l$) with the bidding price of the kth EV (or the lth aggregator), i.e., $p_{ij} < p_{kj}$ (or $p_j^g < p_l^g$). ■

Theorem 2: The proposed group bidding mechanism is ex post budget balanced, i.e., $U_j^a \geq 0$.

Proof: Because $\bar{p_j^g} = \max(p_j^g, j \in \mathbf{W_a})$ and $\bar{p_{ij}} = p_j^g = g(Q_{(i+1)j})$, it is obvious that $U_j^a = \bar{p_j^g} - \bar{p_{ij}} \geq 0$. ■

Theorem 3: The group bidding mechanism is truthful in both the first-level auction and the second-level auction.

Proof: Since the group bidding mechanism consists of the GSF algorithm and the GD algorithm, the truthfulness proof of the group bidding mechanism will be accomplished in two parts. One proof for the truthfulness of the GSF algorithm, and another for the truthfulness of the GD algorithm. ■

Lemma 1: The first-level auction is truthful for all EVs.

Proof: We show that in all the cases EVs cannot improve their utilities by bidding untruthfully.

Case 1: EV i wins when both bidding truthfully and untruthfully. No matter whether EV i bids truthfully or untruthfully, it will get the same paid as an auction winner.

Case 2: EV i fails when both bidding truthfully and untruthfully. The utility of EV i is always zero, and there is no incentive to bid untruthfully.

Case 3: EV i wins when bidding truthfully and fails when bidding untruthfully. According to the utility function of EVs we define, a winner EV's utility is non-negative and a loser EV's utility is zero.

Case 4: EV i fails when bidding truthfully and wins when bidding untruthfully. With the GSF algorithm, if EV i fails when bidding truthfully, it fails either because $q_{ij}^{\max} < q_j^c$ or because $Q_{ij} > (\lceil \eta_j * N_j \rceil - i) * q_j^c$. If $q_{ij}^{\max} < q_j^c$, it is assumed that EV i wants to win by bidding untruthfully. It then has to submit $q_{ij}^{\max} \geq q_j^c$. Suppose EV i wins by submitting $q_{ij}^{\max} \geq q_j^c$. However, its utility remains zero because it cannot afford that winner EVs are appointed to feedback q_j^c kWh electricity. If $Q_{ij} > (\lceil \eta_j * N_j \rceil - i) * q_j^c$, and EV i wants to win by bidding untruthfully, it has to submit $Q_{ij} \leq (\lceil \eta_j * N_j \rceil - i) * q_j^c$. Under the GSF algorithm, $g(Q_{ij}) > g(Q_{(i+1)j})$ and the winner EVs will be paid a price of $g(Q_{(i+1)}j)$. The untruthful Q_{ij}

is smaller than the truthful Q_{ij}, hence the payment of untruthful bidding will be less.

Consequently, analysis of all the cases above proves that all EVs will choose to send the truthful two-tuple bids $(p_{ij}(Q_{ij}), q_{ij}^{\max})$. ■

Lemma 2: The second-level auction is truthful for aggregators.

Proof: We first elaborate that a two-dimensional (2-D) reverse auction is truthful if it is qualified with the following characters [18], [19].

Exactness: for a bid $b_j = (s, a)$, either $g_j = s$ or $g_j = \varnothing$, where g_j is the amount of goods offered by bidder j in a reverse auction.

Monotonicity: if j's bid is granted when j declares the bid (s, v), it is also granted if j declares (s', v') for any $s' \leq s, v' \geq v$.

Participation: $j \notin \mathbf{W} \Rightarrow p_j = 0$, where $\mathbf{W}$ is the set of auction winners.

Critical: given a bidder j, supply of goods and declarations for all other bidders, there exists a critical value v_c such that

$$\forall v, v < v_c \Rightarrow g_j = \varnothing$$
$$\forall v, v > v_c \Rightarrow g_j = s.$$

Exactness and participation are straightforward ensured by the GD algorithm and the utility definition of aggregators. In the GD algorithm, aggregators are sorted by $\frac{p_j^g}{q_j^g}$ in nondecreasing order, and there exists an critical value $\left(\frac{p_j^g}{q_j^g}\right)_c$. Hence the GD algorithm satisfies both monotonicity and criticality. ■

So far, we have proved that both parts of the group bidding mechanism are truthful. It can be concluded that the proposed group bidding mechanism is truthful.

Corollary 1: The PC-GSF algorithm is truthful.

Proof: The only difference between the GSF and the PC-GSF algorithms is that after determining the winner EV set, the maximum feedback power constraint of the aggregator is checked in the PC-GSF algorithm. The same part of the GSF algorithm is operated until the constraint is satisfied. This will not incur any impact on the economic robustness. Consequently, the PC-GSF algorithm is as truthful as the GSF algorithm. ■

V. Performance Evaluation

Simulations are conducted to evaluate the performance of the proposed auction-based group-selling approach for DRM in V2G system. It is expected that our group bidding mechanism can reduce the cost of the grid. We will evaluate if the group bidding mechanism can seek more profit for the EVs in a V2G system. Convergence of the algorithm that realizes the group-selling approach will be verified. We will also investigate the impact of the maximum feedback power of the aggregators on the performance of the propose algorithm. Major simulation parameter settings are listed in Table II.

It is assumed that vehicles will be substituted by EVs in future and charging stations or aggregators for EVs will be as common as gasoline stations. Consequently, we consider 3.3494 million EVs participating in the simulation scenario [15]. The number of aggregators A is set as 16,497, according to the results from searching "gasoline station in Fujian Province" on the Google map. The number of EVs feeding back their electricity at each aggregator is Gaussian distributed with a mean value 203 (≈3,349,400/16,497) and variance 4. The maximum amount of electricity offered by each EV is uniformly distributed over $[7.857\ 33.162]$ kWh [16]. Unit prices asked by EVs under the single bidding mechanism and that under the group bidding mechanism are $g_p(q_{ij}^{\max})$ and $g_p(Q_{ij})$, respectively. η is set as 0.9 for all aggregators.

TABLE II
Major Simulation Parameter Settings

Number of EVs	3.3494 million
Number of aggregators	16497
Distribution of EVs at each aggregator	$N(203, 4)$
Distribution of $q_{ij}^{\max}$	$U[7.857\ 33.162]$
$\eta_j, j \in \mathbf{A}$	0.9

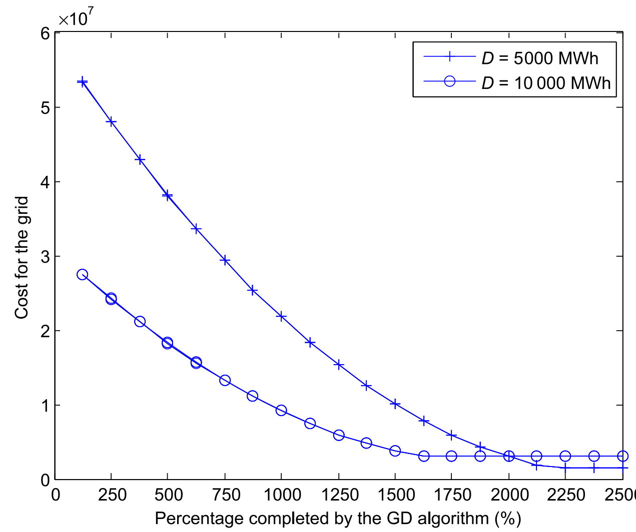

Fig. 3. Convergence of the GD algorithm.

Fig. 3 shows the convergence of the GD algorithm in two different scenarios when the demands from the grid equal 5000 and 10,000 MWh, respectively. The convergence of the GD algorithm is illustrated by the change of the grid's cost when the algorithm is executed. It is observed that in both scenarios that the cost of the grid converges before the algorithm terminates. Moreover, it can be found that when the demand for electricity is lower, the convergence speed of the GD algorithm is faster. This is because that the removal of one group has a larger impact on the cost. However, the cost of the grid with a 5000 MWh electricity demand is absolutely lower than that when the demand is 10,000 MWh.

To verify the capability of cost reduction of the proposed group bidding mechanism, the benchmark is selected as the method that power generators generate an imbalanced amount of electricity between supply and demand. Fig. 4 shows that the cost of the grid when applying the group bidding mechanism is always lower than the method *generating by power generators*. Another observation is that

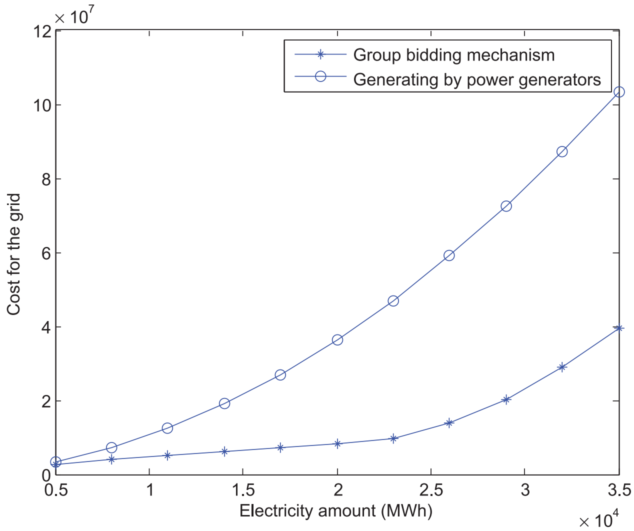

Fig. 4. Cost for the grid under different schemes.

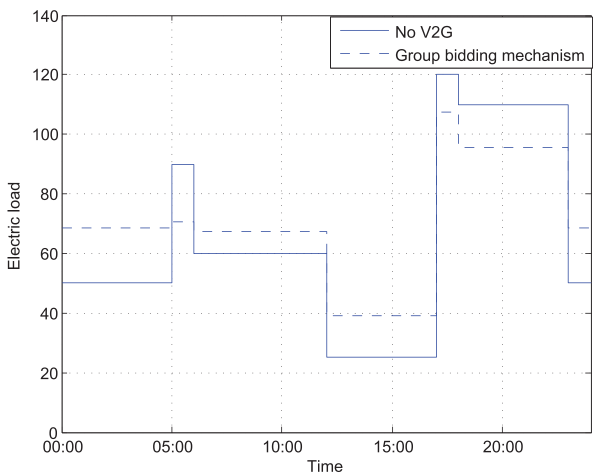

Fig. 5. Electric load curve under different schemes.

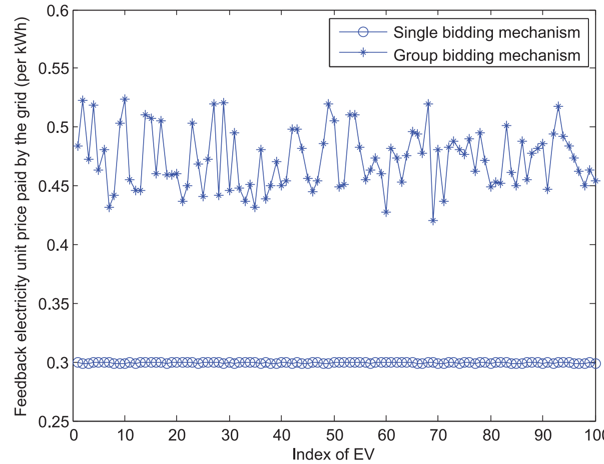

Fig. 6. Feedback electricity unit prices that EV winners charge the electric grid.

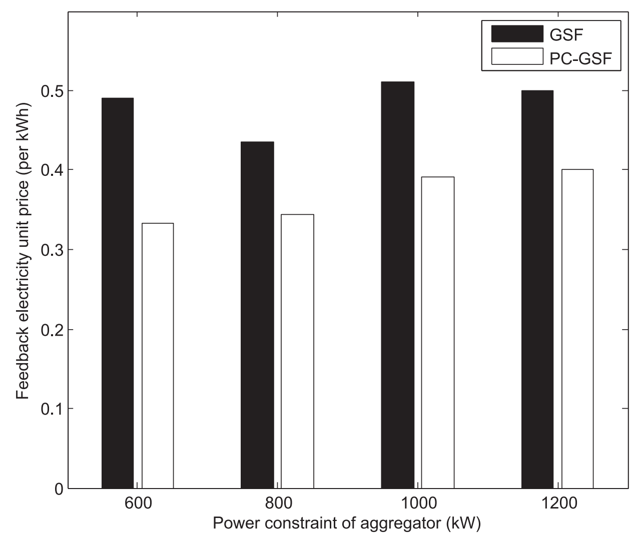

Fig. 7. Impact on feedback electricity unit prices when four aggregators have different power constraints.

the cost gap between the two ways becomes larger when the grid demands more electricity.

Fig. 5 shows that the proposed group bidding mechanism is effective in shaping the electric load curve of the grid. Under the group bidding mechanism in V2G system, peak load and load variation of the grid can be reduced remarkably.

Fig. 6 shows the unit price that each EV auction winner will be paid by using the single bidding mechanism and the group bidding mechanism, respectively. It is clear that under the single bidding mechanism, the unit price for each EV auction winner is always around 0.3 per kWh, which may not motivate the EVs to participate in the V2G system. However, by applying the group bidding mechanism, the EV auction winners can gain much higher unit prices for their feedback electricity.

Fig. 7 represents the unit prices for electricity feedback under different maximum feedback power constraints of the aggregators. It is obvious that the power constraints limit the group size for electricity feedback, and this will lead to lower the unit prices for the EV auction winners. This simulation results imply that there should be a tradeoff between profit incentives for the EVs and the cost for installing aggregators with large feedback power capacity.

VI. Conclusion

DRM is a critical component of the V2G systems. In this paper, we proposed a group bidding mechanism for the V2G DRM. A feedback-based price scheme is designed with the objective of motivating the EVs to participate in the V2G electricity trading system by selling their surplus electricity to the grid. A group bidding mechanism is implemented through a two-level reverse auction. The group bidding mechanism is proven to be truthfulness guaranteed, individually rational, and ex post budget balanced. Simulation results indicate that the proposed approach can help reduce the overall system cost of the grid compared to straightforward strategy of generating the same amount of extra electricity in peak period by power generators. The proposed scheme can effectively provide incentives to the EVs, as they can make profits from feeding power back into the grid. Moreover, we investigate a practical scenario where the aggregators have maximum feedback power constraints. The proposed auction-based group-selling approach for the DRM in V2G systems is demonstrated to be a win–win approach for both EVs and the electric grid.

REFERENCES

[1] W. Kempton and T. Jasna, "Vehicle to grid fundamentals: Calculating capacity and net revenue," *J. Power Sources*, vol. 144, no. 1, pp. 268–279, Jun. 2005.

[2] P. Lin, X. Feng, Q. Zhang, and M. Hamdi, "Groupon in the air: A three-stage auction framework for spectrum group-buying," in *Proc. IEEE Int. Conf. Comput. Commun. (INFOCOM)*, Apr. 2013, pp. 2013–2021.

[3] R. Deng, Z. Yang, M. Y. Chow, and J. Chen, "A survey on demand response in smart grids: Mathematical models and approaches," *IEEE Trans. Ind. Informat.*, vol. 11, no. 3, pp. 570–582, Jun. 2015.

[4] T. Le, B. J. Choi, H. Liang, H. Li, and X. Shen, "DCD: Distributed charging and discharging scheme for EVs in microgrids," in *Proc. IEEE Int. Conf. Smart Grid Commun.*, Nov. 2014, pp. 704–709.

[5] R. Yu, W. Zhong, S. Xie, Y. Zhang, and Y. Zhang, "QoS differential scheduling in cognitive-radio-based smart grid networks: An adaptive dynamic programming approach," *IEEE Trans. Neural Learn. Syst.*, to be published.

[6] M. H. K. Tusha, C. Assi, M. Marier, and M. F. Uddin, "Smart microgrids: Optimal joint scheduling for electric vehicles and home appliances," *IEEE Trans. Smart Grid*, vol. 5, no. 1, pp. 239–250, Jan. 2014.

[7] Y. Xu, W. Zhang, and W. Liu, "Distributed dynamic programming-based approach for economic dispatch in smart grids," *IEEE Trans. Ind. Informat.*, vol. 11, no. 1, pp. 166–175, Feb. 2015.

[8] I. S. Bayram, G. Michailidis, M. Devetsikiotis, and B. Parkhideh, "Electric power allocation in a network of fast charging stations," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 7, pp. 1235–1246, Jul. 2013.

[9] W. Tushar *et al.*, "Three-party energy management with distributed energy resources in smart grid," *IEEE Trans. Ind. Electron.*, vol. 61, no. 99, pp. 1–12, Jul. 2014.

[10] S. Maharjan, Q. Zhu, Y. Zhang, S. Gjessing, and T. Basar, "Demand response management in the smart grid in a large population regime," *IEEE Trans. Smart Grid*, to be published.

[11] Z. Zhu, S. Lambotharan, W. H. Chin, and Z. Fan, "A game theoretic optimization framework for home demand management incorporating local energy resources," *IEEE Trans. Ind. Informat.*, vol. 11, no. 2, pp. 353–362, Apr. 2015.

[12] B. Chai, J. Chen, Z. Yang, and Y. Zhang, "Demand response management with multiple utility companies: A two-level game approach," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 722–731, Mar. 2014.

[13] L. Song, Y. Xiao, and M. V. D. Schaar, "Demand side management in smart grids using a repeated game framework," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 7, pp. 1412–1424, Jul. 2014.

[14] Y. Wang, W. Saad, Z. Han, H. V. Poor, and T. Basar, "A game-theoretic approach to energy trading in the smart grid," *IEEE Trans. Smart Grid*, vol. 5, no. 3, pp. 1439–1450, May 2014.

[15] Document of Pricing Bureau of Fujian Province. (2014). [Online]. Available: http://www.fjjg.gov.cn/fjwjj/jghdzsk/spjg/d/webinfo/2014/10/1414632197510073.htm

[16] Annual Work Report of Fujian Province. (2012). *Government of Fujian Province* [Online]. Available: http://www.gov.cn/test/2012-02/01/content_2056153.htm

[17] M. Zeng, S. Leng, and Y. Zhang, "Power charging and discharging scheduling for V2G networks in the smart grid," in *Proc. IEEE Int. Conf. Commun. (ICC) Workshops*, Jun. 2013, pp. 1052–1056.

[18] V. Krishna, *Auction Theory*. New York, NY, USA: Academic, 2009.

[19] D. Lehmann, "Truth revelation in approximately efficient combinatorial auctions," *J. ACM*, vol. 49, no. 5, pp. 577–602, Sep. 2002.

[20] W. Vickrey, "Counterspeculation, auctions, and competitive sealed tenders," *J. Finance*, vol. 16, no. 1, pp. 8–37, Mar. 1961.

[21] E. Clarke, "Multipart pricing of public goods," *Public Choice*, vol. 11, no. 1, pp. 17–33, Fall 1971.

[22] T. Groves, "Incentives in teams," *Econometrica*, vol. 41, no. 4, pp. 617–631, Jul. 1973.

[23] UK Energy Research Centre, "A review of electricity unit cost estimates," Working paper, Dec. 2006.

Ming Zeng received the B.Eng. and M.Eng. degrees in communications engineering from the University of Electronic Science and Technology of China (UESTC), Chengdu, China. She is currently pursuing the Ph.D. degree in communication and information systems at UESTC.

Her research interests include resource allocation issue in vehicle-to-grid system and wireless communication networks, mechanism design based on auction theory, contract theory, and matching theory.

Supeng Leng (M'06) received the Ph.D. degree in wireless networks from Nanyang Technological University (NTU), Singapore, in 2005.

He is a Professor with the School of Communication and Information Engineering, University of Electronic Science and Technology of China (UESTC), Chengdu, China. He has been working as a Research Fellow with the Network Technology Research Center, NTU. He has authored over 100 research papers in recent years. His research interests include resource, spectrum, energy, routing and networking in broadband wireless access networks, vehicular networks, Internet of Things, next generation mobile networks, and smart grid.

Dr. Leng serves as an Organizing Committee Chair and Technical Program Committee Member for many international conferences, as well as a Reviewer for over 10 international research journals.

Sabita Maharjan (M'09) received the M.E. degree from the Tokyo Institute of Technology, Tokyo, Japan, in 2008, and the Ph.D. degree in networks and distributed systems from the University of Oslo, Oslo, Norway, in 2013.

She is currently a Postdoctoral Fellow with Simula Research Laboratory, Fornebu, Norway. Her research interests include wireless networks, network security, smart grid communications, cyber-physical systems, and machine-to-machine communications.

Stein Gjessing (M'91) received the Dr.Philos. degree in computer science from the University of Oslo, Oslo, Norway, in 1985.

He is a Professor of Computer Science with the Department of Informatics, University of Oslo, and an Adjunct Researcher with Simula Research Laboratory, Fornebu, Norway. His research interests include network resilience, network and transport protocols, cognitive radio networks, vehicular networks, and the smart grid.

Jianhua He (M'07–SM'12) received the B.Eng. and M.Eng. degrees in electronic engineering from the Huazhong University of Science and Technology (HUST), Wuhan, China, and the Ph.D. degree in communications engineering from Nanyang Technological University, Singapore, in 1995, 1998, and 2002, respectively.

He is a Lecturer with the School of Engineering and Applied Science, Aston University, Birmingham, U.K. He has authored or co-authored over 100 technical papers in major international journals and conferences. His research interests include protocol design, modeling, and optimization for wireless network (cellular networks, wireless LAN, WiMax, wireless PAN, and vehicle networks), software defined network (SDN), smart cities, and Internet of Things.